Rural labor market: an analysis for workers in agricultural and non-agricultural activities[1]

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Abstract: *This article aimed to investigate the factors that contribute to wage inequality and to analyze the effects of occupational segmentation of Brazilian workers in rural areas, engaged in agricultural and non-agricultural activities. Quantile regression with correction of sample selection bias and counterfactual decomposition of wages by quantiles was used, utilizing the microdata from the National Continuous Household Survey (PNAD-C) for the years 2012 and 2018. The results showed that there is wage inequality between workers engaged in agricultural and non-agricultural activities, which is higher for those with higher incomes, characterizing agricultural workers as a disadvantaged group. The presence of occupational segmentation was also confirmed, of which the largest share in 2012 corresponds to the personal attributes of the worker and in 2018, in certain quantiles, the duality of the labor market obtained greater explanatory power for the wage difference between the analyzed groups.*

Keywords: *wage differences, rural labor market, quantile regression, wage decomposition*

Introduction

In the last five decades, Brazilian rural areas have undergone an intense process of social and economic transformation, led by the modernization of agriculture and livestock. This world scale phenomenon was known as the Green Revolution and was implanted in several poor and developing countries since the 1960s.

Parallel to the process of modernization of the agricultural and livestock sectors, in Brazil as well as in other countries, the diversification of the income of families living in rural areas has become an important strategy to increase the level of quality of life and livelihood. Income from non-agricultural work contributes 40% of total income in Latin America; and in Sub-Saharan Africa it is between 30% and 42% (Reardon *et al.*, 2007).

The rural sector in Brazil has increased the diversification of activities, both agricultural and non-agricultural. However, there was a decrease in those employed in agricultural activities, whilst there was an increase in the supply of jobs linked to non-agricultural activities. The diffusion of different activities in rural areas, together with the improvement in inclusion with cities, provided a greater number of rural workers linked to non-agricultural activities. (Sakamoto *et al.*, 2016).

The increase in workers in non-agricultural activities can be attributed to three factors: a) more free time in the rural areas; b) improving income and consumption conditions (Kageyama, 2001); and c) increase in the supply of jobs linked to non-agricultural occupations of those individuals residing in rural areas, as well as higher wages (Laurenti, Del Grossi, 2000; Graziano da Silva *et al.*, 2002).

The expansion of rural occupations has the potential to finance agricultural activities (Reardon *et al.*, 2007); contributes to consumption and income, by providing an increase in the capital stock and by reducing underemployment (Lanjouw, Lanjouw, 2001; Birthal *et al.*, 2014; Anang, Yeboah, 2019); generates spillovers in local economic activity, contributes for the spread of knowledge and information in rural areas (Davis *et al.*, 2004; Nilsson, 2019); it improves the empowerment of women, obtaining

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income outside the male productive sphere which is agricultural and livestock production (Staduto *et al.*, 2013). According to Matshe and Yong (2004), there is a growing interest of public policy makers with the objective of encouraging non-agricultural activities in rural areas, by reducing rural poverty and increasing local economic activity.

Sources of non-agricultural income are positively correlated with total income. The various sources of income and for various sizes of properties suggest that the non-agricultural sector can serve as a potential way for rural families with land restrictions to improve their income level (Birthal *et al.*, 2014). The increased integration of rural and urban labor markets, the dynamics of activities outside the rural economy influences the use of labor and the general sector composition of non-agricultural income (Reardon, 1999). The wage gap between rural workers - agricultural and non-agricultural - is due to the segmentation of this market.

Although the literature discusses the role of non-agricultural activities, there are few analyses comparing these two segments of workers, especially the difference in pay over the wage distribution. The wage gap between the segments can potentially be more socially and economically harmful if it is at the base of the wage distribution instead of the top. Usually, studies analyze and show mean differences, so this article contributes to the literature by analyzing by quantiles.

In view of the above, the main objective of the article is to analyze which factors contributed to the inequality in the wage distribution among agricultural and non-agricultural workers living in rural areas of Brazil, and how the evolution of occupational segmentation in the Brazilian rural environment occurred for these occupations in the years 2012 and 2018, which are quite contrasting periods: high and low dynamic economy, respectively.

Method

To carry out this research, microdata from the National Continuous Household Sample Survey (PNAD-C) for Brazil in the years 2012 and 2018 were used. The year 2012 was characterized by low unemployment and economic growth, contrasting with the year 2018 with high unemployment rates and zero growth of the economy (Ipea Data, 2020).

Based on the PNAD-C classification of occupations and the 2002 Brazilian Occupation Classification (CBO) of the Ministry of Labor and Employment - MTE (2017), the major occupational groups were aggregated into two smaller groups. The first refers to individuals who are engaged in agricultural activities, and the second group refers to workers engaged in non-agricultural activities. In this way, it is possible to analyze separately the individuals residing in the rural area, who can work in activities that involve the environment they live in (agricultural), or even those who dedicate themselves to other occupations that do not involve agricultural (non-agricultural) activities, although they are domiciled in the rural area. The variables used to characterize employed workers aged 14 or over, as well as the methods used in this study are shown in Table 1.

The sample selection bias correction procedure proposed by Heckman (1979) was performed by estimating the *probit* model:

$$P_i = \beta_1 + \beta_2 ESC + \beta_3 \mathrm{EXP} + \beta_4 EXP^2 + \beta_5 BR + \beta_6 URB + \beta_7 CONJ + \beta_8 CHEFE + \beta_9 F0\_5 + \beta_{10} F6\_13 + \beta_{11} M + \mu_i \quad (1)$$

Dependent variable	
ln(W)[2]	Natural logarithm of usual income adjusted for hours worked.
Independent variables	
ESC	Qualification level of the worker.
EXP	Worker's experience (Age of person - 5 - age at which they started to work).
EXP²	Experience variable squared.
M	= 1 if a woman, 0 otherwise.
BR	= 1 if white, 0 otherwise.
F	= 1 if the individual works in the formal market, 0 otherwise.
MACRO	N: = 1 if one lives in the North, 0 otherwise; NE: = 1 if one lives in the Northeast, 0 otherwise; SE: = 1 if one lives in the Southeast, 0 otherwise; S: = 1 if one lives in the South, 0 otherwise; CO: = 1 if one lives in the Midwest, 0 otherwise; DF: = 1 if one lives in the Federal District, 0 otherwise;
SET	COM: = 1 if working in the trade sector, zero 0 otherwise; SERV: = 1 if working in the service sector, 0 otherwise; IND: = 1 if working in the industry, 0 otherwise.
PEA*	= 1 if the individual is an economically active person, 0 otherwise.
URB	= 1 if the individual lives in the urban area, 0 otherwise.
CONJ*	= 1 if the individual is considered a spouse, 0 otherwise.
CHEFE*	= 1 if the individual is considered head of the family, 0 otherwise.
F0_5*	Number of children that the individual has from 0 to 5 years old.
F6_13*	Number of children that the individual has from 6 to 13 years old.

Table 1. Description of the variables. *Source: Prepared by the authors based on the PNAD-C microdata 2012 and 2018. Note: * were used only in the sample selection bias correction procedure.*

Next, equations for quantile wage determinations (5th, 25th, 50th, 75th and 90th) were estimated for Brazilian workers who live in rural areas, engaged in agricultural and non-agricultural activities, making it possible to analyze workers with low, medium and high yields. This method results in a more complete analysis between the variables, evaluating different points of the distribution of the dependent variable (Koenker; Basset, 1978; Scicchitano, 2012). The quantile regression can be written as:

$$Y_i = x_i'\beta_\theta + \varepsilon_{\theta i} \tag{2}$$

$$Quant_\theta(Y_i/x_i') = x_i'\beta_\theta \tag{3}$$

The term $Quant_\theta(Y_i/x_i') = x_i'\beta_\theta$ corresponds to the conditional quantile of Y_i (real random variable (*i* = 1,..., n) given x_i' (vector *Kx1* of explanatory variables) and β_θ is a vector of parameters. Rewriting the equation and applying the dependent and independent variables according to the sample used, after the correction proposed by Heckman (1979), we have:

[2] In this research, salary and income will be treated as synonyms. In addition, 2012 earnings were inflated based on the Broad National Consumer Price Index (IPCA), in order to compare the monetary terms of 2012 with those of 2018.

$$\ln(W_i) = \beta_0 + \beta_1 ESC + \beta_2 EXP + \beta_3 EXP^2 + \beta_4 M + \beta_5 BR + \beta_6 F + \beta_7 N + \beta_8 SE + \beta_9 S + \beta_{10} CO + \beta_{11} DF + \beta_{12} COM + \beta_{13} SERV + \beta_{14} IND + \beta_{15} OCUPAGR + \beta_{16}\lambda + e_{qi} \quad (4)$$

Subsequently the estimation of the quantile regressions, the counterfactual decomposition of salaries of Oaxaca (1973) and Blinder (1973) was carried out along the income distribution, that is, this method allows to disaggregate the salary differences by quantiles (Melly, 2005; Scicchitano , 2012). From the estimates of quantile regressions, the conditional distribution of $\ln(W_i)$ are integrated into the group of variables. Representing with $\hat{\beta} = (\hat{\beta}_{(\theta 1)}, \ldots, \hat{\beta}_{(\theta j),} \ldots, \hat{\beta}_{(\theta J)})$ the vector of parameters estimated by the quantile regressions in the different *j* quantiles $0 < \theta_j < 1$ com $j = 1, \ldots, J$ and integrating in all quantiles and observations, an estimator of the π–th unconditional quantile of the hour wage logarithm ($\ln(W_i)$)is given by:

$$q(\tau, x, \beta) = inf\left(q: \frac{1}{N}\sum_{i=1}^{N}\sum_{j=1}^{J}(\theta_j - \theta_{j-1})\ 1(x_i\hat{\beta}(\theta_j) \leq q) \geq \tau\right) \quad (5)$$

Where 1 (.) Corresponds to an indicator function. Thus, the counterfactual distribution of wages can be estimated by replacing the parameters estimated in the distribution of the attributes of rural workers in agricultural or non-agricultural activities. The wage decomposition in each quantile can be broken down into two components:

$$q(\theta, x^B, \beta^B) - q(\theta, x^A, \beta^A) = [q(\theta, x^B, \beta^B) - q(\theta, x^B, \beta^A)] + [q(\theta, x^B, \beta^A) - q(\theta, x^A, \beta^A)] \quad (6)$$

In which:

1. Superscript A represents the advantage group (workers in non-agricultural activities), and superscript B is equivalent to the disadvantaged group (agricultural workers).
2. $[q(\theta, x^B, \beta^B) - q(\theta, x^B, \beta^A)]$ constitutes the difference in wage returns that workers in different activities receive for their characteristics in the labor market, that is, the counterfactual distribution (explained effect or composition effect);
3. $[q(\theta, x^B, \beta^A) - q(\theta, x^A, \beta^A)]$ corresponds to the effect of inequalities in the characteristics of the labor market between individuals engaged in agricultural and non-agricultural activities. It is a proxy for the effect of occupational segmentation (return effect, effect of salary structure or effect of occupational segmentation).

Representations

This study enabled to analyze and investigate the existence of wage differences and occupational segmentation caused by the occupation in which the rural worker is employed. The hypothesis is based on the confirmation of the wage gap between workers in agricultural and non-agricultural activities, as well as the existence of occupational segmentation generated by the job the worker occupies. Such results can contribute to the formulation of policies aimed at the rural environment that aim to reduce wage inequality, as well as segmentation of the Brazilian labor market. Among them, we can mention the implementation of incentives for non-agricultural activities present in the countryside, as these activities generate jobs and income for people who live there.

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Results

The productive and non-productive characteristics of Brazilian workers who live in rural areas engaged in agricultural and non-agricultural activities in the years 2012 and 2018 are shown in Table 2. Workers in agricultural activities earn an average salary of R$ 1,274.75 per month and R$ 7.13 per hour in 2012; and R$ 1,256.77 per month and R$ 7.33 per hour in 2018, showing that the hourly wage increased, but the hours worked per week on average decreased, resulting in a decrease in monthly income. They are also characterized by low qualifications, working approximately 40 hours a week, having 23 years of experience, average age of 43 years, mostly male, non-white, head of family and most of the members working in the informal labor market.

The workers engaged in non-agricultural activities earn R$ 1,139.42 and R$ 7.19 per month and hour, respectively, in 2012, R$ 1,166.31 monthly and R$ 7.54 per hour in 2018, showing higher earnings for two years when compared to agricultural workers. Non-agricultural workers also experienced a reduction in working hours associated with an increase in average hourly wages (as well as agricultural workers). The difference between the two groups is that the average monthly salary of non-agricultural workers increased, indicating that even with the decrease in the number of hours worked, this group obtained a better remuneration. In addition, they have 24 years of experience in average and low schooling, with about 7 years in 2012 and 8 years in 2018. The average age of this group is 37 years, the majority are male, not white, not a head of household and operates in the formal job market (Table 2).

Variables	**2012**		**2018**	
	Agricultural activity	**Non-agricultural activity**	**Agricultural activity**	**Non-agricultural activity**
Hours worked in the week (average)	40,71	37,66	38,99	35,87
Experience (average)	32,25	24,66	32,68	24,04
Years of study (average)	5,29	6,92	6,22	8,31
Monthly salary (average)	1.274,75	1.139,42	1.256,77	1.166,31
Hourly wage (average)	7,13	7,19	7,33	7,54
Age (average)	42,53	36,57	43,91	37,35
Woman (%)	22,28%	36,74%	21,99%	38,83%
Man (%)	77,72%	63,26%	78,01%	61,17%
White (%)	46,10%	37,96%	44,72%	34,75%
Not white (%)	53,90%	62,04%	55,28%	65,25%
Head of family (%)	60,90%	44,20%	59,05%	44,12%
Formal (%)	28,85%	42,04%	39,88%	46,47%
Informal (%)	71,15%	57,96%	60,12%	53,53%
Observations	3.401.202	7.534.795	3.395.187	6.059.712

Table 2. Characteristics of Brazilian rural workers engaged in agricultural and non-agricultural activities - 2012 and 2018. *Source: Prepared by the authors based on the PNAD-C microdata 2012 and 2018.*

Similarities are noted (low qualification, most are male, not white and are inserted in the informal market) and differences such as hours worked per week, experience, age and the percentage of being head of the family. There are disparities between the earnings of workers living in the countryside, for example, an agricultural worker earns R$ 7.33 in 2018, while an individual inserted in non-agricultural activity receives R$ 7.54 in 2018, revealing signs of occupational segmentation due to the occupation of the worker (Table 2).

As previously mentioned, the agricultural labor market has suffered a great impact with the reduction of the rural resident population due to technological advances (Staduto, *et al.*, 2004). The rural population has adapted through the diversification of activities (Alves; Valente, 2003) generating new jobs linked to non-agricultural occupations (Laurenti, Del Grossi, 2000). Such fact can be seen in Table 2, through the decrease, albeit small by 0.18%, in the number of workers engaged in agricultural activities from 2012 to 2018.

It is also noted that 1,475,083 jobs in non-agricultural activities disappeared between 2012 and 2018, a reduction of 19.58% (Table 2). This event is associated with the Brazilian economic dynamics in 2018, not yet recovered from the crisis that occurred in previous years and characterized by high unemployment rates, 12.3% (Ibge, 2020) and low economic growth with a variation in the national GDP of -0.85%, that is, the Brazilian GDP had a small drop between 2012 and 2018 (Ipea Data, 2020). In this case, rural workers in non-agricultural activities are much more vulnerable to economic shocks than those engaged in agricultural activities in rural areas because the industrial and services sectors of the economy were severely affected by the crisis, whilst agricultural and livestock were less impacted.

Figures 1 and 2 show the results of quantile regressions corrected by the sample selection bias (Heckman, 1979) for Brazilian workers in rural areas, who are engaged in agricultural and non-agricultural activities for the years 2012 and 2018.

For rural workers, the variables corresponding to education and experience show positive returns corroborating the human capital theory (Mincer, 1958; Schultz, 1964; Lima, 1980) with greater effects for the upper quantiles when compared to the lower quantiles of the distribution wage. The gender shows salary losses for all quantiles and in both years, indicating that women are paid less than men, and this difference is greater in higher quantiles, that is, among those who have high incomes. Higher earnings, even for low-skilled occupations, seem to be associated with the "glass ceiling" phenomenon, in which women have lower earnings than men even at the top of the wage distribution (Arulampalam *et al.*, 2007; Christofides *et al.*, 2013).

The variable that represents skin color (being white) reveals wage gains, higher for the upper quantiles, showing wage inequality due to color. Such results confirm with the discrimination theory evidenced by Becker (1957), Becker (1971), among others. (Figures 1 and 2). The variable that corresponds to the individuals who work in the formal labor market reveals gains in quantiles in all, despite those working in the informal sector. All Brazilian macro-regions show gains when compared to the base region (Northeast). The sectors of economic activity show different behaviors with reference to the agricultural sector (base sector) (Figures 1 and 2).

Rural workers engaged in non-agricultural activities showed positive returns, with higher returns for those with lower incomes, and lower returns for those with high incomes, revealing an important segmentation of rural workers, thus proving the segmentation theory (Doeringer, Piore, 1970; Vietorisz, Harrinson, 1973; Reich *et al.*, 1973; Lima, 1980; Carneiro, 1997). Such fact is equivalent to saying that workers in non-agricultural activities earn higher incomes than those who engaged in agricultural activities due to their occupation, and these gains are greater when workers have low income. Moreover, this salary gain (when compared to agricultural workers) contributes to the increase in the total income of families in the lower income stratum, being characterized by having less education and less qualified professions. These results confirm and demonstrate the salary difference between the individuals studied (Figures 1 and 2).

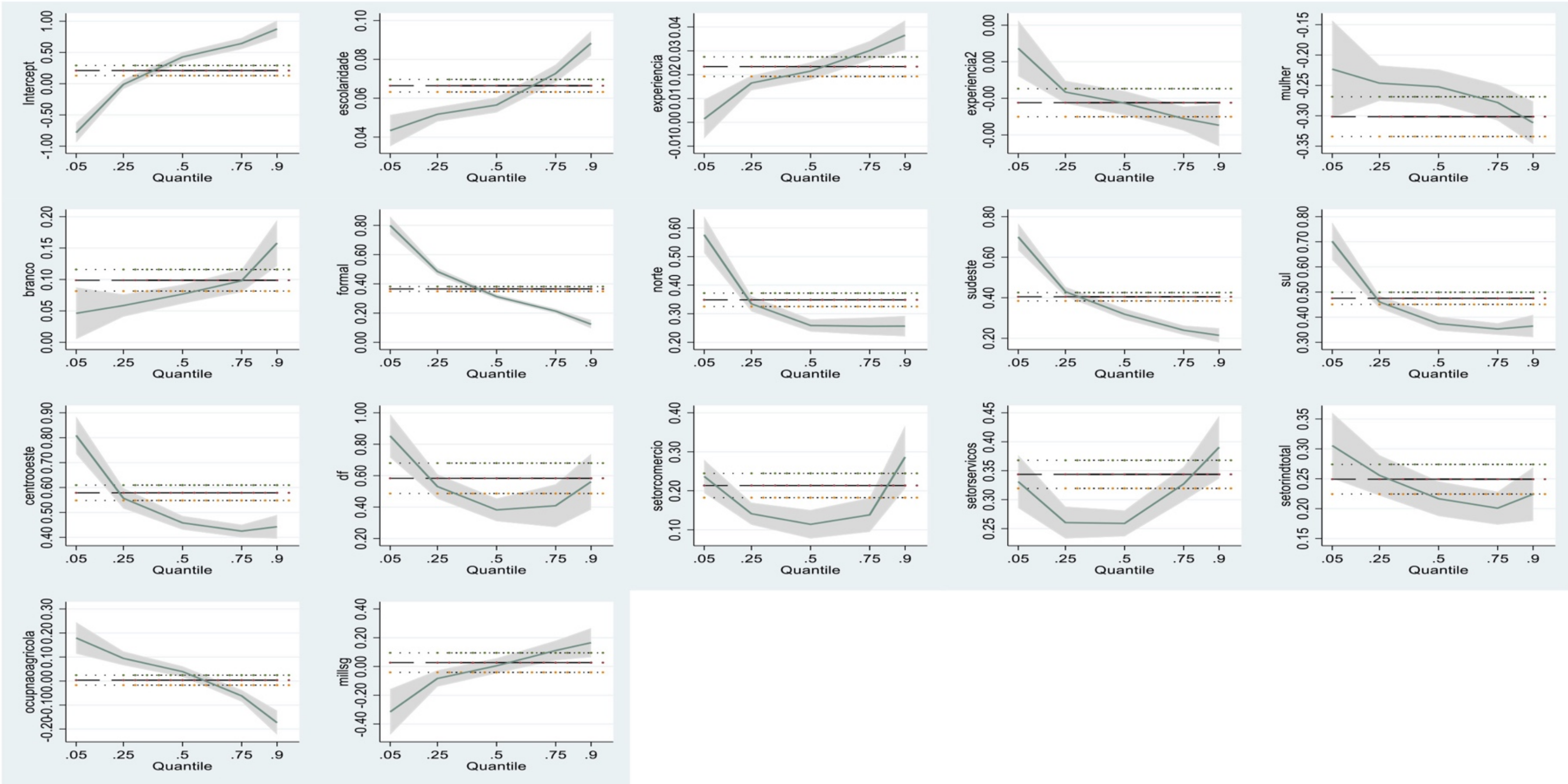

Figure 1. Results of quantile regressions for Brazilian rural workers engaged in agricultural and non-agricultural activities - 2012
Source: Prepared by the authors based on the results of quantile regressions. *Notes: (1) Order of presentation in the variables: intercept; schooling; experience; experience²; woman; white ; formal ; Brazilian macro-regions (North, Southeast, South, Midwest, Federal District); economic activity sectors (commerce, services, industry); non-agricultural occupation; lambda of sample selection bias correction. (2) Standard deviation was calculated for 100 bootstrap replications. (3) The commerce and industry sectors did not present values for the quantile regressions of workers engaged in agricultural activities in 2012.*

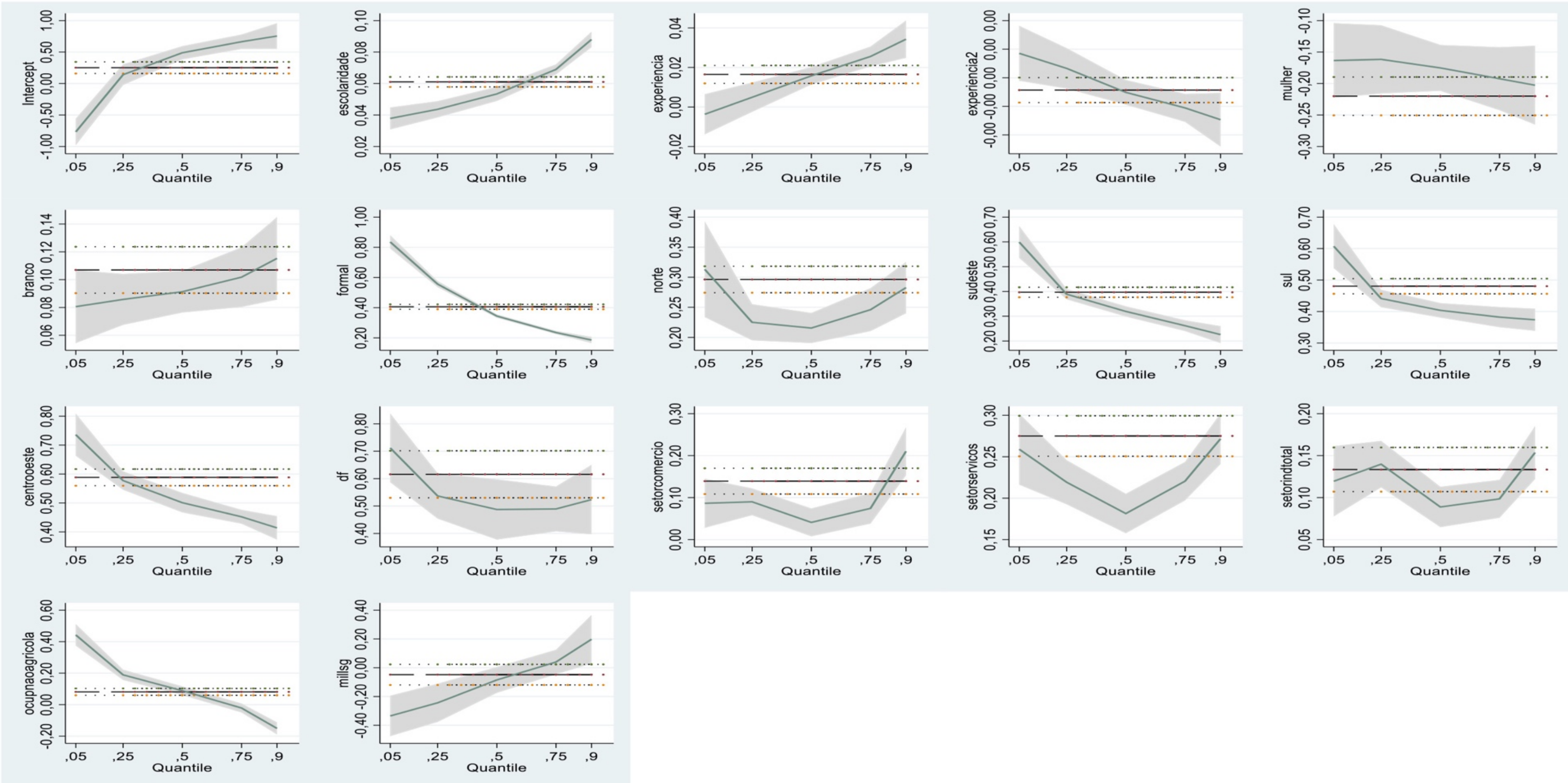

Figure 2. Results of quantile regressions for Brazilian rural workers engaged in agricultural and non-agricultural activities - 2018
Source: Prepared *by the authors based on the results of quantile regressions.* *Notes: (1) Order of presentation in the variables: intercept; schooling; experience; experience²; woman; white ; formal ; Brazilian macro-regions (North, Southeast, South, Midwest, Federal District); economic activity sectors (commerce, services, industry); non-agricultural occupation; lambda of sample selection bias correction. (2) Standard deviation was calculated for 100 bootstrap replications.*

It is important to mention that the coefficients corresponding to the year 2018, both for agricultural and non-agricultural activities, are lower than those of 2012. This shows that the disparity between rural workers has reduced in the analysis period, according to the activities they were occupied (Figures 1 and 2). Agricultural occupations are not yet part of a process of reducing less qualified jobs as technification intensifies and more qualified jobs increase (Cunha, 2009).

There is also a pattern among the variables analyzed: education, experience and white (skin color) have higher returns for the upper quantiles. This means that having a higher qualification, greater experience and being white will translate into an even higher salary increase for those individuals who already have high incomes. On the other hand, the variables experience², woman, formal, southeast, south and midwest, non-agricultural occupation showed higher returns for the lowest quantiles. In other words, being a woman, working in the formal market and living in the regions mentioned, makes the impact of the salary increase greater for those on low incomes. These results highlight the importance of women to family income in agricultural and non-agricultural occupation, which contributes to reducing the vulnerability of families living in rural areas. The northern region, the Federal District and the sectors of commerce, services and industry exhibited different behaviors (Figures 1 and 2).

Given that there are disparities in the wages of Brazilian rural workers employed in different professions, to understand how much of this wage gap stems from the characteristics of workers and how much originates from occupational segmentation, that is, from the job, the Oaxaca (1973) and Blinder (1973) wage decomposition was used for quantiles (Table 3).

For the year 2012, it is observed that the effect explained by the workers' personal and productive characteristics are superior to the effect of the duality of the labor market, that is, the occupational segmentation effect. The explained effect was greater for the 5th and 75th quantiles, while occupational segmentation was higher for the 25th and 50th quantiles. This demonstrates that the personal and productive attributes of the workers have a greater power to explain the wage gap than the occupations (Table 3).

In 2018 there was a different behavior in relation to the year 2012. For some quantiles, the explained effect, that is, the characteristics of workers were more important to explain the wage difference, such as the 5th and 75th quantiles. While in the 25th, 50th and 90th quantiles, the segmentation effect was greater than 50%, which indicates that the duality of the labor market was the main responsible for the wage inequality among workers (Table 3).

The results obtained for both years show that there is a difference in wages among Brazilian rural workers, with individuals engaged in non-agricultural activities having higher remunerations when compared to those engaged in agricultural activities (Figures 1 and 2). In addition, the effect explained by the characteristics and attributes of workers is superior to occupational segmentation for all quantiles in 2012. On the other hand, for 2018 the duality of the labor market, that is, segmentation, explained most of the difference wages for the 25th, 50th and 90th quantiles (Table 3).

Different realities are observed in the Brazilian economy in 2012 and 2018. In 2012, the country was characterized by a dynamic period, defined by a low unemployment rate of 7.4% (Ibge, 2020) and a high rate of growth in activity mainly in the agricultural sector, which was characterized by a variation of 26.20% in the studied period (Ipea Data, 2020). However, in 2018 without full recovery from the recession of previous years, Brazil had a high unemployment rate (12.3%) (Ibge, 2020) and low economic growth, in the period from 2012 to 2018 the variation of the national GDP was of -0.85% of the, and the growth was only 1.1% in relation to the previous year, the economy was in a slow process of economic growth (Ipea Data, 2020).

Quantile	2012				
	5°	25°	50°	75°	90°
Explained effect					
Coefficients	0,2586*	0,2742*	0,1506*	0,1438*	0,0154*
%	101,63%*	71,40%*	77,08%*	155,45%	67,75%*
Occupational segmentation effect					
Coefficients	-0,0042	0,1099*	0,0448*	-0,0513*	0,0253*
%	-1,63%	28,60%*	22,92%*	-55,45%	111,30%
Total difference					
Coefficients	0,2544*	0,3841*	0,1954*	0,0925*	0,0227**
%	100,00%*	100,00%*	100,00%*	100,00%*	100,00%**
Quantile	**2018**				
	5°	25°	50°	75°	90°
Explained effect					
Coefficients	0,2178*	0,2378*	0,0746*	0,1111*	0,0929*
%	56,18*	48,11%*	45,45%*	121,81%*	-487,38%
Occupational segmentation effect					
Coefficients	0,1699*	0,2564*	0,0895*	-0,0199	-0,1119*
%	43,82%*	51,89%	54,55%*	-21,81%	587,38%
Total difference					
Coefficients	0,3877*	0,4942*	0,1642*	0,0912*	-0,0191
%	100,00%*	100,00%*	100,00%*	100,00%*	100,00%

Table 3. Wage decomposition by quantile for Brazilian rural workers engaged in agricultural and non-agricultural activities - 2012 and 2018. *Source: Prepared by the authors based on the PNAD-C microdata 2012 and 2018. Notes: (1) Significant (*) p <0.01, (**) p <0.05, without an asterisk, were not statistically significant. (2) Advantage group: rural workers engaged in non-agricultural activities, based on descriptive statistics and quantile regressions.*

Considering the period studied, there were no major motivations for the agricultural sector to shift the origin of the income disparity between occupations, however the economy as a whole has very poor performance. It appears that in dynamic periods (such as the year 2012), in the case of rural workers, the human capital theory approach prevails to explain the difference between the remunerations of individuals. However, in 2018, marked by a period of crisis, the theory of occupational segmentation shows greater explanatory power for the wage differences among workers (Table 3).

Conclusion

The results highlight the importance of women for family income in agricultural and non-agricultural occupation, which contributes to reducing the vulnerability of families living in rural areas. The presence of occupational segmentation was confirmed, and in 2012 the effect explained by the workers' personal and productive characteristics, which have a greater contribution to the wage gap in all quantiles, while in 2018, occupational segmentation had a greater influence on wage inequality in three quantiles (25th, 50th and 90th).

Thus, the Brazilian economic dynamics influences the wage gap, in which periods with high GDP growth and low unemployment rate, the wage gap stems from the productive characteristics related to human capital, that is, education and experience. On the other hand, in a period still without recovery from previous crises, the theory of segmentation is best expressed as a source of wage differences among rural workers engaged in different activities.
Such analyses show results that contribute to the formulation of policies aimed at the rural environment that aim to encourage non-agricultural activities in the countryside. Policies aimed at reducing poverty and increasing economic activity in the area, as well as reducing wage inequality and occupational segmentation generated by the labor market.

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