Job Quality in Huila: Exploring Its Determinants

Dagoberto Valencia Ortiz[1], Juan David Pulido Vargas[2], Libardo Trujillo Torres[3], José Alejandro Vera Calderón[4], Roberto Adolfo Díaz Díaz[5]

[1] Master's in Economics. Professor at UNAD, Email: dagoberto.valencia@unad.edu.co.
[2] Master's in Economics. Professor at UNAD, Email: juan.pulido@unad.edu.co.
[3]Master's in Economics, Master's in Public Procurement. Professor at UNAD, Email: libardo.trujillo@unad.edu.co.
[4]Master's in Administration. Professor at the University of Tolima, Email: javerac@ut.edu.co.
[5]Master's in Economics. Professor at the University of Tolima, Email: rdiaz@ut.edu.co.

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ABSTRACT
The document addresses the quality of employment in the department of Huila, Colombia, aiming to analyze the factors that determine the working conditions of workers in this region. The study highlights the high rate of informality, which negatively affects the quality of employment and is especially prevalent in Neiva, the department's capital. Utilizing data from the 2023 Gran Encuesta Integrada de Hogares (GEIH), the analysis is based on statistical tools such as Principal Component Analysis (PCA) and an ordered probit model to create an index that measures the quality of employment. The study considers various variables, such as the type of contract, salary, paid vacations, social security affiliation, and job stability. The results show that educational levels, access to labor benefits, and the type of contract play crucial roles in determining the quality of employment. It also becomes evident that academic policies and employment formalization are fundamental for improving working conditions in the department. The analysis concludes that the quality of employment in Huila is low, with a maximum score of 65 points on a scale of 100, indicating medium-low quality jobs. Efforts should focus on promoting education, generating formal employment, and implementing public policies to improve the department's employment quality.

Keywords: job quality, Huila, principal component analysis, ordered probit, labor market

INTRODUCTION
Job quality refers to the working conditions that determine the well-being of employees within an organization. It encompasses various aspects such as job stability, working conditions, economic remuneration, social security, opportunities for professional development (UNDP, 2021), work-life balance, and labor rights (OECD, 2020).
This concept is fundamental when addressing economic development and social equity for the general welfare of the population. Studies like that of Stiglitz (2019) have demonstrated that countries with higher-quality jobs tend to have lower levels of inequality and poverty. This supports both sustainable and equitable economic development, which in the long term can lead to greater social cohesion and political stability.
Nationally, the informal employment rate in Colombia was 58.8% in 2021, with this percentage being higher in rural regions like Huila. This reflects relatively lower job quality compared to more urbanized areas in Colombia (DANE, 2022). Focusing on this region, there are economic and social particularities that could influence the working conditions of the population, such as agricultural activity, low industrialization, geographical dispersion, and a high rate of informality.
In this context, the present study aims to analyze the determinants of job quality in Huila through a principal component analysis, using the Gran Encuesta Integrada de Hogares to create an index that measures and compares job quality in this region of the country. The goal is to understand the factors affecting this phenomenon. Additionally, an ordered probit model will be developed to strengthen the analysis.

Job Quality
Job quality is a concept whose definitions can partially vary depending on the author. However, they converge on a specific point: the individual's working conditions should allow them to manage a balance between their personal and professional life. For example, Pineda and Acosta (2011) define job quality (or

work quality) as "all those dimensions related to people's work that allow them to develop their capacities, expand their life options, and obtain greater degrees of freedom."

On the other hand, Correa, Navarro, and Ramos (2009, p. 4) describe a series of elements called determinants of job quality, among which are adaptability, working time, safety and hygiene, and naturally, remuneration, among others. These factors are essential when seeking the balance between an individual's professional and personal life. For instance, if someone has to stay longer than established at work, they are reducing the degrees of freedom mentioned earlier, even if the aspect of remuneration tries to compensate for it.

Thus, these definitions seek to emphasize that the concept of job quality encompasses aspects beyond the job and the workplace itself, as it is also a key factor in an individual's quality of life. Job quality practically becomes a necessity, given that it is well known that it can determine how a person behaves in society due to factors like stress generated by the nature of the job, time sacrificed to work without being able to engage in other activities, etc.

To conclude this section, it is necessary to highlight that both subjective and objective factors may exist when finding a definition that adapts to the concept of job quality. However, it is important to remember that the context of a situation is fundamental for addressing this concept, and without it, the process of defining job quality in a specific time and place cannot begin.

LITERATURE REVIEW

Ferrada and Arcos (2019) analyze the working conditions in three regions of southern Chile (Los Lagos, Aysén, and Magallanes) between 1990 and 2011 using synthetic indicators that consider dimensions such as income, social security, working hours, and employment contracts. These were primarily selected based on the work by Farné (2003) and McClure (2008). The authors suggest constructing a Job Quality Index isolated from subjectivity in weightings, allowing the data's inherent behavior to determine them. The study concludes that conditions vary depending on the region; for example, the Magallanes region presents a better Job Quality Index (JQI), while Los Lagos has the lowest rating. Ferrada and Arcos also assert that these differences stem from the distinct economic orientations of each territory and that the indicators did not show substantial improvements over the studied period.

Furthermore, Davcheva et al. (2020) explore the importance of various traditional indicators that could explain job quality, including intrinsic job characteristics like the type of contract, employment relationship, and schedule predictability—understood as information that allows workers to know their work schedules in advance to manage their time outside company activities. The study also analyzes educational differences and preferences. The sample comprises 562 Spanish employees, and the selected statistical method focuses on hierarchical multiple regression analysis to examine correlations between variables, analyzed in groups to capture their interactions. Gender is used as a control variable. The study concludes that all indicators, except schedule predictability, are equally significant regarding perceived job quality. Gender also showed variations in the interaction between current and preferred employment relationships; for women, preferences for full-time jobs increased the perceived job quality.

Similarly, the study by Deguihem et al. (2020) explores the notion of job quality and how it can be measured in Bogotá, Colombia. To develop a multidimensional job quality indicator, the authors used data from the 2013 GEIH survey and applied Multiple Correspondence Analysis. The research found that job quality is not solely linked to informal or independent workers; social factors like social class and educational level also determined job quality in Bogotá. The study emphasizes the importance of considering multiple dimensions when measuring job quality and understanding the region's labor market.

Moreover, Cascales (2021) proposes a new model for estimating job quality based on intrinsic job characteristics in European countries. These job attributes relate to the workers' ability to apply their ideas at work, make important decisions, relationships with immediate supervisors and colleagues, perceptions about their job, and deadlines for assigned tasks. The data come from the 2015 European Working Conditions Survey covering 27 countries. For index construction, Cascales uses Exploratory Factor Analysis (EFA), a tool that describes the interdependence among a set of variables by calculating latent variables called factors, which can explain the studied phenomenon in fewer dimensions. The contribution of this research lies in developing a new approach to studying job quality by considering factors beyond the conventional ones.

Additionally, Montoya and Jurado (2021) present an alternative measure of the aggregate employment level, both formal and informal, for Colombia over 12 years from 2007 to 2019. The data are sourced from the Gran Encuesta Integrada de Hogares, conducted by the National Administrative Department of Statistics (DANE). The sample includes individuals of both genders aged between 15 and 64 years, with at least one year of education, who report the economic sector in which they perform their activities, and consider labor informality. The methodology is based on the method of Ho and Jorgenson (1999), supported by earlier work by Gollop in 1987. This methodology accounts for job quality amidst high degrees of heterogeneity in this production factor. The study's results show that educational level positively impacts job quality, differences exist in job quality between formal and informal employment, and reducing informality positively affects job quality.

In the same vein, the study by Dolcet et al. (2022) examines the Job Quality Index in the tourism sector of developing countries, specifically in Uruguay, by constructing a Job Quality Index (QoE) using Principal Component Analysis—a statistical technique that reduces dimensionality by summarizing the information from independent variables into smaller sets, facilitating interpretation. The variables include employment, income, hours worked, job security, and social security. The authors selected this economic sector due to its characteristics of low job quality. The findings reveal a gender gap in job quality disadvantaging women—a difference not observed in other economic sectors like commerce. There is also greater dispersion in the distribution of job quality affecting less-skilled labor and, in some cases, skilled labor. Within the sector, hotels, travel agencies, and restaurants show the best job quality indices.

Furthermore, Fernández et al. (2022) study the labor market situation in Latin America compared to the United States by examining job quality and income of salaried and non-salaried workers in 13 Latin American countries. They use microdata from household surveys for each country, focusing on private-sector workers in urban areas. The analysis is conducted on a pooled dataset, and the authors disaggregate information by company size, using data on income, access to social security, occupational profiles, and informality. They group countries with similar labor market characteristics through clustering methods to simplify the analysis. The research suggests that gaps between Latin American labor markets and the U.S. persist, wages remain low even for qualified human capital, and productivity lags worsen working conditions.

Moreover, Picatoste, Novo, and Membiela (2022) revisit the conceptualization of job quality and propose a synthetic indicator with different components based on the OECD's Job Quality Index to estimate this metric for young workers between 2005 and 2015. The variables include income quality, labor market security (understood as job stability), quality of the work environment, and demographic data. The authors conducted comparative analyses and hypothesis tests such as Levene's test, and t-tests for equality of means, p-values, and confidence intervals. They found significant differences indicating that young people have lower job quality compared to other age groups and perceive lower income quality.

Similarly, Basantes (2022) addresses the importance of measuring job quality in micro and small enterprises in Ecuador. The author aims to establish an index structured by multiple determinants, such as type of contract, hours worked, social security, and income level, based on the index developed by Farné (2003). After conducting regressions with the mentioned variables and a set of control variables including economic activity sector, occupational groups, and occupational category, Basantes concludes that the type of contract, hours worked, social security, and income level play a fundamental role in the job quality of micro and small enterprises in Ecuador.

Additionally, Aramayo, Pereira, and Iraizos (2023) propose a logit regression model to determine factors associated with the Multidimensional Job Quality Index in Bolivia, using data from Household Surveys from 2011 to 2021. The authors analyze parameters such as labor income, type of contract, job tenure, health insurance affiliation, pension affiliation, age, education, gender, economic sector, company size, department, and working hours. The estimates show that having a permanent work contract decreases the probability of low-quality employment by 40.9%. Conversely, not contributing to health insurance and pensions increases the likelihood of low-quality employment by 20.9%. Regarding gender, being a woman increases the probability of having poor-quality employment by 4.7% between 2011 and 2019, but this probability decreases in the following two years.

Finally, González et al. (2023) focus their study on assembly plants and examine job quality in original equipment manufacturing automotive companies in Mexico. They analyze wage scales, labor benefits, and the influence of unions across different companies. The study acknowledges that evaluating the evolution of job quality over time requires longitudinal data. For this research, a database was created using various sources, and the Kruskal-Wallis test was employed to identify significant associations between job quality and the period when companies were established. The limitation of available information is recognized, representing a snapshot of the situation in that specific year, highlighting the need for longitudinal data. The results indicate that wages and contractual social benefits are lower in companies with fewer years of establishment in the country.

METHODOLOGY

Various methodological tools have been used over time to estimate job quality. However, one of the most common tools is synthetic or composite indices, which allow for dimensionality reduction when

considering a large number of variables. In this document, we propose evaluating the phenomenon in question through Principal Component Analysis (PCA) and an ordered probit model, which allows for analyzing the determinants of job quality in the Department of Huila for the third quarter of 2023.
In this regard, Zhe (2014) states that Principal Component Analysis is a statistical technique used to transform a set of correlated variables into a set of linearly uncorrelated variables called principal components. PCA seeks to find the directions in which the data have the greatest variance, allowing for dimensionality reduction by eliminating redundancy and capturing the most relevant information in a dataset.
According to Zhe (2014), PCA is the method by which data can be made easily multidimensional by transforming a set of correlated variables into a new set of uncorrelated linear combinations, known as principal components. Essentially, PCA is performed to capture as much variance as possible in the data using fewer components. PCA finds those directions in which the data vary most and allows for reducing the number of dimensions without significant loss of information. The first principal component describes the maximum amount of variability in the data, and each successive component describes the maximum amount of remaining variability not explained by the previous components.
Mathematically, PCA can be represented as:

$$P_i = b_{i1}X_1 + b_{i2}X_2 + \ldots + b_{ik}X_k \quad (1)$$

Where Pi is the PC, bik is the weight (some call it the regression coefficient) for the variable Xk. It is often convenient for all variables, Xk, to be standardized to zero mean and unit standard deviation.
Where bik is the weight used to calculate the principal components. The covariance or correlation matrix is utilized to calculate these weights bik. This matrix produces an orthogonal basis of eigenvectors, each of which has a non-negative eigenvalue since the matrix is symmetric positive definite. These eigenvectors correspond to the PCs when multiplied by the original inputs, as shown in Equation 1, and the eigenvalues are proportional to the variances explained by the PCs (Zhe, 2014).
According to Lever et al. (2017), in PCA analysis, the principal components (PCs) are selected to maximize the variance of the projected points while ensuring that each PC is uncorrelated with the previous PCs. Abdi and Williams (2010) point out that when conducting multivariate analysis, it's important to use the appropriate technique for handling the data. Therefore, principal component analysis is employed, which is based on linear algebra. This method is used to analyze data tables where observations are generally described by a large number of intercorrelated quantitative dependent variables, aiming to extract the most important information from the tables and represent it in new orthogonal variables called "principal components."
This multivariate statistical technique focuses on studying the structure of observations and simplifying the description of variables by representing them as points on maps. It facilitates the identification of trends, patterns, and outliers in a much more efficient manner than would be possible without using principal component analysis (Richardson, 1975).

DATA AND RESULTS

To perform the econometric estimations, data were taken from the 2023 Gran Encuesta Integrada de Hogares (GEIH) for the months of June, July, and August, using the modules on general characteristics, health, and education social security, and employed individuals for the Department of Huila, with an initial sample of 9,705 observations.
The variables used for constructing the index are based on the literature review and the consensus among different authors on this topic (see Mora and Rojas, 2014; Mora et al., 2016). The following table describes the variables used for constructing the Job Quality Index proposed in this document.

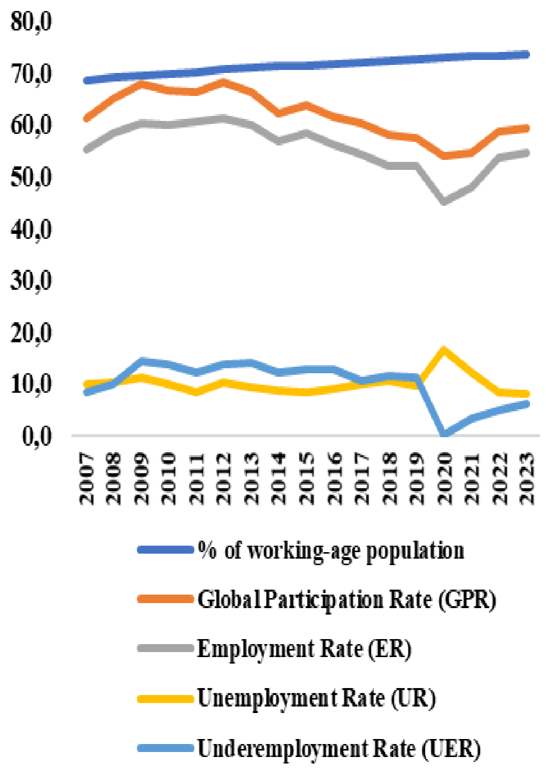
Table 1. Variables Used for Constructing the Job Quality Index

Variable	Description
Type of Contract	The employment contract is either indefinite term or fixed term
PaidVacations	For your current contract, do you receive or are you entitled to paid vacations?
Christmas Bonus	For your current contract, do you receive or are you entitled to a Christmas bonus?
Right to SeverancePay	For your current contract, do you receive or are you entitled to severance pay?
HourlyWage	Hourly wage in Colombian pesos

Affiliated to Health and Pension System	Individuals affiliated with the health and pension system
Job Stability	Do you consider your current job or employment to be stable?
Compatibility of Work Schedule and Family	Are your working hours compatible with your family responsibilities?
UnionMembership	Are you affiliated with or part of a guild or labor union association?

Source: Prepared by the authors

The Department of Huila presents stable indicators in terms of the labor market. For the year 2023, the percentage of the working-age population stood at 73.6%, which is 3.9 percentage points below the national average. Regarding the overall participation rate, the department recorded a percentage of 59.2 and an employment rate of 54.4. Notably, in 2023, the department showed an unemployment rate lower than the national average; for Huila, it was 8.1% compared to the national average of 10.2%, representing a difference of 2.1 percentage points. Finally, it is important to mention that according to information presented by the National Administrative Department of Statistics (DANE), for the quarter of October to December 2023 in the department's capital, 53.1% of the total employed population belonged to the informal sector..



Source: Own elaboration based on GEIH

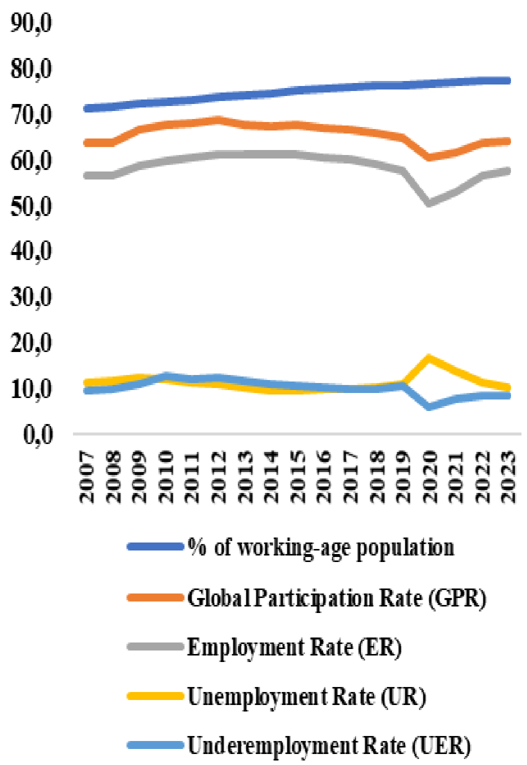


Figure 1. Labor Market Indicators of Huila

Figure 2. Labor Market Indicators of Colombia

Similarly, it is necessary to analyze the informality rate in the territory. Figure 3 shows the informality present in Neiva, the capital of the Department of Huila. The graph evidences a high rate of informality, reaching quarters where it exceeds 50%. This could be inferred, as has been stated in other articles, as a determinant that negatively affects job quality

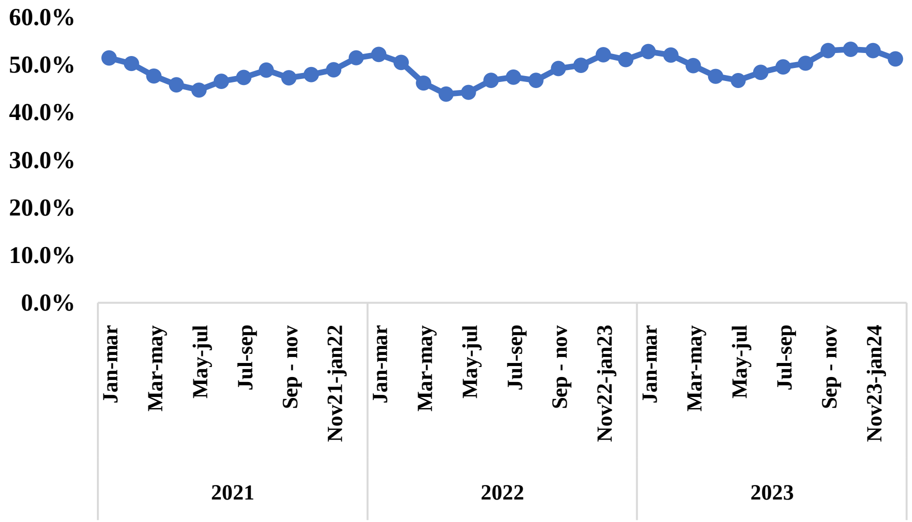


Figure 3. Informality Rate in Neiva 2021 - 2023
Source: Own elaboration based on GEIH

Results Of Principal Component Analysis

Principal Component Analysis was conducted following the steps suggested by the methodology, namely the correlation matrix and scree plots to select the number of factors, as these allow for explaining the greatest amount of variance, above 60%. The factors were then extracted, a factor analysis was performed, and the number of factors that optimize the analysis was determined using Kaiser's criterion, selecting components with eigenvalues greater than or equal to one. Subsequently, the factors were rotated, computed, and normalized. The results of the index indicate that the maximum score obtained is 65 out of 100.

It is important to note that multiple variables had incomplete information, and a value of one was assigned on the job quality weighting scale. Additionally, the scale used in this analysis has been modified based on the obtained results. The scale assigns a value of 1 to a job quality index that is less than or equal to 40 points, between 40.1 and 50 points to medium job quality, and values above 50.1 points to high job quality. This scale differs from the one used by Farné (2003), which considers index scores below 60 points as indicative of low job quality. The results obtained in the index for the department may be related to the high rates of informality present in the territory, as evidenced in Figure 3.

Results Of The Ordered Probit Model

According to Guillermo & Castañeda (2021), the ordered probit model allows for explaining the probability of an event based on a set of individual-specific characteristics and other exogenous variables, in this case related to working conditions. Furthermore, estimating the model's marginal effects enables the analysis of the impact of work condition variables and individual characteristics on the likelihood of being in a quality job or not.

Peón & Valencia (2020) point out that when working with data, it is often necessary to perform certain adjustments, such as deseasonalization or, in this case, assuming that the errors are normally distributed, especially when involving ordered outcomes. To address this, the ordered probit model is employed. The purpose of applying this type of model, based on certain assumptions, is to achieve estimation through the maximum likelihood method. However, it may fail to capture important aspects of the error distribution (Salisu, 2016).

Moreover, using this type of model involves taking the observed variable and defining the observable variable, which is a categorical variable that can take three values or categories. This distinguishes the ordered probit model from the standard probit model, which not only handles binary variables but also allows the observed variable to be analyzed based on three categories (Johnston et al., 2019).

Subsequently, the results of the ordered probit model are presented.

Table 3. Marginal Effects of the Ordered Probit Model

		Delta-method				
	dy/dx	Std. Err.	z	P>z	[95% Conf.	Interval]
sex						

_predict						
1	-.0162657	.0143271	-1.14	0.256	-.0443463	.0118148
2	.0130706	.0115136	1.14	0.256	-.0094957	.0356369
3	.0031951	.0028805	1.11	0.267	-.0024506	.0088409
age						
_predict						
1	-.0039332	.0005445	-7.22	0.000	-.0050005	-.0028659
2	.0031606	.0004429	7.14	0.000	.0022926	.0040286
3	.0007726	.0001807	4.28	0.000	.0004185	.0011267
vs						
_predict						
1	-.1230389	.0395531	-3.11	0.002	-.2005616	-.0455162
2	.0988701	.0320016	3.09	0.002	.0361481	.1615921
3	.0241688	.0088784	2.72	0.006	.0067674	.0415701
salary premium						
_predict						
1	-.020204	.0263398	-0.77	0.443	-.071829	.0314211
2	.0162353	.0211827	0.77	0.443	-.0252821	.0577527
3	.0039687	.0052138	0.76	0.447	-.0062502	.0141877
layoff						
_predict						
1	-.1094554	.0392155	-2.79	0.005	-.1863163	-.0325945
2	.0879548	.0314781	2.79	0.005	.0262589	.1496508
3	.0215005	.0087844	2.45	0.014	.0042835	.0387176
pension						
_predict						
1	.0381145	.0124136	3.07	0.002	.0137843	.0624447
2	-.0306276	.0100573	-3.05	0.002	-.0503395	-.0109157
3	-.0074869	.0027644	-2.71	0.007	-.0129049	-.0020689
asi						
_predict						
1	-.0058888	.0173804	-0.34	0.735	-.0399539	.0281762
2	.0048868	.0144228	0.34	0.735	-.0233814	.033155
3	.001002	.0029642	0.34	0.735	-.0048077	.0068118
el						
_predict						
1	-.0174063	.0089644	-1.94	0.052	-.0349762	.0001636
2	.0144444	.0074492	1.94	0.052	-.0001557	.0290446
3	.0029619	.0016235	1.82	0.068	-.0002202	.0061439
cjlf						
_predict						
1	.0056551	.0111701	0.51	0.613	-.0162378	.0275481
2	-.0046929	.0092759	-0.51	0.613	-.0228733	.0134875
3	-.0009623	.0019036	-0.51	0.613	-.0046933	.0027688
prm						

_predict						
1	.021011	.0222833	0.94	0.346	-.0226635	.0646856
2	-.0174358	.0185	-0.94	0.346	-.0536951	.0188235
3	-.0035752	.0038483	-0.93	0.353	-.0111178	.0039673
med						
_predict						
1	-.0480555	.0173016	-2.78	0.005	-.0819661	-.0141449
2	.0398784	.014393	2.77	0.006	.0116685	.0680882
3	.0081771	.0033243	2.46	0.014	.0016615	.0146927
tt						
_predict						
1	-.0622607	.0194811	-3.20	0.001	-.1004429	-.0240784
2	.0516664	.0162106	3.19	0.001	.0198943	.0834386
3	.0105943	.0038789	2.73	0.006	.0029917	.0181968
eds						
_predict						
1	-.0853516	.0177082	-4.82	0.000	-.120059	-.0506441
2	.0708282	.0147627	4.80	0.000	.0418937	.0997626
3	.0145234	.0041048	3.54	0.000	.0064783	.0225686
teind						
_predict						
1	.0393866	.0100493	3.92	0.000	.0196904	.0590828
2	-.0326846	.0083917	-3.89	0.000	-.0491321	-.0162371
3	-.006702	.002118	-3.16	0.002	-.0108532	-.0025509
smin						
_predict						
1	.0637147	.0095917	6.64	0.000	.0449153	.082514
2	-.052873	.0080491	-6.57	0.000	-.068649	-.037097
3	-.0108417	.002632	-4.12	0.000	-.0160003	-.005683

Source: Own elaboration

Results Of The Ordered Probit Model

The results of the ordered probit model indicate that the majority of the variables are significant. Specifically, the variable of having paid vacations decreases the probability of low-quality jobs by 12% and increases the probability of having a medium-quality job by 9%, according to the given weighting. Receiving a Christmas bonus reduces the likelihood of facing a low-quality job by 2%, while having severance pay increases the probability of medium job quality by 8% and high job quality by 2%. Holding primary education levels reduces the likelihood of being in medium-quality jobs by 1.7%. Additionally, it is observed that increases in educational levels have a greater impact on medium job quality than on high quality, which may be due to the informality present in the department. Furthermore, a salary below or equal to the minimum wage for the year 2023 decreases the probability of medium job quality by 5%.

CONCLUSIONS

Firstly, it is necessary to continue studying the political implications of this study. While the findings highlight the importance of promoting education and job formalization, a deeper analysis is required to determine which public policies would be most efficient and effective in the context of Huila. For example, designing incentives based on formalization within the tax system, focusing on two key sectorsagriculture and tourismseems to be a crucial policy for improving labor conditions in these areas.

Indeed, the outcomes below demonstrate that high informality rates badly affect job quality. In this light, it would be beneficial to conduct further research on how informality affects the region's economy in the long run. In fact, informality not only reduces tax revenue and limits workers' social protection but also perpetuates poverty in the region.
Alternatively, this should be compared with other areas in Colombia that are similar to Huila. In this way, a much clearer indication of how labor market conditions in Huila position themselves compared to other regions characterized by high levels of informality and low access to formal education would be determined. This type of identification of good practices and approaches in other regions could potentially be applied to Huila.
Therefore, efforts should be made to develop concrete recommendations for the partnership between the public and private sectors. Collaboration between these two sectors can indeed be key to achieving better job quality, whether through joint training programs or the promotion of quality employment in emerging industries. Undoubtedly, this synergy would lead to an increased contribution of public policies to the improvement of working conditions.
Furthermore, the labor market situation of women, youth, and other vulnerable groups also requires deeper reflection. While it is obvious that job quality is determined by factors such as education level, gender differences and the lack of opportunities for these groups are equally important factors that, collectively, contribute to low job quality. Therefore, specific policies must be formulated to ensure that these individuals are included in better employment opportunities.
Lastly, the potential of innovation and technology to enhance job quality in Huila cannot be overlooked. In this regard, digitalization can provide significant formal employment opportunities for a large number of people, access to education and training, and inclusive and competitive labor markets.

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