RESEARCH

Educational Mismatch and Performance of Workers with Higher Education in Mexico: A Gender-Differentiated Study

Rendimiento y desajuste educativo de los trabajadores con educación superior en México. Un estudio diferenciado por género

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Abstract

This study aims to analyze the relationship between educational mismatch and performance, differentiated by gender. The data for the analysis comes from the 2022 National Occupation and Employment Survey. The results were estimated using frequency statistics, Mincer's earnings equation, and the quantile regression model. Among the main findings, it is highlighted that educational mismatch affects 50% of workers with higher education, performance is better in jobs aligned with their training, and the wage gap persists both within educational levels and in jobs that match their educational background.

Keywords: Education analysis, wage gap, educational mismatch, academic performance.

JEL Codes: J3, J7, I21

Resumen

Este estudio tiene como objetivo analizar la relación entre el desajuste y el rendimiento educativo diferenciado por género. Los datos para el análisis proceden de la Encuesta Nacional de Ocupación y Empleo 2022. Los resultados se estimaron con estadísticas de frecuencia, la ecuación de ingresos de Mincer y el modelo de regresión cuántilica. De los principales resultados se destaca que el desajuste educativo afecta al 50% de los trabajadores con educación superior, el rendimiento es mejor en empleos ajustados a la formación y la brecha salarial persiste tanto dentro del nivel de estudios como en los trabajos ajustados a su formación educativa.

Palabras clave: Análisis de la educación; diferencia salarial, desajuste educativo, Rendimiento académico.

Códigos JEL: J3, J7, I21

1. Introduction

The importance of studying performance and educational mismatch contributes to understanding the conditions of the country's human capital. This knowledge is useful for building a fairer society with better and more equitable opportunities for the potential development of workers.

The well-established human capital theory, proposed by Becker (1994) and Mincer (1974), argues that higher levels of education lead to higher incomes. It would be expected that the impact of education on productivity would help reduce inequality in both employment and wages. This would be the case if the labor market offered jobs consistent with the qualifications of the workforce. However, in practice, the complexity of work environments and the diverse characteristics of worker––beyond their educational backgrounds––result in significant variations in employment conditions. Therefore, analyzing the type of work performed and measuring its alignment with the educational and training levels attained would provide deeper insights into academic performance.

The objective of this study is to analyze educational mismatch by gender and the returns to education among workers with higher education. Human capital theory states that income increases as the level of education rises. Based on this premise, we assume that income inequality decreases for university-educated workers. However, it is necessary to examine whether this potential reduction is due to an education mismatch within educational levels rather than inequality between different education levels. To achieve this objective, our analysis is based on the approaches of Budría and Moro (2006) and Rahona et al. (2013).

This study utilizes data from the second quarter of 2022 from the National Occupation and Employment Survey (ENOE). The dataset includes individuals who reported having higher education, being employed and earning and income. To estimate educational mismatch, we calculated the frequency of workers by occupation and the years of schooling required their positions. To measure the returns to education––considering access to full income distribution––we applied ordinary least squares (OLS) and quantile regression methos, separately for men and women.

The results indicate that, among workers with higher education, educational mismatch––specifically overeducation––affects approximately 50% of workers. Regarding academic performance, workers in occupations aligned with their educational level tend to achieve higher returns. Ultimately, in terms of income, workers employed in well-paying jobs––regardless of whether their education matches their position––still benefit from returns to education. However, when analyzing within educational levels, we find that wage disparities persist, regardless of gender or job-education alignment.

The study is structured as follows: it begins with the theoretical framework, followed by the methodological design, results, discussion, and concludes with final remarks.

2. Theoretical Framework

The term returns to education refers to the impact of an additional year of education on a worker's income. Mincer (1974) empirically demonstrated the human capital theory proposed by Becker. (1994), considering education as an investment. He developed the earnings equation, also known as Mincer's equation, which allows for the estimation of educational returns in terms of wages. Human capital theory supports studies on educational mismatch, as it considers both worker productivity and wages. Furthermore, worker's skills and qualifications may not always align with labor market demands. This inconsistency is supported by the skills mismatch theory developed by Jorgenson (1967), which argues that educational mismatch can lead to inefficient resource allocation, negatively affecting economic growth and productivity. Another theoretical approach is Thurow's (1975) job competition model, where workers compete for jobs, and education plays a crucial role as an indicator of worker capability. This model suggests that overeducation can become a permanent phenomenon. In a later study, Thurow (1981) stated that educational inequality is more pronounced in societies where access to education is determined by socioeconomic status. Individuals with greater financial and cultural resources are more likely to access high-quality education, which increases their chances of securing well-paid jobs.

In the labor market, educational mismatch is defined as the difference between the level of education attained by a worker and the level required for their job. Duncan and Hoffman (1981) categorized educational mismatch into three types: overeducated, undereducated, and well-matched workers. Similarly, Gontero and Novella (2021) considered mismatch from two perspectives: vertical and horizontal. The vertical mismatch refers to workers having a higher or lower level of education than required for their job, while the horizontal mismatch applies to university graduates working in occupation unrelated to their field of study.

The literatura presents various studies on educational mismatch. For instance, Moreno and Valenzuela (2021) analyzed returns to education and educational mismatch based on workers' cognitive and physical skills. Using a multinomial logistic choice model, they concluded that women's educational attainment places them in more complex occupations, with wages similar to those of men.

In another study, Valenzuela et al. (2018) examined educational mismatch in the Mexican labor market, considering intrinsic human capital heterogeneity (such as experience and skills). Their key findings indicate that overeducation is rewarded but at a lower rate than that of well-matched education.

McGuinness and Pouliakas (2017) analyzed the effects of overeducation on earnings using the Oaxaca decomposition technique to estimate wage penalties. Their findings suggest that differences in human capital and job skill requirements are significant factors in explaining wages. Overeducation mainly penalizes workers with higher education, while job characteristics and low-skill content contribute to the wage gap. These findings are consistent with Herranz and de la Iglesia (2015), who studied educational mismatch in Spain, comparing data from 2007 and 2012. Their analysis concluded that overeducation results in income penalties.

Flisi et al. (2017) argued that overeducation and overqualification are the primary causes of occupational mismatch. They pointed out that workers acquire knowledge that is not always transferred into the necessary skills for job performance.

Regarding returns to education and wage distribution in the context of educational mismatch, Rahona et al. (2013) found that returns for university-educated women are lower across the entire income distribution and that they experience greater wage penalties in case of educational mismatch.

Similarly, Budría and Moro (2006) analyzed returns to education and wage inequality using quantile regression across different population groups. Their findings suggest that for university-educated workers, inequality widens the gap between those in well-matched jobs and those in mismatched jobs, contributing to a broader income disparity.

These findings highlight the importance of analyzing whether educational alignment can help reduce labor inequality within Mexico's human capital.

3. Methodological Design

3. 1 Data and Descriptive Analysis

The data used in this study come from the National Occupation and Employment Survey (ENOE) for the second quarter of 2022. This survey is designed and conducted by the National Institute of Statistics and Geography (INEGI); an autonomous agency of the Mexican government responsible for managing national information.

The ENOE aims to provide data on the occupation and employment of the Economically Active Population (EAP). The survey includes information on the characteristics of the interviewees and the labor market, such as wages by occupation and hour, hours worked, education level, area of professional training, as well as the occupation within the job. The survey allows the disaggregation of data based on different points of interest. In this case, the analysis focuses on individuals who reported having higher education (bachelor's degree, master's degree, or doctorate), being employed, and receiving wages.

The sample size was 176,847 salaried individuals, from which those with higher education were selected. Therefore, the analysis sample include 49,175 individuals, which, when expanded, represents approximately 13.8 million people. Table 1 provides descriptive statistics for the variables, differentiated by gender.

From the descriptive statistics, we can highlight that the average age ranges from 17 to 75 years, with 53.37% of the population being male. The years of schooling for both men and women with higher education are 16, 18, and 20 years for a bachelor's degree, master's degree, and doctoral degree, respectively. It is noteworthy that men with higher education represent 25.29% of the total population, while women represent 31.63%. Regarding the degree distribution, men with a bachelor's degree represent 53.82%, with a master's degree 48.36%, and with a doctoral degree 52.25%. Hourly wages for men with higher education are 2.7% higher than those of women. Additionally, the work experience for men is higher, with an average of 16.71 years, while for women it is 14.36 years.

3.2 Wage Inequality

Wage inequality refers to the disparity in earnings between workers performing the same type of work.

Table 1. Descriptive Statistics of Variables for Salaried Individuals by Gender in Mexico

	MenW	omen
Gender	53.37	46.63
Education Level		
Bachelor's Degree	53.82	46.18
Master's Degree	48.36	51.64
Doctorate	52.254	7.75
Occupation Status		
Salaried Employees	51.364	8.64
Employers	74.962	5.04
Self-employed Workers	58.424	1.58
Unpaid Workers	38.74	61.26
Occupation by Years of Education		
Officials, Directors, and Managers	59.39	40.61
Professionals	50.91	49.09
Technicians	44.435	5.57
Auxiliary Workers in Administrative Activities	39.81	60.19
Salespeople, Sale Agents, and Sales Employees	50.99	49.01
Workers in Personal Services and Surveillance	52.134	7.87
Workers in Agricultural, Livestock, Forestry, Hunting, and Fishing Activities	90.91	9.09
Artisanal, Construction, and other Trades Workers	72.84	27.16
Industrial Machinery Operators, Assemblers, Drivers, and Transport Drivers	81.481	8.52
Workers in Elementary and Support Activities	61.27	38.73
Field of Study		
Education Sciences	28.397	1.61
Teaching Education	33.55	66.45
Arts	51.04	48.96
Humanities	47.07	52.93
Social Sciences and Behavioral Studies	31.25	68.75
Information Sciences	46.7	53.3
Law and Criminology	56.94	43.06
Business and Accounting	49.56	50.44
Administration and Management	49.4	50.6
Biological and Environmental Sciences 4	8.19	51.81
Physical, Chemical, and Earth Sciences	60.22	39.78
Mathematics and Statistics	57.75	42.25
Information and Communication Technology Innovation	74.52	25.48
Information and Communication Technology Innovation	68.16	31.84
Mechanical, Electrical, Electronic, Chemical Engineering, and Related Professions	82.191	7.81
Manufacturing and Processes	64.74	35.26
Architecture and Construction	79.18	20.82
Agronomy, Horticulture, Silviculture, and Fisheries	85.28	14.72
Veterinary	75.352	4.65
Medical Sciences	56.214	3.79
Nursing	20.3	79.7
Dentistry	41.85	58.15
Therapy, Rehabilitation, and Alternative Treatments	31.06	68.94
Health-Related Disciplines	43.53	56.47
Personal Services and Sports	50.73	49.27
Transportation Services	82.691	7.31
Occupational Safety	57.14	42.86
Security Services	75.682	4.32

Source: Own elaboration based on data from ENOE 2nd quarter 2022.

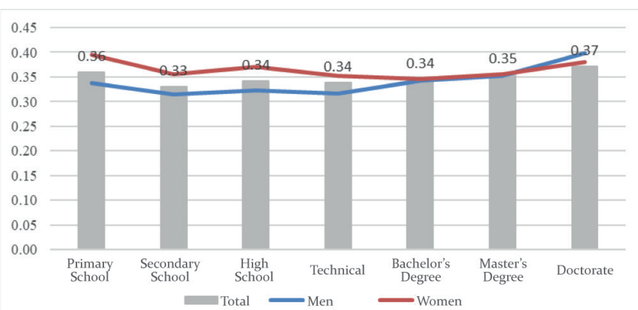
This inequality can stem from various factors such as gender, race, education, and others. It can manifest both in the wages received for similar work and in differences in total income due to occupational segregation, which is the concentration of different groups in distinct types of jobs that are remunerated differently.

According to Blanco (2014), inequality creates barriers for certain segments of society, leading to underutilization of the skills of some groups. This results in a loss of talent that could contribute to economic development.

This study aims to analyze educational mismatch by gender and the returns on education for workers with higher education, starting from the assumption that individuals' income increases as their level of education rises. This leads to the presumption that wage inequality would tend to decrease with higher educational attainment.

From Figure 1, constructed using data from the database used in this study, we observe that when differentiating by gender and education level, wage inequality increased for both men and women. However, gender inequality tended to decrease for workers with bachelor's degrees and master's degrees.

Figure 1. Income Inequality by Gender and Education Level of Workers in Mexico, 2022



Source: Own elaboration based on data from ENOE 2nd quarter 2022.

The reduction in income inequality may be attributed to inequality within the education level, rather than inequality between education levels. Below, an analysis is presented on educational mismatches for workers with higher education to determine whether the decrease in salary inequality is due to the education level.

3.3 Methodological Tools

The analysis to determine educational mismatch begins by constructing a frequency distribution from the education level variable and the occupation variable, based on the proposal by Valenzuela, Alonso, and Moreno (2018). It should be noted, as Bundría (2011) mentions, that for measuring educational match, the database should have sufficiently detailed information on education levels and occupations. The ENOE meets these two requirements.

The education level variable contains 9 levels of education; for this analysis, we select workers from the employed population who reported having a university degree.

The construction of the occupation variable is done using the variable referring to the main tasks or functions performed at work. This is presented in the database with 4 digits according to the National System of Occupation Classification (SINCO-2019). First, from the 4 digits, two variables are created: one with the first digit, forming a new variable called division, and the second with the first and second digits forming the main group variable. Then, the occupation variable is created from the nine groups of the division variable and those corresponding to 25-29 of the main group of variables. The school years are those required for the occupation, and the equivalence of education is built based on the number of years required in Mexico for each level of education. Table 2 present information regarding the school years and the education equivalencies required for each occupation.

Table 2. Required School Years and Educational Equivalencies by Occupation.

Occupation	School Years	Education Equivalency
Officials, Directors, and Managers	16	Higher Education
Professionals	16	Higher Education
Technicians	14	Technical Education
Administrative Support Workers	12	High School
Salespeople, Employees in Sales, and Sales Agents	12	High School
Personal Services and Security Workers	9	Secondary School
Agricultural, Livestock, Forestry, Hunting, and Fishing Workers	9	Secondary School
Craft Workers, Construction Workers, and other Trades	9	Secondary School
Industrial Machinery Operators, Assemblers, Drivers, and Transport Operators	9	Secondary School
Workers in Basic and Support Activities	6	Primary School

Source: Own elaboration based on data from ENOE 2nd quarter 2022

On the other hand, to estimate the returns to education, the Ordinary Least Squares (OLS) equation and the quantile regression equation, separating men and women, as proposed by Budría and Moro (2008), were used. The OLS estimation assumes that the impact of education on income is constant across the entire distribution, while quantile regression considers the effects of education on income is constant across the entire distribution, while quantile regression considers the effects of education or income at different quantiles of the distribution. By using both regression models, the impact of education on wage inequality between and within education levels can be evaluated. OLS estimates the average difference between educational levels, while quantile regression allows for the estimation of conditional income quantiles, to explain the entire distribution of income. Additionally, the quantile difference analysis identifies income differences between individuals within the same educational level.

The quantile regression model is expressed as:

$$lnIng\_x\_hrs_i = X_i\beta_\theta + e_{\theta i} \text{with} Quant_\theta(lnIng\_x\_hrs_i|X_i) = X_i\beta_\theta$$

where X_i is the vector of exogenous variables and β_θ is the vector of parameters, $Quant_\theta(lnIng\_x\_hrs_i|X_i)$ represents the i-th quantile of the logarithm of hourly income given X. The i-th quantile of regression, is defined as a solution to the problem, $0<\theta<1$, is defined as a solution to the problem.

From the general model of the Mincer income equation:

$$lnIng\_x\_hrs_i = \beta_0 + \beta_\theta schooling\ years_i + \beta_1 Experience + \beta_2 Experience^2 + e_i$$

Where:

$lnIng\_x\_hrs_i$ is the logarithm of hourly wage,

β_0 is the return on one year of investment in education,

schooling years is the years of schooling completed by the worker,

Experience is calculated as (age -6- schooling years),

Experience² (age-6-schooling years)².

The adjusted model is defined as:

$$lnIng\_x\_hrs_i = \alpha_\theta + \delta_{\theta 1} X_i + \beta_{\theta 1} educational\ level + e_{\theta i}$$

Where:

$lnIng\_x\_hrs_i$ is the logarithm of hourly wage,

X_i is a vector of explanatory variables that include those in the Mincer equation,

Educational level corresponds to the degree obtained by the worker, which can be bachelor's, master's, or doctorate,

The main objective of this work is to analyze the returns to education in workers with higher education, and the possible educational mismatch, with the purpose of verifying that income inequality by gender decreases as the level of education increases, and that this decrease is due to the mismatch within the level of education rather than inequality between education levels.

4. Results

4.1 Educational Mismatch

Based on the frequencies of workers according to occupation and the years of schooling required for the position, Figure 2 shows a graph of how the jobs performed correspond to the educational level attained by workers, differentiated by age, group, and gender. It is observed that workers with higher education, the younger ones and men, have less correspondence on average than women, with percentages of 47.64% and 53.47%, respectively.

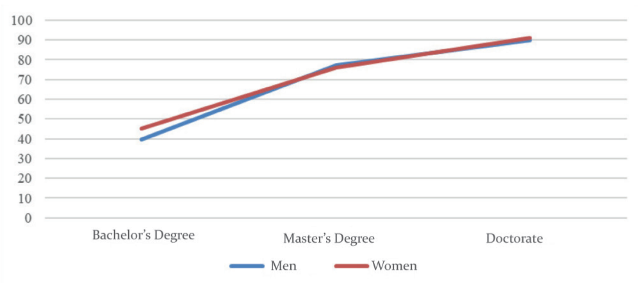
Figure 2. Educational mismatch frequencies of workers by age, group, and gender

Source: Own elaboration based on ENOE 2nd quarter 2022.

This result shows that the lack of correspondence between the level of education and the job performed, which can be reflected as overeducation, also known as educational mismatch, affects approximately 50% of workers, who hold a higher educational level than required for their job.

On the other hand, the correspondence in the position performed in relation to the academic degree, presented in Figure 3, shows that it is lower for men compared to women with bachelor's degree and doctoral degrees.

Figure 3. Educational mismatch frequencies of workers with higher education by gender.

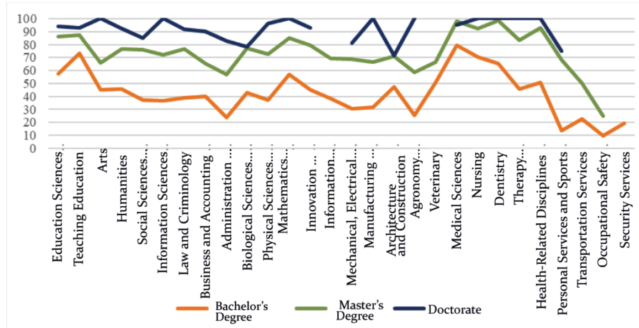


Source: Own elaboration based on data from ENOE 2nd quarter 2022.

An aspect worth delving into is the educational mismatch, differentiating by level of education and area of study. In the ENOE, the field of study is categorized into 10 broad areas, 28 specific fields, and 118 detailed fields, as described in the CMPE (2016). For this study, the 28 specific fields are used. Figure 4 presents the graphs for three levels of higher education and by area of professional training. It is clearly observed that as the level of education increases, the match improves, with averages of 42.29%, 73.60%, and 92.15% corresponding to the bachelor's degree, master's degree, and doctorate, respectively. Another point to highlight is that, for the bachelor's degree, the fields with a match greater than 75% are those in medical sciences, while the fields with the lowest match, below 25%, are those in administration and management, as well as in work security services. For the master's level, the fields with the best match are those related to health sciences, followed by education, natural sciences, mathematics and statistics, and humanities, social sciences, and law; the worst-adjusted fields are in work security.

Regarding workers with doctoral studies, the match is better in all areas, with only two fields below 75%, namely personal services and sports, and architecture and construction.

Figure 4. Frequencies of educational mismatch, by level of education and field of study.



Source: Own elaboration based on data from ENOE 2nd quarter 2022. Note: For the doctoral level, the line presents empty spaces, since the analyzed sample did not contain information on individuals with a doctorate in certain fields of study.

4.2 Returns to Education

This section presents the results of the education return models and quantile regression models, separated by gender, while also considering the alignment of education to job positions or, in some cases, overeducation. Based on the model estimates, the analysis first examines the return on education, represented by the coefficient of years of schooling, and then evaluates the income received by workers, represented by the model constants.

Table 3 summarizes the returns to education. It shows that returns are higher for workers whose education aligns better with their job positions. The rates of return to education were 5.6% for men and 6.4% for women, demonstrating that having an education level aligned with a job position is more profitable for women. On the other hand, for men, returns are higher for those with good incomes, as shown in the 0.75 and 0.90 quantiles. However, in no case do they exceed the returns for women, whose returns increase as the quantiles rise. This means that workers in well-paid jobs obtain significantly higher returns from a university education than those in low-paid jobs. These results suggest that for workers with higher education, returns increase as they move up in the income distribution, meaning that workers in jobs well-matched to their education tend to achieve higher returns.

Table 4 summarizes the values of β_0 which correspond to the constants of the equations and represent the hourly wage values in natural logarithms when workers have zero years of experience. To determine the hourly wages with zero years of experience, the antilogarithm is applied to the constant values. The results for the Mincer regression models indicate that these values are $20.57 and $16.88 for men, and, $17.25 and $16.72 for women, for adjusted education and overeducation, respectively. Moreover, educational mismatch penalizes women more in the lower quantiles. At quantile 0.10, the penalty for men is 27%, whereas for women, it is 33%.

To compare effects at different points in the distribution, quantile difference regression analyses were conducted for both men and women. The results show that differences between quantiles 0.75 and 0.25 are statistically significant at the 5% level. Thus, when analyzing income changes across quantiles, wages increase across the entire distribution, though only slightly in the first two quantiles. The most notable wage increase occurs from quantile 0.50 onward, especially for men. This suggests that workers whose education aligns with their job positions tend to have better wages, particularly in high-paying jobs. For women, a similar trend is observed, although wages remain lower overall.

On the other hand, for individuals working in jobs requiring lower educational qualifications than they possess, wages also show a tendency to increase within the distribution. However, the income penalty for overeducation is more pronounced in quantiles below 0.50. After this point, wages become more similar between workers in adjusted occupations and those who are overeducated.

This result suggests that workers employed in well-paying jobs, regardless of whether their education level aligns with the position, still experience returns on their education.

Table 3. Returns to Education for Workers with Higher Education by Gender, 2022

MEN	Q(.10)	Q(.25)	Q(.50)	Q(.75)	Q(.90)	OLS
Adjusted Education	0.047	0.050	0.049	0.067	0.063	0.056
Standard Error	0.003	0.000	0.001	0.010	0.012	0.005
Overeducation	0.061	0.068	0.056	0.044	0.053	0.055
Standard Error	0.007	0.005	0.000	0.007	0.008	0.003
WOMEN						
Adjusted Education	0.047	0.051	0.054	0.073	0.079	0.064
Standard Error	0.004	0.000	0.000	0.009	0.010	0.005
Overeducation	0.064	0.067	0.058	0.055	0.055	0.052
Standard Error	0.008	0.006	0.000	0.008	0.010	0.004

*All values are significant at the 5% level.
Source: Own elaboration based on Mincer regression and quantile regression outputs.

Table 4. Coefficient of Hourly Wages in Natural Logarithms by Gender in Mexico, 2022

MEN	Q(.10)	Q(.25)	Q(.50)	Q(.75)	Q(.90)	OLS
Adjusted Education	2.819321	2.861771	2.899587	3.128597	3.648395	3.023606
Standard Error	0.057	0.003	0.012	0.173	0.204	0.077
Overeducation	2.221718	2.462117	2.760303	3.179624	3.41042	2.826229
Standard Error	0.113	0.081	0.002	0.105	0.126	0.051
WOMEN						
Adjusted Education	2.766278	2.838687	2.804158	2.995934	3.260728	2.847678
Standard Error	0.070	0.001	0.003	0.150	0.171	0.076
Overeducation	2.08532	2.337173	2.727969	2.940501	3.647858	2.816538
Standard Error	0.122	2.337	0.003	0.120	0.160	0.063

*All values are significant at the 5% level.
Source: Own elaboration based on Mincer regression and quantile regression outputs.

5. Discussion and Conclusions

The main objective of this study is to analyze the returns to education and the possible educational mismatch among workers with higher education. The aim is to verify whether gender income inequality decreases as the level of education increases and whether this reduction is due more to the mismatch within the same educational level rather than to inequality between different levels of education.

To achieve this objective, the first step was to confirm that gender inequality tends to decrease as workers' level of schooling increases. It was found that for those with undergraduate and master's degrees, inequality is the same between men and women. This result supports human capital theory, confirming that education yields better returns for women. Consequently, the first hypothesis is validated, affirming that gender wage inequality decreases as workers' level of schooling increases. However, income inequality itself tends to be greater, leading to the rejection of the second hypothesis, meaning that income inequality does not decrease as the level of education rises.

Regarding educational mismatch, it was observed that among workers with higher education, younger individuals in general and men exhibit a greater mismatch than women, at 47.64% and 53.47%, respectively. These findings are consistent with those reported by Valenzuela et al. (2018). In this sense, educational mismatch, when analyzed by educational attainment, indicates that as the level of education increases, the alignment improves. However, the issue persists, as it was identified that approximately 50% of workers are overeducated, holding a higher educational level than required for their job positions. This result aligns with Duncan and Hoffman's (1981) findings, which state that more than 40% of U.S. workers reported having more education than their jobs required. Similarly, Rahona et al. (2013) found that 47% of women and 41.1% of men have an educational level that matches their job requirements, meaning that a high percentage hold positions that do not align with their qualifications.

Regarding returns to education, it was found that for workers with higher education, returns are higher as they move into higher quantiles. This means that workers whose occupations align with their education tend to achieve higher returns. This finding validates the third hypothesis, which states that educational mismatch influences income inequality. In other words, workers whose education matches their job positions tend to earn more than those in mismatched jobs. A similar trend is observed for women, although their income levels remain lower, confirming the fourth hypothesis that educational alignment influences income inequality depending on the worker's gender.

Furthermore, we found that educational mismatch leads to an income penalty in the lower quantiles, ranging from 27% for men to 33% for women. In this regard, Budría and Moro (2008) found that among university-educated workers, inequality creates a gap between those in jobs that align with their education and those in mismatched positions, further widening income inequality. McGuinness and Pouliakas (2017) add that job characteristics and the low skill content of some positions explain the wage gap. They also highlight that overeducation disproportionately penalizes workers with higher education.

Similarly, Rahona et al. (2013) argue that women generally experience greater wage penalties due to educational mismatch and that their returns to education are systematically lower. However, when analyzing university graduates, they conclude that wage discrimination appears to be less pronounced among highly qualified women.

Based on these findings, we can assert that the effects of inequality vary depending on whether job characteristics align well with the worker's educational background. When analyzing wage inequality within higher education levels, it is evident that inequality exists and depends on educational alignment and the worker's income position within the distribution. Finally, it is confirmed that income inequality decreases as education levels rise. However, when analyzed within the same level of education, inequality persists regardless of gender or job alignment.

To further explore educational mismatch, this research will continue using more robust data analysis techniques. Additionally, given that we have access to the full salary distribution, we will analyze the so-called "glass ceiling" phenomenon in the labor market. This concept refers to the existence of barriers or obstacles that prevent women from accessing leadership or executive positions (Camarena & Saavedra, 2018).

References

Becker, G. (1994). Human Capital: A theoretical and Empirical Analysis, with Special Reference to Education (3rd ed.). University of Chicago Press.

Blanco, E. (2014). La desigualdad social en el nivel medio superior de educación de la Ciudad de México. Papeles de Población, 20(80), 249-280.

Budría, S., & Moro A. (2008). Education, educational mismatch and wage inequality: Evidence for Spain. Economics of Education Review, 27, 332341.

Camarena Adame, M. E., & Saavedra García, M. L. (2018). El techo de cristal en México. La ventana. Revista de estudios de género, 5(47), 312-347. http://www.scielo.org.mx/scielo.php?script=sci_arttext&pid=S1405-94362018000100312&lng=es&tlng=es

Duncan, G., & Hoffman, S. (1981). The incidence and wage effects of overeducation. Economics of Education Review, 1, 75-86. https://doi.org/10.1016/0272-7757(81)90028-5

Flisi, S., Goglio, V., Meroni, E., Rodrigues, M., & Vera Toscano, E. (2017). Medición del desajuste ocupacional: sobreeducación y exceso de habilidades en Europa: evidencia de PIAAC. Social Indicators Research, 131, 1211-1249. https://doi.org/10.1007/s11205-016-1292-7

Gontero, S., & Novella, R. (2021). El futuro del trabajo y los desajustes de habilidades en América Latina. Santiago de Chile, Comisión Económica para América Latina y el Caribe. https://repositorio.cepal.org/server/api/core/bitstreams/6f8ee77b-714f-4ad7-8100-7253082dd1d0/content

Herranz, F., & De la Iglesia, M. (2015). El desajuste educativo en España. Una comparativa entre 2007 y 2012 Chapter 29. En Investigaciones de Economía de la Educación (Vol. 10, pp. 573-596). Asociación de Economía de la Educación.

Instituto Nacional de Estadística y Geografía INEGI. (2019). Sistema Nacional de Ocupaciones. SINCO 2019. México. https://www.inegi.org.mx/app/biblioteca/ficha.html?upc=702825198411

Jorgenson, D. W. (1967). Investment, Employment, and Income Distribution in a Growing Economy. Yale University Press.

McGuinness, S., & Pouliakas, K. (2017). Deconstructing theories of overeducation in Europe: A wage decomposition approach. In S. W. Polachek et al. (Eds.), Skill Mismatch in Labor Markets (pp. 81-127). Emerald Publishing Limited.

Mincer, J. (1974). Schooling, Experience, and Earnings. New York: Columbia University Press, National Bureau of Economics.

Moreno, J., & Valenzuela, N. (2021). Asignación y Desajuste en el Mercado Laboral de México: El rol de las habilidades bajo sesgos de selección múltiple y muestras complejas. Análisis Económico, 36(93), 5–26. https://doi.org/10.24275/uam/azc/dcsh/ae/2021v36n93/Moreno

Rahona, M., Murillo, I., & Salinas, M. (2013). Rendimiento educativo y diferencial salarial por género en España. Revista del Ministerio de Empleo y Seguridad Social: Revista del Ministerio de Trabajo, Migraciones y Seguridad Social, (106), 111-126.

Thurow, L. (1975). Generating Inequality. Nueva York: Basic Books.

Thurow, L. (1981). The Zero-Sum Society. Penguin Books.

Valenzuela, N., Alonso , R., & Moreno, J. (2018). Desajuste educativo en el mercado laboral en México y su efecto en los salarios. Revista de Economía, 35(91), 65-92. https://doi.org/10.33937/reveco.2018.96