Migration of labor: differential of income between rural and urban trade union workers in Brazil

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Received 29 January 2019
Revised 9 May 2019
20 August 2019
Accepted 21 August 2019

Abstract

Purpose – The objective of this work was to analyze the income differential of the rural–urban worker in relation to the rural–rural worker and in relation to the urban–urban worker in the Brazilian labor market. Two databases were used, the 2005 and 2015 PNADs (Pesquisa Nacional Por Amostra de Domicílios).

Design/methodology/approach – The methodology is the decomposition approach proposed by Firpo *et al.* (2007, 2009). This method adopts estimates of unconditional quantile regressions, based on the concepts of influence function and recentered influence function (RIF).

Findings – Among the main results, income differentials were shown to benefit the urban–urban worker when compared to the rural–urban worker, and income differences to the benefit of the rural–urban workers, when these were compared to the rural–rural workers. The educational variable was relevant in explaining the income disparity and expressing increasing effects in the higher quantiles.

Originality/value – The methodology used in this work is considered recent in the literature as it is based on the RIF regression (Firpo *et al.*, 2007, 2009). The main advantage of this method is the possibility of assigning a "composition effect" and a "wage structure effect" for each variable that determines the level of income at different points of the income distribution.

Keywords Income differential, Migration, Rural–urban, Decomposition

Paper type Research paper

1. Introduction

Beginning in the 1960s, the Brazilian rural job market underwent an important transformation, due to the modernization and expansion of the agricultural sector [1], as well as the creation of several government agencies [2], with the objective of improving agricultural performance and public policies for the sector.

The structural changes occurred mainly in labor-intensive properties of large proportion, which led to a considerable replacement of the labor force for machinery and equipment. This process, combined with other economic, social and climate aspects, such as the drought problem in the Northeast region of Brazil, was responsible for the greater migratory flow of people from the rural countryside to the urban centers, in the 1960s to the 1980s [3], a phenomenon known as the rural exodus.

Demographic censuses of the Brazilian Institute of Geography and Statistics (*Instituto Brasileiro de Geografia e Estatística* [IBGE]) show that in 1950, the urbanization rate in Brazil was 36.1%, and in 1970, it increases to 55.9%. In 2000, records show that 137,756 million people were urban dwellers, thus in 50 years, the urban population increased by 633.4%, and

Journal of Economic Studies
Vol. 47 No. 4, 2020
pp. 939-966

0144-3585
DOI 10.1108/JES-01-2019-0047

JEL Classification — J61, J70

the urbanization rate increased by 81.2%. The 2010 Census shows that this contingent reached 84%, that is, with a population of 194 million people in Brazil, about 161 million lived in urban areas. This substantial increase in urbanization is attributed to population growth and rural migratory movement [4] (Instituto Mauro Borges De Estatísticas E Estudos Socioeconômicos, 2012).

In this context, the relevance of analyzing the mobility of rural labor to the Brazilian urban job market should be evident. Migration movements can be understood as of permanent [5] or temporary nature. It is noteworthy that most of the works found in the Brazilian literature on rural–urban migration give greater attention to permanent displacements [6]. The literature [7] which studies short-term commuting does not distinguish between workers who live in rural areas but who move to work in urban areas.

Works on income differentials in the Brazilian job market show that the rural worker has lower remuneration when compared to the urban worker. For example, Russo *et al.* (2016) have shown this gap based on data from the 2013 PNAD, both in the national context, as well as considering the different regions of Brazil separately (except the Center-West). According to the authors, the educational level is considered the most important variable in explaining income differentials between these workers, however, income disparities are also explained by factors related to discrimination in the rural and urban job market.

Using a different approach, this work aims to analyze the existence of a possible income gap between workers with temporary mobility, by comparing the income of the rural-urban worker in relation to the income of two other groups, the urban-urban worker and the rural-rural worker. The analysis is focused on Brazil in the periods of 2005 and 2015, and aims, specifically, to answer: does the rural-urban worker have personal/productivity characteristics that make that individual more likely to be employed in the urban job market? Are factors that are not related to labor productivity important in explaining income disparities between these groups of workers? The hypothesis is that the rural-urban worker is more qualified and better paid than the rural-rural worker.

In this work, the definition of a rural-urban worker is the person who is registered in the national Census as residing in a rural area, but is unionized as an urban employee. The rural-rural worker resides in a rural area, and is unionized as a rural worker. While the urban-urban worker resides in an urban area and is unionized as an urban employee. The choice of analyzing individuals residing in the rural area but who are unionized as urban employees becomes relevant because it allows us to verify if these workers are different in terms of attributes (personal, productivity, educational characteristics, among others) when compared to the other two groups of workers. Only unionized workers were used in the sample, since the *Pesquisa Nacional Por Amostra de Domicílio* (PNAD) does not provide another variable (besides the type of union) that identifies the work environment (rural or urban) of the individual.

The analysis of the year 2015 is justified because it corresponds to the most recent PNAD available at the time of this research. Nevertheless, 2015 corresponds to a period of political and economic crisis in Brazil, with intense retraction of the gross domestic product (GDP), and instabilities in the Brazilian job market. Thus, it was considered pertinent to make a comparison of that ten year period, where 2005 [8] was a year of moderate economic growth.

Thus, this work seeks to contribute to the literature on income inequality between rural and urban workers and rural–urban migration (specifically the "pendulum migration" of labor) by measuring the determinants of income differentials and labor migration, making it possible to identify if where the worker resides is different from where that person works [9] and if that fact has relevance on the income differential. No other works of the kind were found on the Brazilian literature [10]. Furthermore, this work innovates by using a recently developed methodology the unconditional quantile regression method to explain income disparities among the individuals analyzed.

A better comprehension of the causes of income differentials between groups of individuals is necessary so that it may be possible to invest in specific policies to fight or reduce these disparities. Thus, this work presents itself as an instrument to facilitate the elaboration of public policies aimed at alleviating economic and social imbalances between rural and urban workers (migrants and nonmigrants).

The methodology used in this work is considered recent in the literature [11], as it is based on the recentered influence function (RIF) regression (Firpo *et al.*, 2007, 2009). The main advantage of this method is the possibility of assigning a "composition effect" and a "wage structure effect" for each variable that determines the level of income at different points of the income distribution.

The main results of this work suggest that income differentials that benefit the urban–urban worker, when compared to the rural–urban worker. This income differential was greater in the higher quantiles. As for the analysis considering the rural–rural worker and the rural–urban worker, the latter group presented a positive income differential, thus the disparities were lower in the higher income levels. In general terms, the composition effect and the wage structure effect seem to act to widen income disparities. The education, activity sector and geographical region variables were all relevant in explaining these income disparities, presenting increasing effects on the higher income quantiles.

Apart from this introduction, this work features four more sections. The second section presents the literature review; the third section features the methodology used. Next, the results are discussed, and finally, the concluding remarks are presented.

2. Literature view

2.1 Theory of labor migration and the empirical evidence of rural–urban migration

In general, the theories that study the rural–urban migratory movement are influenced by the effects of the unequal economic development which occurs in rural and urban environments. Furthermore, migration is usually linked to the human capital theory, considered as the main explanation for a worker to be positively selected [12].

In that sense, Justo (2006) points out that the models discussed in the international literature that seek to explain population displacements can be divided into two categories. The first category analyzes the migratory movements from the aggregate point of view, considering the characteristics of the place of origin or destination of the migration. In this case, the motivation of the migration is explained by the income differentials between the localities. In the second category, the models seek to explain the migration through the individual decision, considering personal observable or unobservable characteristics that affect the purpose of migrating.

The migratory phenomenon analyzed from the point of view of the human capital theory is explained by the following perspective: to migrate is a rational choice based on the comparison between the expected benefits and the financial and psychological costs associated with the displacement between two or more regions. Thus, the person will be more likely to migrate if that individual expects a positive net return (Sjaastad, 1962). The basic hypothesis is that the rational individual migrates in response to economic incentives.

The dual economy models developed by Lewis (1954), and Ranis and Fei (1961) were the first to begin the debate in the economic literature on the phenomenon of rural migrations. These models indicate that economic development produces a differential between labor productivity in rural and urban environments, which can lead to large migratory flows from rural areas to urban centers. Labor migration is, therefore, a response to the income differential between those two areas.

One of the first models to elaborate an economic explanation of the process of rural–urban migration emerged with Todaro (1969) and Harris and Todaro (1970). This model argues that the main determinant for the decision to migrate from the countryside to urban centers is the differential between the expected urban income and the rural income. The expected urban income is defined as urban income weighted by the probability of employment in the city. Thus, the potential migrant compares their current rural income with the income they expect to earn in the city, considering the probability of being unemployed for a certain period in the urban sector (Lima, 1995).

Although it is widely accepted in the literature that economic aspects are the main determinants of migration, authors such as Barrios *et al.* (2006), Beine *et al.* (2011) and Marchiori *et al.* (2011) argue that there are other important factors in the decision to migrate. According to those authors, migratory displacement is no longer understood as being only a process where people move from poorer regions to richer places. In this sense, Castles (2011) affirms that the migration phenomenon needs to be analyzed as part of a set of social changes resulting from political, socioeconomic and environmental transformations.

Black *et al.* (2011) identify five families of "drivers" (economic, political, demographic, social and environmental), which affect migration decisions. The economic driver contemplates job opportunities and income differentials between places of origin and destination. In addition to issues of conflict, security and discrimination, aspects of government policies include the political driver. The demographic driver includes the structure and size of the population, as well as the degree of disease incidence and mortality. The social driver includes family and cultural expectations, such as opportunities related to education and health. The environmental driver includes exposure to climate risk and the availability of ecosystem services. In addition to these aspects, the potential migrant will still consider individual and family characteristics, such as age, gender, ethnicity, religion and marital status, among others, as well as obstacles and facilitators involved in their decision to migrate.

After this synthesis on the classic theories that seek to explain the migration of workers has been presented, some empirical works on the Brazilian literature referring to the rural–urban migratory process and the differential of income between the rural and urban labor market are discussed below. Some of the main works in the country are those of Martine (1987, 1992), Lima (1995), Amaral *et al.* (2002), Justo (2006), Ramalho and Silveira Neto (2007, 2012) and Russo *et al.* (2016). It should be emphasized that in the Brazilian academic literature, there are only a few empirical studies on rural–urban migration, mainly referring to movements considered to be of short duration (*e.g.* pendulum migration).

In terms of Brazil, the country's rural exodus reached its peak in the first two decades of the twentieth century. According to Martine (1987), from 1960 to 1970, approximately 13 million people migrated from rural areas to urban centers, which accounted for 33% of the rural population at the beginning of the period. From 1970 to 1980, the population of migrants who left the rural area was approximately 16 million, corresponding to 38% of the rural population (Lima, 1995).

Amaral *et al.* (2002) point out that, especially in the 1970s, factors such as the accelerated appropriation of land, the technical modernization of rural areas, the concentration of properties and the evolution of social relationships of production generated changes in labor relations, leading to a reduction in the demand for labor in rural activities and, consequently, increased the occupational and spatial mobility of the labor force. Those years have historically been marked by the absorption of "population surpluses," mainly agricultural workers, in Brazilian cities.

In an attempt to explain the rural–urban migration phenomenon, Martine (1992), in the same sense as Amaral *et al.* (2002) and Lima (1995), adds that the Brazilian rural exodus, which occurred in mass, can be attributed to the model of industrial development in the urban environment and the process of modernization of agriculture. According to Justo (2006), the strengthening of the national internal market resulting from the Brazilian industrialization process provoked a movement of population exodus in the rural environment, derived from the expansion of the agricultural frontiers with marked land concentration, as well as the insertion of the rural workers in various urban segments.

Ramalho and Silveira Neto (2007), in this same sense, consider that the expansion of the service sector in urban centers, combined with the mechanization of agriculture in rural areas, are characteristics that continue to encourage population migration towards those locations; in addition, the authors highlight the importance of greater availability of public goods and services in these urban areas. It should be emphasized that traditional factors such as rural poverty, the phenomenon of droughts, land concentration and unemployment in general, increase the movement of people out of rural areas toward urban centers. The authors use a methodology based on the *mover–stayer* econometric model, which seeks to correct any potential bias caused by the self-selection of individuals in the migration process.

Based on demographic censuses, the authors used the main theoretical argument of the human capital approach and the heterogeneous attributes of individuals. As mentioned above, Ramanho and Silveira Neto (2007) use a *mover–stayer* econometric model, which seeks to correct the potential bias caused by the self-selection of individuals in the migration process. The results show that the rural–urban migrant is basically an individual who is not white and is composed of people that have a higher degree of education than the nonrural migrants. This finding suggests that the rural–urban migrant is positively selected in several characteristics, especially in terms of age and education, since the younger and more educated have more expectations about obtaining potential income returns by migrating to the urban centers.

The sectors that most employed the rural population in urban areas were commerce and services and industry, which represent approximately 63% of the employed workers. In relation to those who remained in rural areas, approximately 79% of the workers were allocated in the primary sector. Another relevant information found was the percentage of migrants below the poverty line, which was lower than in the nonrural migrant group. This result is evidence that rural–urban migration is a viable option for individuals to escape poverty in the rural environment (Ramalho and Silveira Neto, 2007).

Ramalho and Silveira Neto (2012) analyzed the insertion of rural migrants in the Brazilian formal and informal job markets. The authors used the 2000 Demographic Census as a database. The authors adopt a structural model of joint determination of the occupational choice and income of the migrant, as well as counterfactual exercises. The results showed that the probability of entry of a migrant worker into the formal sector is conditioned, in particular, by the endowment of human capital. The rural–urban migrant who enters the formal segment is positively selected. The average wage in the formal sector exceeds the income of the informal wage earner, particularly when considering the level of wages in the public sector. In relation to the sectors of activity, the authors identified barriers to entry in some segments of the job market. According to the results, the majority of migrants employed as wage earners in the informal economy in urban centers seek, after a certain time, to move to the formal sector. Thus, the informal sector functions as a transitional state for the rural–urban migrant searching for employment in the formal sector.

Russo *et al.* (2016) analyzed the income differential between rural and urban workers in Brazil (disregarding the migration process) based on data from the 2013 PNAD. The authors aimed to discuss income inequality according to the different Brazilian regions and used the Oaxaca–Blinder decomposition (1973), considering the correction of selection bias through the Heckman procedure (1979). Among the main results, it was observed that rural workers obtained worse wages than urban workers, both in the national context and by regions, except for the Center-West region of the country. According to the authors, the educational level is considered the most important variable in explaining income differentials between such individuals, however, income disparities are also determined by factors related to discrimination in the rural and urban job market.

According to Ney and Hoffmann (2009), among the factors that contribute to income disparity between rural and urban workers in Brazil, a significant portion of this inequality is explained by the level of schooling. Access to the education system, especially at the higher levels of education, is still restricted to the urban population, excluding those in rural areas. This occurs for a number of reasons, such as the early entry of individuals into the job market, the distance from rural properties to schools and limited availability of transportation.

A general analysis of the authors reviewed in this section reveals that the income disparity between the rural worker and the urban worker (whether of rural origin or not) is something consensual among the authors. The literature shows that the urban worker is differentiated in terms of human capital and, consequently, obtains higher labor remuneration.

2.2 Pendulum migration in Brazil

Following the concept of migration adopted in this work, it is reasonable to assume that a large part of the rural–urban worker group consists of commuting migrants. Thus, it was considered pertinent to briefly discuss this type of migration in Brazil.

According to Ojima *et al.* (2007), pendulum migration [13] can be defined as the mobility of people in a regional context, *i.e.* where the place of residence is different from the one in which the person reports as a place of work or school. In this kind of population displacement, the daily mobility of people between work and residence (or school) areas is considered.

Works on pendulum mobility in Brazil usually deal with displacements between urban or regional agglomerations. The daily routine of individuals is considered as the time interval of displacement. Empirical research in the Brazilian literature on pendulum displacement is more frequently developed based on the microdata of the demographic census. Information on commuting in the censuses has existed since 1980, except for some limitations that occurred in the 1991 Census.

In the 2010 Census, the information on work and school displacements was divided and also incorporated additional information, including the time of commuting between work and home; such information can be considered fundamental for the planning of public policies, which frequently focuses on the transportation sector. However, although demographic censuses are important tools of analysis to understand the process of pendulum mobility, they contain methodological limitations, since the censuses only spatially identify the displacements when the municipality of residence of an individual is different from the municipality where that person works (Ojima *et al.*, 2015).

Ojima *et al.* (2007) analyzed the proportion of people who commuted by the total population that worked or studied in 1980 and 2000 in Brazilian cities. As a result, the authors found that in 1980, the proportion of commuting displacements over the total population was 4.4%, and in 2000, it increased to 6.2%. The pendulum displacement basically corresponds to the population of working age (15–64 years), the age group responsible for approximately 92% of the total number of people who worked or studied in a municipality other than the one where they lived in the year 2000. The main age range remained between 20 and 24 years. Regarding gender, these movements expressed a higher concentration among men, although it decreased significantly in the two decades considered. In addition, in 1980, men corresponded to approximately 75% of the people of more than ten years who made pendulum movements in Brazil. However, in the year 2000, this proportion decreased to about 60% of the commuting movements.

During the period under review, commuting displacements became more heterogenous in terms of age structure, with the relative aging of the commuting population and greater female participation in the movements, that is, the mobility of people was expanded to a greater part of the population. The pendulum migrant is positively selected, being a group of workers with better educational level and obtain higher income, if compared with the people who live and work in the same municipality (Ojima *et al.*, 2007).

In relation to the years 2000 and 2010, the demographic censuses of these periods show that the number of people living in a municipality other than of the place where they work in Brazil has evolved at a significant pace, rising from 7.3 million to 11 million people in the two decades. These pendulum displacements, although concentrated mainly in the Southeast (53%), showed expansion in the other regions of the country (Ojima and Marandola Jr, 2012).

3. Methodology

3.1 Data

The database used in this work is composed of microdata from the National Household Sample Survey (PNAD) for the years 2005 and 2015, made available through the Brazilian Institute of Geography and Statistics (IBGE). It should be noted that the year 2015 corresponds to a period of political and economic crisis in Brazil, with an intense contraction of the GDP, and instabilities in the job market. Thus, it was considered pertinent to make a comparison with the period of ten years before (2005) [14], the year in which the Brazilian economy showed moderate economic growth.

For the selection of the sample, some filters were used, since some categories of workers were excluded [15]: autonomous, independent, liberal professionals, civil servants and those linked to some other type of union. People younger than 16 years and older 65 years were also excluded, since people belonging to these two groups are more likely to be out of the job market. Workers with income in their main job greater than R$ 1,000,000.00 were likewise excluded. Sampling weights and stratification were considered in all estimates, making the PNAD sample complex. The variables used in this section are shown in Table 1.

In relation to the groups of workers analyzed in this research, the following definitions are applied:

(1) *Rural–urban worker*: An individual who is identified in the census as residing in a rural area and is unionized as an urban employee;

(2) *Urban–urban worker:* An individual who is identified in the census as residing in a urban area and is unionized as an urban employee;

(3) *Rural–Rural worker:* An individual who is identified in the census as residing in a rural area and is unionized as a rural employee;

It should be made clear that, in this section, the concept of labor migration [17] refers to the case where the person has a census situation in the rural area (place of residence) but is unionized as an urban employee (place of work), thus the workforce would be migrating from the rural area to urban centers. There is no other variable in the 2005 and 2015 PNADs that identifies whether the person works in the rural or urban area, which is why this proxy was used. In this case, what justifies considering the individual to be an urban employee or a rural worker is his or her type of union.

The urban–urban worker and the rural–rural worker are considered as nonmigratory workers. It should be noted that there was no possibility of identifying if the worker registered in the census in the rural area and is unionized in the urban environment returns from the urban environment to the rural environment every day. It is assumed, however, that this worker moves from the area of residence to the work area, and vice versa, in short periods, which can be daily, weekly or some other short-term interval.

3.2 Econometric model

This subsection describes the empirical model used in the estimations and decompositions of the income differential between groups of workers. The equations estimated consider a set of explanatory variables, which, according to the literature, influence work-related income. The linearized work income function can be represented by the following equation:

$$lny_{ik} = \beta_k X_{ik} + \varepsilon_{ik} \tag{1}$$

where lny_{ik} is the natural logarithm of the work income of individual i ($i = 1, \ldots, n$) who works in area k (urban $= u$ or rural $= r$); X_{ik} represents the set of explanatory variables, including individual characteristics, activity sector and geographical region. β is the return vector associated with the individuals' characteristics, and ε_{ik} corresponds to the error term, so that $E[\varepsilon_i/X] = 0$.

Estimates of the income differential between the groups of workers were performed by income distribution quantiles (q10, q25, q50 and q90). The methodology presented by Firpo *et al.* (2007) was used for that purpose. It is a generalization of the income differential decomposition featured in Oaxaca (1973) and Blinder (1973).

According to Firpo *et al.* (2007, 2009) and Miro and Franca (2016), this decomposition approach adopts estimates of unconditional quantile regressions based on the concept of influence function (IF) and RIF, combined with a reweighting procedure inspired by Dinardo *et al.* (1996). In the literature, it is commonly referred to as the RIF regression.

Table 1. Definition of the variables [16] used

Dependent variable	Description
Ln work income/hour	Natural logarithm of the income per hour worked due to the individual's main job
Explanatory variables	*Description*
Education	Years in school for the worker
Exper.	Experience[a] = (Age – Age in which the worked entered the job market)
Exper. 2	Experience squared
Worker *dummy*	Rural–urban Worker = 1, and 0 if otherwise Rural–rural Worker = 1, and 0 if otherwise Urban–urban Worker = 1 and 0 if otherwise
Sex *dummy*	Male = 1 and Female = 0
Race *dummy*	White = 1 and Nonwhite = 0
Region[b] *dummy*	Northeast region = 1 and 0 if otherwise Southeast region = 1 and 0 if otherwise Center-West region = 1 and 0 if otherwise South Region = 1 and 0 if otherwise
Activity *dummy*	Considered 1 for the sector that the individual works in, 0 for the other sectors
Agriculture	
Industry	
Construction	
Trade and repair transportation	
Education, health and social services	

Note(s): The variables male gender; white race, agricultural activity and North region were left out of the estimates as a base category in their respective groups of dummy variables

[a]In general terms, as a proxy for the experience variable, the literature adopts the measure of "age – years of study – six years", where six represents the modal year of admission to school. According to Resende and Wyllie (2006), this proxy ignores the simultaneous counting of years of study and work experience. As an alternative to reduce the problem of selection bias, the authors suggest as proxy experience, the difference between the variables: "Age – Age in which entered job market"; a procedure used by Costa *et al.* (2016) and Cavalcante and Justo (2017). It should be emphasized that this measure is also not free of bias due to periods of inactivity

[b]Considered a very important variable in this work, because of the hypothesis that labor migration can occur with different intensity and circumstances in each macro-region of the country

Source(s): Prepared by the authors

3.2.1 Unconditional quantile decomposition method: recentered influence function (RIF). Firpo *et al.* (2007, 2009) argue that it is possible to estimate the effect of a set of variables X on different statistics on the distribution of a random variable y, applying the concepts of IF and RIF. Being y a random variable (which, in this case, represents the worker's income) with cumulative distribution function $F_y(y)$ and $v(F_y)$ being a statistic of that distribution, that statistic can be mathematically presented as:

$$v(F_y) = \int \varphi(y) dF_y(y) \tag{2}$$

where $\varphi(y)$ is a function related to the statistic of interest. For the case of the mean, for example, $\varphi(y) = y$. The RIF for that variable is defined by $FIR(y,v) = v(F_y) + FI(y,v) = \varphi(y)$. Thus, $E[FIR(y,v)] = v(F_y)$.

In this experiment, the interest is in the effects or returns that the set of variables X represents in the different unconditional quantiles of y, so that$v(F_y) = q_\tau$, the τ-th quantile of F_y. The IF is represented by

$$FI(Y;q_\tau) = \frac{\tau - I\{y \leq q_\tau\}}{f_y(q_\tau)} \tag{3}$$

In that expression, $f_y(q_\tau)$ is the probability density function of y verified in q_τ, and $I\{y \leq q_\tau\}$ is an indicator variable that denotes the occurrence of y up to the limit of the quantile. By definition, the RIF is expressed by

$$FIR(y,q_\tau) = q_\tau + \frac{\tau - I\{y \leq q_\tau\}}{f_y(q_\tau)} = c_{1,\tau} I\{y > q_\tau\} + c_{2,\tau} \tag{4}$$

where $c_{1,\tau} \equiv \frac{1}{f_y(q_\tau)}$ and $c_{2,\tau} \equiv q_\tau - \frac{1-\tau}{f_y(q_\tau)}$.

In order to relate the statistics of interest to the set of X variables, a vector of random variables, one can apply the law of iterated expectations and obtain

$$v(F_y) = \int FIR(y,v) dF_Y(y) = \int E[FIR(y,v)|X=x] dF_X(x) \tag{6}$$

where $F_X(x)$ is the cumulative distribution function of X. This result indicates that any statistics of interest can be represented as an expected value and can be represented as

$$E[FIR(y,v)|X=x] = c_{1,\tau} E[I\{y > q_\tau\}|X=x] \tag{7}$$

Firpo *et al.* (2009) show that the unconditioned partial effects of changes in $F_X(x)$ can be obtained by

$$\alpha(v) = \int \frac{dE[FIR(y,v)|X=x]}{dx} dF_X(x) \tag{8}$$

in which $\alpha(v)$ denotes the vector of partial effects of changes on each variable of X, assuming that the distribution of y as a function of X remains constant. This result means that the partial effects of changes in $F_X(x)$ can be estimated by regression methods, in which case, regressing the RIF of y in terms of a statistic of interest, relative to a set of covariates X.

The unconditional quantile function can be applied directly, similar to the estimation of a linear regression model by ordinary least squares. The first step of the application is to estimate the RIF for theτth quantile of y. The second step is to estimate the regression $FIR(Y;q_\tau)$ in relation to the set of variables X:

$$E[FIR(y, q_\tau)|X] = X\beta_\tau \tag{9}$$

The β_τ coefficients represent an approximation of the marginal effect of each explanatory variable on the unconditional quantile q_τ. It is emphasized that the conditional quantile regression provides estimates, *ceteris paribus*, of the return of each individual characteristic, where this return is variable among individuals according to the unconditional quantile to which they belong; meanwhile, the unconditional quantile regression estimates the effect of small changes, *ceteris paribus*, on a characteristic of the individuals in each quantile of the distribution, thus allowing to evaluate the effect on several distribution statistics (Fournier and Koske, 2012).

Thus, this work aims to identify how the explanatory variables influence the income gap between rural–urban, urban–urban and rural–rural workers in the Brazilian job market.

Based on the above procedure, it is possible to obtain the decomposition of the income differential between workers in a given quantile τ, applying a generalization of the Oaxaca–Blinder method based on the RIF.

$$\Delta^{q_\tau} = q_\tau\left(F_{y_u|k=u}\right) - q_\tau\left(F_{y_r|k=r}\right)$$

$$\Delta^{q_\tau} = \left[q_\tau\left(F_{y_u|k=u}\right) - q_\tau\left(F_{y_u|k=r}\right)\right] + \left[q_\tau\left(F_{y_u|k=r}\right) - q_\tau\left(F_{y_r|k=r}\right)\right]$$

$$\Delta^{q_\tau} = \Delta_X^{q_\tau} + \Delta_S^{q_\tau} \tag{10}$$

where $q_\tau(F_{y_u|k=u})$ indicates the work income observed by the individuals in the work area $k = u$ (urban) in quantile τ and $q_\tau(F_{y_r|k=r})$, is the same information, but for the work area $k = r$ (rural). The $q_\tau(F_{y_u|k=r})$ term represents the counterfactual performance for quantile τ. Using this counterfactual, it is possible to decompose the yield differential into two terms: The first is called the "composition effect," $\Delta_X^{q_\tau}$, which captures the effect of differences in observed characteristics, while the second is defined as the "wage structure effect," showing differences in the returns of the characteristics of each group.

Applying the expected value of the RIFs and assuming a linear specification, in terms of the estimated equations, we have

$$\widehat{\Delta}^{q_\tau} = \left(\overline{X}_u\widehat{\beta}_{\tau u}\right) - \overline{X}_r\widehat{\beta}_{\tau r}$$

$$\widehat{\Delta}^{q_\tau} = \left[\overline{X}_u\widehat{\beta}_{\tau u} - \overline{X}_r\widehat{\beta}_{\tau u}\right] + \left[\overline{X}_r\widehat{\beta}_{\tau u} - \overline{X}_r\widehat{\beta}_{\tau r}\right]$$

$$\widehat{\Delta}^{q_\tau} = \widehat{\beta}_{\tau u}\left[\overline{X}_u - \overline{X}_r\right] + \overline{X}_r\left[\widehat{\beta}_{\tau u} - \widehat{\beta}_{\tau r}\right] \tag{11}$$

One of the criticisms of Oaxaca's (1973) decomposition is that the effect of each variable depends directly on the choice of the omitted group of estimates, that is, when using categorical explanatory variables, the result of the estimation varies depending on the chosen base group. Oaxaca and Ransom (1999) and Yun (2005, 2008) present some suggestions to solve this problem. These methods consist of estimating the regression several times, changing the chosen base group. Subsequently, the coefficients are estimated as parameters.

However, according to Fortim *et al.* (2011), there are no satisfactory methods to solve this situation. Thus, in this work, because of the large number of regressions that would be required to accomplish this "correction," these suggested corrections were not implemented. Works such as by Meireles (2014), Miro and Franca (2016) and Mariano (2016), all works which also use the unconditional quantile regression method, do not attempt any corrections. These authors argue that this fact does not invalidate the analysis presented.

4. Results

4.1 Descriptive statistics

Before discussing the results from the unconditional quantile regressions, descriptive statistics of the variables are presented below. Table 2 shows the number of individual observations [18], the mean and percentage values for the rural–urban, rural–rural and urban–urban worker profile [19] for the years 2005 and 2015. The data, besides allowing evaluating differences in the characteristics between the groups of workers, make it possible to observe if there were significant changes in the ten-year interval.

A brief analysis of these results makes it possible to verify relevant differences between rural and urban workers. The first relevant evidence is that the rural–urban worker obtains less income than the urban–urban worker, nevertheless, expresses a higher level of income when compared to the rural–rural worker. The literature concerning income differentials highlights the disparities in human capital as the main cause of income inequalities; therefore, these results are justified, at least in part, because of the educational levels. It can also be noted that the urban–urban worker registers the highest level of schooling, while at the other extreme, the rural–rural worker shows the lowest average number of years of studying.

From 2005 to 2015, the results show an increase in the educational levels of the three groups of workers, on average, of a year of school. The proportion of people in the range of zero to four years of schooling decreases over time, but in contrast, the percentage of workers with 12 or more years of schooling increased. This small improvement in educational levels is more significant in the rural–urban worker group. In general, part of the educational changes may be related to public policies to encourage higher education in Brazil (and other educational levels), such as Financiamento Estudantil, or Student Financing (FIES), Programa Universidade para Todos (Prouni) or University for All Program [20] and racial quotas. However, it is apparent that rural–rural worker schooling is still very low [21], on average, five years of school in 2015.

Another important information is that the rural–rural worker, in the two analyzed periods, is older [22] and with greater experience in the labor market. One possible explanation for this is the fact that in rural areas, due to, among other reasons, the flexibility of labor laws, people enter the agricultural labor market very young and, in most cases, remain in this sector with low qualification for the rest of their lives. Even though these individuals will gain more work experience in relation to others, there is no proportional increase in income. Thus, in this case, it is expected that there will be no contribution of the variable experience in reducing the income differential for the benefit of the rural-rural worker.

It is also noteworthy to emphasize the increase of the participation of women and nonwhite individuals [23] in the job market in the three groups of workers. In relation to the activities performed, there was a reduction of the percentage of workers in the agricultural sector in all groups, and an increase in the number of workers especially in the construction, trade and transportation sectors, in the decade analyzed. In regional terms, in 2015, rural–urban and rural–rural workers are mainly located in Northeast of Brazil, while 55.10% of urban–urban workers are in the Southeast region. This can be justified by urbanization itself, which occurred differently in the mentioned regions.

In general, the results show that the rural–urban worker is positively selected when compared to the rural–rural worker, but significant income and human capital disparities are

Table 2.
Profile of the rural-urban (RU), rural–rural (RR) and urban–urban (UU) worker/Brazil, 2005 and 2015

Variables			2005 PNAD					2015 PNAD		
Worker	RU	RR	UU	$Diff_{RU-RR}$	$Diff_{RU-UU}$	RU	RR	UU	$Diff_{RU-RR}$	$Diff_{RU-UU}$
Variables (mean)										
Monthly income	1340.98	551.61	2037.9	789.37*	−696.92*	1424.41	615.90	2153.1	808.51*	−728.69*
Hourly income	7.65	3.07	11.60	4.58*	−3.95*	8.74	3.82	16.91	4.92*	−8.17*
Weekly income	42.07	37.33	43.70	4.74*	−1.63*	41.69	31.49	42.27	10.2*	−0.58*
Age	36.00	45.30	35.84	−9,0.30*	0.16	35.69	46.30	37.79	−10.61*	−2.10*
Work experience	22.69	35.16	20.88	−12.47*	1.81	21.57	35.25	22.27	−13.68*	−0.70*
Years of schooling	8.57	3.85	10.81	4.72*	−2.24*	9.91	5.31	11.49	4.6*	−1.58*
Variables (%)										
Schooling	100.00	100.00	100.00	0.00	0.00	100.00	100.00	100.00	0.00	0.00
0–4 years of schooling	17.19	60.30	5.39	−43.11*	11.80*	8.58	44.97	3.99	−36.39*	4.59*
5–8 years of schooling	25.66	30.86	17.54	−5.20*	8.12*	22.41	32.74	11.40	−10.33*	11.01*
9–11 years of schooling	19.26	5.36	17.00	13.90*	2.26*	16.97	10.30	14.71	6.67*	2.26*
12 or more years of schooling	37.88	3.48	60.06	34.40*	−22.18*	52.04	12.00	69.90	40.04*	−17.86*
Gender	100.00	100.00	100.00	0.00	0.00	100.00	100.00	100.00	0.00	0.00
Male	70.23	69.75	66.12	0.48*	4.11*	70.07	62.46	64.00	7.61*	6.07*
Female	29.77	30.25	33.88	−0.48*	−4.11*	29.93	37.54	36.00	−7.61*	−6.07*
Race	100.00	100.00	100.00	0.00	0.00	100.00	100.00	100.00	0.00	0.00
White	51.68	41.19	61.84	10.49*	−10.16*	47.89	33.03	51.01	14.86*	−3.12*
Nonwhite	48.32	58.81	38.16	−10.49*	10.16*	52.11	66.97	48.99	−14.86*	3.12*
Activity sector	100.00	100.00	100.00	0.00	0.00	100.00	100.00	100.00	0.00	0.00
Agriculture	11.62	92.34	1.09	−80.72*	10.53*	6.93	88.24	0.58	−81.31*	6.35*
Transformation industry	43.76	3.82	40.83	39.94*	2.93*	36.77	4.53	32.02	32.24*	4.75*
Construction	6.53	0.67	5.37	5.86*	1.16*	14.36	1.97	8.76	12.39*	5.60*
Trade and repairs	13.59	1.68	24.28	11.91*	−10.69*	19.61	3.11	27.44	16.50*	−7.83*
Transportation	8.55	0.45	13.63	8.10*	−5.08*	10.03	0.86	14.76	9.17*	−4.73*
Education/health/social services	15.95	1.05	14.80	14.90*	1.15*	12.30	1.28	16.44	11.02*	−4.14*
Brazilian regions	100.00	100.00	100.00	0.00	0.00	100.00	100.00	100.00	0.00	0.00
North	14.27	9.90	4.07	4.37*	10.2*	4.88	10.03	4.15	−5.15*	0.73
Northeast	24.70	51.52	13.67	−26.82*	11.03*	32.97	55.10	17.22	−22.13*	15.75*
Center-West	3.39	3.84	5.97	−0.45	−2.58*	1.95	3.93	7.12	−1.98*	−5.17*
South-East	29.66	13.18	54.43	16.48*	−24.77*	28.13	17.13	52.51	11*	−24.38*
South	27.97	21.56	21.86	6.41*	6.11*	32.07	13.80	19.00	18.27*	13.07*
Number of observations	577	4,728	14,214	–	–	741	3,982	17,122	–	–
Expanded Sample	289,801	2,347,309	6,647,948	–	–	449,692	2,451,620	9,845,808	–	–

Note(s): *represents significance at the 5% level
Source(s): Prepared by the authors using data from the 2005 and 2015 PNADs

observed when related to the urban–urban worker. It should also be noted that even in the recessive economic scenario of 2015, there was an increase in the deflated earnings of workers, compared to the 2005 earnings.

According to Ramalho and Silveira Neto (2007, 2012), Ojima *et al.* (2007) and Russo *et al.* (2016), in general, urban workers are more educated and better paid than rural workers. In this work, the results converge in that same sense; however, this information must be compared with the literature [24] with caution, since the classification criterion in this work is different than those mentioned above.

4.2 RIF regressions

The first step of the unconditional quantile regression analysis was to estimate the work income in the distribution quantiles (10, 25, 50, 75 and 90) based on the RIF, and then apply the Oaxaca–Blinder method to obtain the decomposition of the income differentials. In this section, we discuss the main results of the RIF regressions [25] referring to the years 2005 and 2015.

Most of the coefficients were statistically significant and showed a nonconstant trend, both in the distribution and among the groups of workers. This nonconstant behavior of the coefficients justifies the analysis by means of a quantile regression.

The coefficients estimated for the variable years of schooling showed that the return of education is positive and expresses an increasing trend in the higher quantiles. This is in accordance with the literature [26] on human capital, indicating that, for higher income levels, the return on education is greater. For the three groups of workers, the return of education was statistically significant. As was to be expected, the years of schooling generated higher returns for the urban–urban worker group. Comparing the results of 2005 and 2015, it can be observed that the effects of schooling were lower in the last year. This fact may be related to the economic crisis and the fall in the number of employment in Brazil in recent years. In general, this result is in agreement with those of the study by Cavalcante and Justo (2017).

Income returns with the experience variable in general were positive and increasing in the quantiles, except for the rural–rural worker, who indicated negative coefficients up to the 50th quantile and some statistically non–significant effects (*i.e.* q10, q25 and q50, for year 2015). These results are relevant because, according to the descriptive statistics, the rural–rural worker has a greater number of years of work experience. This variable, however, was not relevant in the lower quantiles (q10, q25 and q50) as a determinant of income for this group of workers. The main explanation is that these individuals, at the low income levels, begin to work early in rural activities, which probably compromises school performance, thus they remain unqualified and, consequently, the probability of raising their income in the following years diminishes.

The returns of the gender variable *female* and the *nonwhite* race variable, in general, corroborate the literature on income differential, pointing out negative coefficients, except for some values in the lower and upper quantiles of the income distribution that were positive, specifically in the rural–urban workers. Among other authors who show “discrimination” of income by sex and race are: Moraes (2005), Mattos and Machado (2006), Bartalotti and Leme (2007), Machado *et al.* (2008), Mariano *et al.* (2016) and Pereira and Oliveira (2016). As for the return of activities, it is observed, for the year 2005, in the three groups of workers, there was no well-defined trend in the quantiles. In the year 2015, there is a general positive return for the sector of activity, when comparing to agriculture, but the return of the sector of activity to the ruralurban worker in 2015, was not statistically significant.

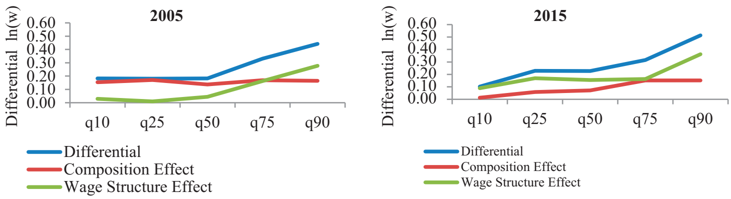
Finally, it is worth mentioning the returns of the different regions in Brazil. Using the North region as a reference, most of the coefficients for the Northeast showed a negative sign in the three groups of workers in both periods analyzed. The returns of the other regions showed positive effects in the urban–urban worker group, while in the other groups of workers, apart from not having a well-defined pattern, there were statistically nonsignificant effects. According to Miro and Franca (2016), higher returns are expected in regions where relative human capital shortages predominate.

4.3 Decomposition of income differentials, by distribution quantiles

This section presents the results of the decomposition of the income differentials in terms of logarithms of income and the contribution of the composition effect (explained effect) and the effect wage structure (not explained effect) on the analyzed workers. The decomposition makes it possible to verify how much of the income differential can be related to the composition effect, which shows the difference of income attributed to the different productive characteristics between the groups of workers, and how much can be explained by differences in wage structures, that is, differences in the returns of similar characteristics among different groups of workers. The method used enables a detailed decomposition of each explanatory variable on these two effects. Once the RIF equations were estimated, the Oaxaca–Blinder decomposition was applied to obtain the income differential.

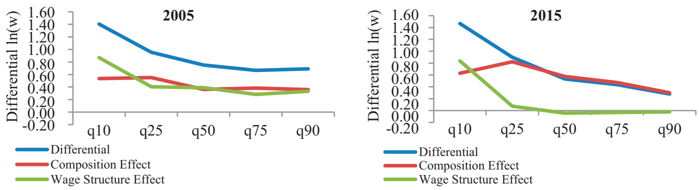
The coefficients [27] are presented in graphic form in Figures 1 and 2. Figure 1 shows the income differential between the rural–urban worker and the urban–urban worker, highlighting the contribution of the composition effect and the wage structure effect in 2005 and 2015.

Both the composition effect and the wage structure effect are positive and statistically significant (Figure 1), pointing to a differential of income in favor of the urban–urban worker. The total differential is determined by the two components. It is interesting to highlight the fact that these two groups of workers are contained in the same type of union (urban employee). Thus, the factor that differentiates them in general is the place of residence; however, according to the descriptive statistics, we observe a relatively high percentage of rural–urban workers (compared to urban–urban workers) inserted in rural activities. This can contribute to the rural–urban worker obtaining lower income than the urban–urban worker.



Source(s): Prepared by the authors based on data from the 2005 and 2015 PNADs

Figure 1.
Decomposition of the income differential between the rural–urban worker and the urban–urban worker, 2005 and 2015



Source(s): Prepared by the authors based on data from the 2005 and 2015 PNADs

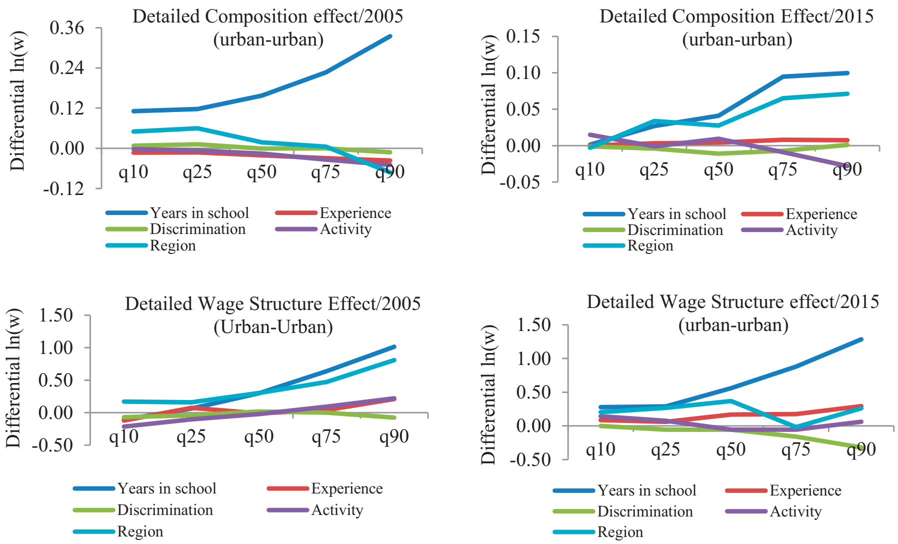
Figure 2.
Decomposition of the income differential between the rural–urban worker and the rural–rural worker, 2005 and 2015

In 2005, the composition effect is greater than the wage structure effect up to the quantile 75; in 2015, this effect surpassed the composition effect, indicating that the ruralurban worker approached, in terms of observable characteristics, the urban–urban worker, such as in education, hours worked and activity sector. It is observed, however, that there is an increase of the structural effect, that is, the predominance of unobservable factors evidencing an increase of discrimination in favor of the urban–urban worker. In the two years analyzed, the total income differential was increasing in the higher quantiles.

Figure 2, similar to the previous analysis, shows the income differential between the rural–urban worker and the rural–rural worker, as well as the contribution of the composition effect and the wage structure effect, for the years 2005 and 2015. One can observe the existence of a decreasing income differential in the distribution of income in favor of the rural–urban worker. In 2005, both the composition effect and the wage structure effect act to widen the differential in all quantiles, but the prevalence of one effect on the other varies as a result of the distribution, but in 2015, the wage structure effect, in the upper tail of the distribution (quantiles 50, 75 and 90), acts to reduce income disparity.

The detailed composition effect and wage structure effect are reproduced in Figures 3 and 4. The "detailed" contribution was performed similarly to the procedure used by Miro and Franca (2016). Thus, the discrimination effect is equal to the aggregate coefficients of female and nonwhite dummy variables. The activity effect is the aggregate of the coefficients of the other sectors in relation to the agricultural activity, and the region effect corresponds to the aggregate return of the Southeast, South, Center West and Northeast regions, compared to the North region.

Comparing the rural–urban worker and the urban–urban worker (Figure 3), the variables education and regional location were the most important factors to explain the composition effect, both in 2005 and in 2015. For higher income levels, the education gap becomes the main determinant of income disparities among workers. It can be noted that the contribution of educational level was greater in 2005, when compared to 2015. A possible explanation is that the expansion of higher education in Brazil tends to reduce the educational return. It is noted



Source(s): Prepared by the authors based on data from the 2005 and 2015 PNADs

Figure 3. Decomposition of the income differential between the rural–urban worker and the urban–urban worker: detailed composition effect and wage structure effect, 2005 and 2015

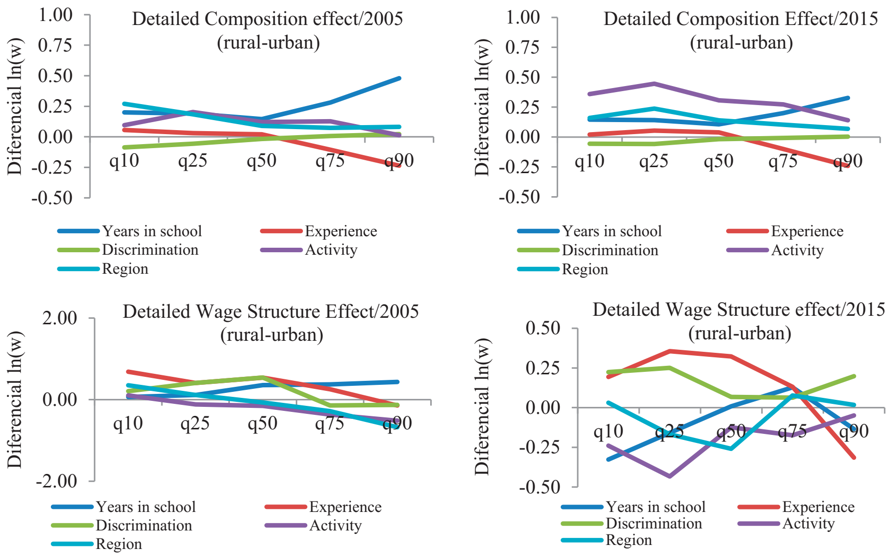


Figure 4.
Decomposition of income differential between rural–urban worker and rural–rural worker: detailed composition effect and wage structure effect, 2005 and 2015

Source(s): Prepared by the authors based on data from the 2005 and 2015 PNADs

that both the schooling variable and the regional location variable were statistically significant, except for the effects of the regions in the upper quantiles.

Regarding the wage structure effect, the contribution of the variables to the 2005 data did not indicate a well-defined pattern. The region effect was superimposed on the other variables in the ten to 50 quantiles, and from the 75 quantiles, years in school was more relevant (in the lower quantiles, the effects of schooling were not significant). In 2015, in addition to the educational and regional variables, the experience variable indicated a tendency to widen the income disparity in all quantiles. It should be noted that the effects of the region were not significant in the upper tail of the distribution (q75 and q90), whereas the experiment was not significant in q10, q25 and q75.

In relation to the rural–urban worker, when compared to the rural–rural worker (Figure 4), the composition effect was more adequately explained by the education variable in 2005 and the activity sector variable in 2015. The contribution of the level of education to the difference in income is greater in the tails of the income distributions in both years. The effect of the variables on the wage structure varies depending on the quantile. In general, the discrimination factor (for being female and not white) was high, especially in the lowest income levels of 2005 (q25 was not statistically significant at the 5% level).

Among the main results, we highlight the contribution of the wage structure effect in the year 2015. It was observed that this effect acts to widen the income disparity between the rural–urban worker and the urban–urban worker, evidencing discrimination of income which benefits the urban-urban individual. Also, when comparing the rural–urban worker and the rural–rural worker, the wage structure effect, on the upper tail of the distribution (quantiles 50, 75 and 90), is negative, acting to reduce income disparity, that is, for higher income levels, the unexplained characteristics tend to benefit the rural–rural worker.

Regarding the effects of the variables, years in school is highly relevant to explain income differences between the two groups of workers. Thus, workers living in rural areas, especially those linked to a rural union, had the lowest levels of schooling and the lowest income levels.

These results corroborate the importance of the human capital theory in explaining income disparities.

Therefore, the results suggest that more commitment and strategic planning by the government is needed in order to decrease barriers to access to the educational system in the Brazilian rural environment. Some interesting policies would be the improvement of the school transportation system, investing in the qualification of rural school teachers, the improvement of media access and information in rural areas, increasing the monitoring of the early entry of young people in the job market and, in parallel, researching other measures to reduce school abandonment in rural areas. These are just some of the measures that can contribute to increasing the qualification of rural workers and reduce these income differences.

5. Concluding remarks

This work aimed to analyze work income inequality in Brazil among workers with pendulum migration movements between rural and urban areas, *i.e.* rural–urban, rural–rural and urban–urban workers in the years 2005 and 2015. The main contribution was the attempt to study an aspect not commonly explored in the literature – the mobility of individuals residing in rural areas which work in urban centers. For that purpose, data from the 2005 and 2015 PNADs were used.

As a methodological procedure, the logarithm of the work income per hour per distribution quantile was estimated for each worker group by means of the RIF, and then, the Oaxaca–Blinder decomposition was applied to the different income quantiles.

The intention is to use the present results to contribute to the literature that studies the income inequality between rural and urban workers and the migration of people from rural to urban areas. Among the main results, income differentials were shown to benefit the urban–urban worker, when compared to the rural–urban worker, and income differentials seem to benefit the rural-urban worker, when that individual was compared to the rural–rural worker.

Income disparities (in terms of logarithms of income/hour) between the urban–urban and the rural–urban workers were found to be greater in the higher income levels, both in 2005 and in 2015. The wage structure effect was shown to be relevant in explaining income disparities. The composition effect, in general, was particularly important with the education, activity sector and geographical region of the worker variables.

The results, both in the mean and in the distribution quantiles, show that the differences in the productive attributes of the workers have a high level of explanation on work income inequality. These results corroborate the theory that discusses income inequality based on the differences in human capital and the educational lag in rural areas.

Thus, some considerations can be made about these results. First, what makes a person living in rural areas migrate from the rural unionized work to the urban unionized work is the possibility of a higher income. It was observed that the rural–urban worker is positively selected among the workers residing in rural areas, mainly because of the human capital level. The rural–urban worker, however, compared to the individual who is unionized and resides in the urban environment (urban-urban worker), has characteristics with a lower probability of economic returns, explaining the disparity of income.

The main conclusions reached in this research suggest that income disparities could be reduced if the educational level of rural residents (in rural or urban unions) was higher. Therefore, specific public policies aimed at the educational improvement of residents in the rural environment, as well as reducing barriers of entry in the schooling system, policies focusing on minimizing school abandonment and improving transportation would be important to decrease the income differences in relation to the urban–urban worker.

As for future works on this topic, it is suggested to study income differential according to the different regions of the country, in a disaggregated manner, or even considering the variables on a state level. The rural–rural worker of the Northeast region of Brazil, for example, probably has different characteristics from that of the South region. Thus, to separate according to the region would be one way of making the sample more homogeneous and to make the analysis even more robust.

Notes

1. These changes became known as "the green revolution," characterized by aset of technological innovations in the agricultural sector. The main purpose was to expand productivity in agriculture through practices such as genetic cross-fertilization, use of pesticides, fertilizers and mechanization of agricultural activities. In Brazil, this process occurred in the mid-1960s. For details on the subject, refer to the study by Matos (2010).
2. EMATERCE, EMBRAPA, INCRA, among others created to improve the agricultural sector in Brazil.
3. Lima (1995) discusses the representativeness that the Brazilian rural exodus assumed in the period from 1960 to 1980. The percentage values referring to this process were detailed in the second section of this work. Justo (2006) analyzed rural–urban migration in Brazil in the 1980–2000 period.
4. In recent years, the Brazilian government has adopted a set of actions aimed at reducing rural poverty and keeping the population in the countryside. Among the main government programs implemented were the National Program for Strengthening Family Agriculture (PRONAF), and the *Garantia Safra*, *Bolsa Estiagem*, *Bolsa Família* and *Agroamigo* programs.
5. Permanent migration refers to the displacement of people for a fixed or indeterminate period. Temporary migration has as its main characteristic the temporality factor. This type of migrant moves for a period that can be days or a longer period of time but without the goal of permanently moving to the destination.
6. For example: Justo (2006), Ramalho e Silveira Neto (2007, 2012).
7. Among others: Ântico (2005), Ojima *et al.* (2007), Ojima and Marandola Jr (2012) and Ojima *et al.* (2015).
8. The 2005 income numbers were updated to 2015 levels using data from the National Consumer Price Index (*Índice Nacional de Preços ao Consumidor* INPC) compiled by the IBGE. Available at: https://www.ipea.gov.br/portal/images/stories/PDFs/TDs/td_0897.pdf. Accessed on May 5, 2019.
9. It should be noted that the workplace is a proxy represented by the type of union (rural or urban).
10. In the international literature, Mensah *et al.* (2016), for example, point out that despite the importance of education in migration decisions, there is little literature on the rural-urban aspect.
11. It has advantages compared to others, for example: Dinardo *et al.* (1996) and Machado and Mata (2005).
12. This expression is used in the literature, for example, Ramalho and Silveira Neto (2007) and Justo (2006), in order to explain the cases in which the migrant is selected through personal attributes or characteristics, among other factors, which make them potentially more productive in the job market.
13. Generally considered between two cities or between city and countryside.
14. The 2005 income was updated to 2015 based on data from the National Consumer Price Index (INPC) Restricted from IBGE. Available at: http://www.ipea.gov.br/portal/images/stories/ PDFs/TDs/td_0897.pdf.
15. Due to the limited data in the PNAD, to identify the migration of work between the rural and urban areas, it was only possible to consider unionized workers.
16. The variables used are in agreement with the literature regarding unconditional quantitative regressions. Among the main works, those of Firpo *et al.* (2007, 2009), Meireles (2014), Miro and Franca (2016), Oliveira and Silveira Neto (2016). In addition, it is based on the availability of PNAD data.
17. It is probable that a relevant part of these individuals (rural–urban workers) reside in small or medium-sized municipalities, where the distance traveled between rural and urban areas is closer

than the daily commutes of workers moving between large cities. Due to data limitations, this research did not intend to identify this aspect.

18. In all analyzes of this work, the expanded sample was used, which considers the variable "weight," available in PNAD data. It is noteworthy that the number of observations, mainly of the rural–urban workers, was relatively low, which was something expected, due to the restriction of using only unionized workersemployees.
19. Mean comparison tests and ratio tests were performed between groups of workers. The rural–urban worker was used as reference category. For the mean tests, the *t*-test was used; the null hypothesis is that the mean of each variable between the groups are equal. For the ratio test, the two-tailed test was used. The null hypothesis is that the proportion of people with a certain characteristic is equal between two groups of workers.
20. FIES (*Financiamento Estudantil*) and Prouni (*Programa Universidade Para Todos*) are government programs aimed at facilitating higher education in Brazil through scholarships.
21. According to Rodrigues (2017), students from urban schools show a difference in school performance that is higher than the performance of rural school students, and a large part of this differential is explained by the characteristic effect of the schools and the student's family.
22. Rural–urban migration is more common among young people, with older people remaining in the countryside.
23. This may be due to various policies that have caused more people to declare themselves to be nonwhite, for example racial quotas.
24. No works using the same rating criteria were found for comparison.
25. Due to space limitation, the tables with the estimates are featured in the Appendix.
26. For example: Miro and Franca (2016).
27. Due to space limitation, the tables with the estimates are featured in the Appendix.

References

Amaral, E.F.L., Rodrigues, R.N. and Fígoli, M.G.B. (2002), "Síntese da migração em Goiás e no Distrito Federal nas últimas décadas", *Sociedade Cultura*, Goiânia, Vol. 5 No. 2, pp. 127-136.

Ântico, C. (2005), "Deslocamentos pendulares na região metropolitana de São Paulo", *São Paulo em Perspectiva*, São Paulo, Vol. 19 No. 4, pp. 110-120.

Barrios, S., Bertinelli, L. and Strobl, E. (2006), "Climatic change and rural-urban migration: the case of Sub-Saharan Africa, Core Discussion Paper.

Bartalotti, O. and Leme, M.C.S. (2007), "Discriminação salarial além da média: uma abordagem de decomposição contra factual utilizando regresses", *Encontro Nacional De Economia, 35, 2007, Recife Anais ... Recife*, Vol. 1, pp. 1-19.

Beine, M., Docquier, F. and Ozden, C. (2011), "Diasporas", *Journal of Development Economics*, pp. 30-41.

Black, R., Adger, W., Arnell, N., Dercon, S., Geddes, A. and Thomas, A. (2011), "The effect of environmental change on human migration", *Global Environmental Change, Migration and Global Environmental Change–Review of Drivers of Migration*, Vol. 21 No. 1, pp. S3-S11, doi: 10.1016/j.gloenvcha.2011.10.001.

Blinder, A.S. (1973), "Wage Discrimination: reduced form and structural estimates", *Journal of Human Resources*, Evanston, No. 8, pp. 436-455.

Castles, S. (2011), "Concluding remarks on the climate change-migration nexus", in Piguet, E., Pécoud, A. and Guchteneire, P. *Migration and Climate Change*, pp. 415-427.

Cavalcante, W.V. and Justo, W.R. (2017), "Migração de retorno para o Nordeste e o Impacto Sobre a renda dos Estados no período 2003-2012", *Encontro Pernambucano De Economia Políticas Para O Desenvolvimento Estadual V Enpecon, 2017, Recife. Anais... Recife.*

Costa, R.A., Costa, E.M. and Mariano, F.Z. (2016), "Diferenciais de rendimentos nas áreas rurais do Brasil", *Revista de Política Agrícola*, Brasília, DF, Vol. 25 No. 4, pp. 112-135.

Dinardo, J., Fortin, N.M. and Lemieux, T. (1996), "Labor market institutions and the distribution of wages, 1973-1992: a semiparametric approach", *Econometrica*, Vol. 64 No. 5, pp. 1001-1044.

Firpo, S., Fortin, N. and Lemieux, T. (2007), *Decomposing Wage Distributions Using Recentered Influence Function Regressions*, Mimeo, Columbia, pp. 1-60, available at: https://www.economics.uci.edu/files/docs/micro/f07/lemieux.pdf (accessed 9 May 2019).

Firpo, S., Fortin, N. and Lemieux, T. (2009), "Unconditional quantile regressions", Econometrica, New York, Vol. 77 No. 3, pp. 953-973.

Fortin, N., Lemieux, T. and Firpo, S. (2011) "Decomposition methods in economics", *Handbook of labor economics*, Vol. 4, pp. 1-102.

Fournier, J. and Koske, I. (2012), "*Less Income Inequality and More Growth–Are They Compatible? the Drivers of Labour Earnings Inequality–An Analysis Based on Conditional and Unconditional Quantile Regressions*", OECD Economics Department Working Papers, Paris, No. 930, available at: http://library.bsl.org.au/jspui/bitstream/1/3254/1/Less%20Income%20Inequality%20and%20More%20Growth%20Part%207.pdf (accessed 9 May 2019).

Harris, J.L. and Todaro, M.P. (1970), "Migration, unemployment, and development: a two-sector analysis", *The American Economic Review*, Vol. 60, pp. 126-142.

Instituto Brasileiro De Geografia E Estatística (2005), "Pesquisa Nacional por Amostra de Domicílios", Rio de Janeiro, available at: http//:www.ibge.gov.br (accessed May 2019).

Instituto Mauro Borges De Estatísticas E Estudos Socioeconômicos (IMB) (2012), *Mobilidade pendular da população em Goiás*, SEGPLAN, Goiás, available at: http://www.imb.go.gov.br/down/mobilidade_ pendular_da_populacao_em_goias.pdf (accessed May 2019).

Justo, W.R. (2006), *Migração inter-regional no Brasil: determinantes e perfil do migrante brasileiro no período de 1980-2000*, Tese (Doutorado em Economia) Universidade Federal de Pernambuco, Recife.

Lewis, W.A. (1954), "Economic development with unlimited supplies of labour", *Manchester School*, Vol. 22, pp. 139-191.

Lima, R.C. (1995), "Um Exame dos Determinantes das Migrações Rural-Urbanas no Brasil", Cadernos de Ciência e Tecnologia, Brasília, Vol. 12 Nos 1/3, pp. 55-67.

Machado, J.F. and Mata, J. (2005), "Counterfactual decomposition of changes in wage distributions using quantile regression", *Journal of Applied Econometrics*, Vol. 4 No. 20, pp. 445-465, available at: https://onlinelibrary.wiley.com/doi/full/10.1002/jae.788 (accessed May 2019).

Machado, A.F., Oliveira, A.M.H.C. and Antigo, M. (2008), "Evolução do diferencial de rendimentos entre setor formal e informal no Brasil: o papel das características não observadas", Revista Economia Contemporânea, Rio de Janeiro, Vol. 12 No. 2, pp. 355-388.

Marchiori, L., Maystadt, J. and Schumacher, I. (2011), "The impact of climate variations on migration in Sub-Saharan Africa", paper presented at *CSAE 25th Anniversary Conference: Economic Development in Africa*, Oxford, UK.

Mariano, F.Z., Costa, E.M., Guimarães, D.B. and Souza, D.T. (2016), "Diferenciais de rendimentos entre raças e gêneros nas regiões metropolitanas, por níveis ocupacionais: uma análise através do pareamento de Ñopo", *Encontro Nacional De Economia, 24, 2016, Foz do Iguaçu-PR. Anais… Foz do Iguaçu*.

Mariano, F.Z. (2016), *Ensaios sobre o ensino profissionalizante no Ceará*, 136 f. Tese (Doutorado em Economia) Universidade Federal do Ceará, Fortaleza.

Martine, G. (1987), "Êxodo rural, concentração urbana e fronteira agrícola, in Martine, G.G. and Garcia, R.C. (Eds), *Os impactos sociais da modernização agrícola*, São Paulo, Caetés.

Martine, G. (1992), "Population redistribution and state policies: a Brazilian perspective", in Goldscheider, C. (Ed.), *Migration, Population Structure, and Redistribution Policies*, West View Press, Colorado.

Matos, A.K.V. (2010), "Revolução verde, biotecnologia e tecnologias alternativas", *Cadernos da FUCAMP, Monte Carmelo MG*, Vol. 10 No. 12, pp. 1-17.

Mattos, R.S. and Machado, A.F. (2006), "Diferencial de rendimentos por cor e sexo no Brasil (1987-2001)", *Econômica*, Niterói, Vol. 8 No. 1, pp. 5-27.

Meireles, D.C. (2014), *Diferenciais de rendimentos por gênero: uma análise dos efeitos composição e estrutura salarial no Brasil (1976, 1987, 1996 e 2009)*, Dissertação (Mestrado em Economia), Universidade Federal do Rio Grande do Norte, Natal.

Mensah, F., A Yiadom, L. and B Boateng, W.B. (2016), "Effect of education on migration decisions in Ghana: a rural-urban perspective", *Journal of Economics Studies*, Vol. 43 No. 2, pp. 336-356.

Miro, V.H. and Franca, J.M.S. (2016), "Decompondo o diferencial regional de salários entre Sudeste e Nordeste: uma aplicação da abordagem quantílica incondicional", *Revista Econômica do Nordeste*, Fortaleza, Vol. 47 No. 3, pp. 109-129.

Moraes, S.M.A. (2005), *Discriminação salarial por gênero nos segmentos industriais do Brasil: uma análise para os anos de 1993, 1998 e 2003.2005, 115 f,*Dissertação (Mestrado em Desenvolvimento Econômico), Universidade Federal do Paraná, Curitiba.

Ney, M.G. and Hoffmann, R. (2009), "Educação, concentração fundiária e desigualdade de rendimentos no meio rural brasileiro", *Revista de Economia e Sociologia Rural*, Brasília, Vol. 47 No. 1, pp. 147-181.

Oaxaca, R.L. and Ransom, M.R. (1999), "Identification in detailed wage decompositions", *The Review of Economics and Statistics*, Vol. 81 No. 1, pp. 154-157.

Oaxaca, R.L. (1973), "Male-female wage differentials in urban labor markets", *International Economic Review*, Vol. 14 No. 3, pp. 693-709.

Ojima, R. and Marandola, E. Jr (2012), "Mobilidade populacional e um novo significado para as cidades: dispersão urbana e reflexiva na dinâmica regional não metropolitan", *Revista Brasileira de Estudos Urbanos e Regionais*, Anpur, Rio de Janeiro, Vol. 14 No. 2, pp. 103-116.

Ojima, R., Silva, R.B. and Pereira, R.H.M. (2007), "A mobilidade pendular na definição das cidades-dormitório: caracterização sócio demográfica e novas territorialidades no contexto da urbanização brasileira", Cadernos PUR/UFRJ, Rio de Janeiro, Vol. 21 No. 2, pp. 111-132.

Ojima, R., Monteiro, F.F. and Nascimento, T.C.L. (2015), "Deslocamentos pendulares e o consumo do espaço: explorando o tempo de deslocamento casa-trabalho", *Revista Paranaense de Desenvolvimento*, Curitiba, Vol. 36 No. 128, pp. 133-147.

Oliveira, R.C. and Silveira Neto, R.M. (2016), "Estrutura Produtiva ou Escolaridade? Uma Análise dos Fatores Explicativos da Desigualdade de Renda entre as Regiões Sudeste e Nordeste por quartil para o Período entre os anos de 1970 e 2010", *Revista Econômica do Nordeste*, Fortaleza, Vol. 57, pp. 75-91.

Pereira, R.M. and Oliveira, C.A. (2016), "Os diferenciais de rendimento por gênero no Rio Grande do Sul: uma aplicação do modelo de heckman e da decomposição de Oaxaca-blinder", *Redes*, Santa Cruz do Sul, Vol. 21 No. 1, pp. 148-173.

Ramalho, H.M.B. and Silveira Neto, R.M. (2007), "Capital Humano e Retorno à Migração: o caso da migração rural-urbana no Nordeste do Brasil", *Encontro Regional De Economia, 13, 2007. Forúm Bnb De Desenvolvimento, Encontro Regional De Economia, 12, 2007, Fortaleza, Anais, Fortaleza.*

Ramalho, H.M.B. and Silveira Neto, R.M. (2012), "A Inserção do Migrante Rural no Mercado de Trabalho Urbano no Brasil: uma análise empírica da importância dos setores informal e formal", *Estudos Econômicos*, São Paulo, Vol. 42 No. 4, pp. 731-771.

Ranis, G. and Fei, J.C. (1961), "A theory of economic development", *The American Economic Review*, Vol. 51, pp. 533-56.

Resende, M. and Wyllie, R. (2006), "Retornos para educação no Brasil: evidências empíricas adicionais", *Revista de Economia Aplicada*, [São Paulo], Vol. 10 No. 3, pp. 349-365.

Rodrigues, L.O. (2017), *Ensaios sobre diferencial de desempenho escolar entre alunos de escolas rurais e urbanas no Brasil*, Dissertação (Mestrado em Economia), Universidade Federal do Ceará UFC, Economia, Fortaleza.

Russo, L.X., Alves, A.F. and Parré, J.L. (2016), "O diferencial de rendimento entre trabalhadores rurais e urbanos no Brasil e em suas regiões", *Congresso Da Sociedade Brasileira De Economia, Administração E Sociologia Rural, 54, Maceió, Anais... Maceió*.

Sjaastad, L.A. (1962), "The costs and retuns of human migration", *Journal of Political Economy*, [New York], Vol. 70 No. 5, pp. 80-93.

Todaro, M.P. (1969), "A model of labor migration and urban unemployment in less developed countries", *The American Economic Review*, Vol. 59 No. 1, pp. 138-148.

Yun, M. (2005), "A simple solution to the identification problem in detailed wage decompositions", *Economic Inquiry*, Vol. 43 No. 4, pp. 766-772.

Yun, M. (2008), "Identification problem and detailed Oaxaca decomposition: a general solution and inference", *Journal of Economic and Social Measurement*, Vol. 33 No. 1, p. 27.

Further reading

Corseuil, C.H. and Foguel, M.N. (2002), "Uma Sugestão de Deflatores para Rendas Obtidas a Partir de Algumas Pesquisas Domiciliares do IBGE", Instituto de Pesquisa Econômica e Aplicada (IPEA), Texto para Discussão No. 897, available at: https://www.ipea.gov.br/portal/images/stories/PDFs/TDs/td_0897.pdf (accessed 20 April 2020).

Instituto Brasileiro De Geografia E Estatística (2015), "Pesquisa Nacional por Amostra de Domicílios", Rio de Janeiro, available at: http//:www.ibge.gov.br (accessed May 2019).

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Appendix

Variables	2005 q10	2005 q25	2005 q50	2005 q75	2005 q90	2015 q10	2015 q25	2015 q50	2015 q75	2015 q90
Years in school	0.0409*	0.0600*	0.0998*	0.1632*	0.2474*	0.0250*	0.0419*	0.0745*	0.1359*	0.1743*
	(0.0020)	(0.0018)	(0.0022)	(0.0033)	(0.0075)	(0.0018)	(0.0020)	(0.0023)	(0.0042)	(0.6276)
Experience	0.0147*	0.0182*	0.0253*	0.0350*	0.0481*	0.0070*	0.0155*	0.0233*	0.0298*	0.0257*
	(0.0026)	(0.0028)	(0.0036)	(0.0047)	(0.0083)	(0.0017)	(0.0019)	(0.0022)	(0.0035)	(0.0052)
Experience^2	−0.0002*	−0.0002*	−0.0002*	−0.0001*	−0.0001	−0.0001*	−0.0002*	−0.0002*	−0.0002*	0.0000
	(0.0001	(0.0001)	(0.0165)	(0.0001)	(0.0002)	(0.0000)	(0.0000)	(0.0000)	(0.0001)	(0.0001)
Female	−0.1934*	−0.2535*	−0.3017*	−0.2909*	−0.4037*	−0.0830*	−0.2111*	−0.3004*	−0.3721*	−0.3509*
	(0.0161)	(0.0145)	(0.0165)	(0.0239)	(0.0485)	(0.0121)	(0.0145)	(0.0164)	(0.0281)	(0.0469)
Nonwhite	−0.0810*	−0.1131*	−0.1776*	−0.2528*	−0.4237*	−0.0343*	−0.0819*	−0.1105*	−0.2668*	−0.3008*
	(0.0145)	(0.0137)	(0.0168)	(0.0238)	(0.0406)	(0.0103)	(0.0126)	(0.0159)	(0.0271)	(0.0403)
Industry	−0.0170	0.0077	−0.0650*	−0.1507*	−0.3747*	0.3616*	0.1789*	0.2097*	0.1054	0.1296
	(0.0182)	(0.0171)	(0.0232)	(0.0337)	(0.0682)	(0.1404)	(0.1131)	(0.1146)	(0.1564)	(0.1428)
Construction	−0.0599*	0.0006	−0.1576*	−0.1623*	−0.1405	0.4072*	0.2311*	0.2223*	0.1338	0.3932*
	(0.0376)	(0.0330)	(0.0232)	(0.0520)	(0.1067)	(0.1410)	(0.1139)	(0.1160)	(0.1588)	(0.1521)
Commerce	−0.0733*	−0.1156*	−0.2094*	−0.3504*	−0.5591*	0.2790*	0.0688	0.0816	−0.0357	0.0103
	(0.0210)	(0.0197)	(0.0232)	(0.0347)	(0.0700)	(0.1406)	(0.1134)	(0.1147)	(0.1565)	(0.1437)
Transportation	0.0830*	0.0975*	0.0362	−0.3179*	−0.6245*	0.3840*	0.2361*	0.2527*	−0.0393	0.0002
	(0.0209)	(0.0214)	(0.0285)	(0.0419)	(0.0785)	(0.1406)	(0.1133)	(0.1155)	(0.1577)	(0.1457)
Education	0.0580*	0.1010*	0.0362*	−0.0433	−0.1816*	0.4139*	0.2715*	0.3301*	0.3371*	0.4281*
	(0.0216)	(0.0206)	(0.0267)	(0.0447)	(0.0981)	(0.1407)	(0.1140)	(0.1159)	(0.1596)	(0.1547)
Northeast	−0.2432*	−0.1592*	−0.0269	0.0188	0.1127*	−0.1105*	−0.1272*	−0.0471*	−0.0859*	0.0076
	(0.0359)	(0.0279)	(0.0289)	(0.0375)	(0.0625)	(0.0267)	(0.0266)	(0.0271)	(0.0431)	(0.0573)
Center-West	0.1189*	0.1073*	0.1715*	0.1703*	0.2852*	0.1214*	0.1835*	0.1728*	0.1114*	0.1388*
	(0.0358)	(0.0303)	(0.0328)	(0.0434)	(0.0759)	(0.0254)	(0.0279)	(0.0313)	(0.0516)	(0.0712)
Southeast	0.1879*	0.2000*	0.2374*	0.1788*	0.1513*	0.1470*	0.2016*	0.1832*	0.1112*	0.2025*
	(0.0306)	(0.0257)	(0.0279)	(0.0360)	(0.0569)	(0.0226)	(0.0243)	(0.0265)	(0.0426)	(0.0712)
South	0.2064*	0.1682*	0.1120*	0.0307	−0.0428	0.1660*	0.2367*	0.1864*	0.0391	0.0750
	(0.0321)	(0.0275)	(0.0299)	(0.0398)	(0.0661)	(0.0236)	(0.0260)	(0.0294)	(0.0426)	(0.0652)
Constant	0.5578*	0.5771*	0.4517*	0.3168*	0.0743	0.7529*	0.8838*	0.7118*	0.5865*	0.6276*
	(0.0498)	(0.0459)	(0.0550)	(0.0769)	(0.1442)	(0.1440)	(0.1182)	(0.1207)	(0.1689)	(0.1785)
N	14,173	14,173	14,173	14,173	14,173	9,769	9,769	9,769	9,769	9,769
R^2	0.1126	0.1833	0.2496	0.2592	0.1805	0.106	0.1839	0.2199	0.2075	0.1413
F	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000

Note(s): *statistically significant at 5%. Standard errors in parentheses
Source(s): Prepared by the authors based on data from the 2005 and 2015 PNA

Table A1. RIF urban–urban worker: when estimated in relation to the rural–urban worker

Table A2.
RIF rural–urban worker: when estimated in relation to the urban–urban worker

Variables	2005 q10	2005 q25	2005 q50	2005 q75	2005 q90	2015 q10	2015 q25	2015 q50	2015 q75	2015 q90
Years in school	0.0509*	0.0540*	0.0722*	0.1043*	0.0626*	0.0008	0.0169*	0.0257*	0.0594*	0.0626*
	(0.0098)	(0.0098)	(0.0090)	(0.0132)	(0.0188)	(0.0042)	(0.0078)	(0.0094)	(0.0147)	(0.0188)
Experience	0.0268*	0.0124	0.0339*	0.0452*	0.0162*	0.0021	0.0152*	0.0158*	0.0293*	0.0162
	(0.0100)	(0.0094)	(0.0088)	(0.0102)	(0.0168)	(0.0060)	(0.0069)	(0.0086)	(0.0128)	(0.0168)
Experience^2	−0.0004*	−0.0001	−0.0005*	−0.0006*	−0.0001*	0.0000	−0.0003*	−0.0002*	−0.0005*	−0.0001
	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0003)	(0.0001)	(0.0001)	(0.0002)	(0.0003)	(0.0003)
Female	0.0037	−0.0807	−0.3633*	−0.3728*	0.0520*	−0.0458	−0.1021*	−0.2237*	−0.0005	0.0520
	(0.0757)	(0.0787)	(0.0736)	(0.0977)	(0.1347)	(0.0526)	(0.0001)	(0.0742)	(0.1116)	(0.1347)
Nonwhite	−0.0731	−0.1597*	−0.1689*	−0.1834*	0.0565	−0.0599	−0.0476	−0.0500	−0.0868	0.0565
	(0.0757)	(0.0739)	(0.0746)	(0.1018)	(0.1253)	(0.0407)	(0.0001)	(0.0630)	(0.1036)	(0.1253)
Industry	0.2317*	0.1098	−0.0653	−0.1852*	0.1772*	0.1890	0.1214	0.2480*	0.1967	0.1772
	(0.0944)	(0.0879)	(0.0843)	(0.1291)	(0.2722)	(0.1390)	(0.1437)	(0.1459)	(0.2381)	(0.2722)
Construction	0.4189*	0.1098	−0.0731	−0.4085*	0.3300*	0.2034	0.1519	0.3319*	0.2391	0.3300
	(0.1504)	(0.1824)	(0.1560)	(0.1914)	(0.3037)	(0.1407)	(0.1558)	(0.1561)	(0.2532)	(0.3037)
Commerce	0.1971*	0.0179	−0.1430	−0.5134*	−0.1998*	0.2136	0.0392	0.0913	−0.1458	0.2815
	(0.1252)	(0.1229)	(0.1224)	(0.1572)	(0.2558)	(0.1387)	(0.1516)	(0.1565)	(0.2369)	(0.2558)
Transportation	0.2963*	0.2056*	−0.1199	−0.4695*	0.0689*	0.2216*	0.1379	0.4167*	−0.1458	0.0689
	(0.1146)	(0.1228)	(0.1382)	(0.1882)	(0.3381)	(0.1408)	(0.1499)	(0.1596)	(0.2768)	(0.3381)
Education	0.3206*	0.3104*	0.2618*	−0.2034	0.2815*	0.2472*	0.1071	0.3689*	0.4093	0.2815
	(0.1013)	(0.1112)	(0.1111)	(0.1668)	(0.3597)	(0.1476)	(0.1644)	(0.1759)	(0.2830)	(0.3180)
Northeast	−0.5293*	−0.4808*	−0.3418*	−0.5313*	−0.4028*	−0.1645*	−0.4230*	−0.5190*	−0.2192	−0.4028
	(0.1149)	(0.1104)	(0.0950)	(0.1351)	(0.3180)	(0.0446)	(0.0875)	(0.1031)	(0.1962)	(0.3180)
Center-West	−0.0180	0.0611	0.1155	−0.0748	0.0511*	−0.2530*	−0.1082	−0.1785	0.2084	0.0511
	(0.1186)	(0.1318)	(0.1344)	(0.2375)	(0.4848)	(0.1658)	(0.1680)	(0.1976)	(0.3248)	(0.4848)
Southeast	0.0039	0.0611	−0.1246	−0.3181*	−0.0648*	−0.0931*	−0.0991	−0.2255	0.1467	−0.0648
	(0.0894)	(0.1072)	(0.1009)	(0.1523)	(0.3564)	(0.0457)	(0.0892)	(0.1116)	(0.2197)	(0.3564)
South	0.0039	0.0611	−0.1526	−0.4850*	−0.1579*	−0.0495	0.0290	−0.0671*	0.1162	−0.1579
	(0.0928)	(0.1108)	(0.1110)	(0.1549)	(0.3430)	(0.0380)	(0.0799)	(0.1083)	(0.2146)	(0.3430)
Constant	0.1830*	0.0611*	0.9913*	1.4000*	1.8477*	1.3725*	1.3504*	1.5430*	1.2469*	1.8477*
	(0.2122)	(0.1929)	(0.1958)	(0.2618)	(0.5236)	(0.1541)	(0.1921)	(0.2331)	(0.3691)	(0.5236)
N	562	562	562	562	355	355	355	355	355	355
R^2	0.2432	0.2286	0.2513	0.2458	0.1113	0.0651	0.2137	0.2375	0.1735	0.1113
F	0.0000	0.0000	0.0000	0.0000	0.0013	0.0191	0.0000	0.0000	0.0000	0.0013

Note(s): *statistically significant at 5%. Standard errors in parentheses
Source(s): Prepared by the authors based on data from the 2005 and 2015 PNA

Table A3. RIF rural–urban worker: when estimated in relation to the rural–rural worker

Variables	2005 q10	2005 q25	2005 q50	2005 q75	2005 q90	2015 q10	2015 q25	2015 q50	2015 q75	2015 q90
Years in school	0.0509*	0.0540*	0.0722*	0.1043*	0.1536*	0.0008*	0.0169*	0.0257*	0.0594*	0.0626*
	(0.0098)	(0.0098)	(0.0090)	(0.2458)	(0.0217)	(0.0042)	(0.0078)	(0.0094)	(0.0147)	(0.0188)
Experience	0.0268*	0.0124	0.0339*	0.0452*	0.0522*	0.0021	0.0152*	0.0158*	0.0293*	0.0162
	(0.0100)	(0.0094)	(0.0088)	(0.0102)	(0.0173)	(0.0060)	(0.0069)	(0.0086)	(0.0128)	(0.0168)
Experience^2	−0.0004*	−0.0001	−0.0005*	−0.0006*	−0.0006*	0.0000	−0.0003*	−0.0002*	−0.0005*	−0.0001
	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0003)	(0.0001)	(0.0001)	(0.0002)	(0.0003)	(0.0003)
Female	0.0037	−0.0807	−0.3633*	−0.3728*	−0.5090*	0.0000	−0.1021*	−0.2237*	−0.1794*	0.0520
	(0.0657)	(0.0787)	(0.0736)	(0.0977)	(0.1716)	(0.0526)	(0.0629)	(0.0742)	(0.1116)	(0.1347)
Nonwhite	−0.0731	−0.1597*	−0.1689*	−0.1834*	−0.1312	−0.0599*	−0.0476	−0.0500	−0.0868	0.0565
	(0.0757)	(0.0739)	(0.0746)	(0.1018)	(0.1516)	(0.0526)	(0.0551)	(0.0630)	(0.1036)	(0.1253)
Industry	0.2317*	0.1098	−0.0653	−0.1852	−0.4418*	0.1890	0.1214	0.2480*	0.1967	0.1772
	(0.0944)	(0.0879)	(0.0843)	(0.1291)	(0.2284)	(0.1390)	(0.1437)	(0.1459)	(0.2381)	(0.2722)
Construction	0.4189*	0.0944	−0.0731	−0.4085*	−1.0270*	0.2034*	0.1519	0.3319*	0.2391	0.3300
	(0.1504)	(0.1824)	(0.1560)	(0.1914)	(0.2180)	(0.1407)	(0.1558)	(0.1561)	(0.2532)	(0.3037)
Commerce	0.1971*	0.0179	−0.1430	−0.5134*	−0.9397*	0.2136*	0.1519	0.0913	−0.1458	−0.1998
	(0.1252)	(0.1229)	(0.1224)	(0.1572)	(0.2202)	(0.1387)	(0.1516)	(0.1565)	(0.2369)	(0.2558)
Transportation	0.2963*	0.2056*	−0.1199	−0.4695*	−0.9349*	0.2216*	0.1379	0.4167*	0.1992	0.0689
	(0.1146)	(0.1228)	(0.1382)	(0.1882)	(0.2675)	(0.1408)	(0.1499)	(0.1596)	(0.2768)	(0.3381)
Education	0.3206*	0.3104*	0.2618*	−0.2034	−0.5788*	0.2472*	0.1071	0.3689*	0.4093*	0.2815
	(0.1013)	(0.1112)	(0.1111)	(0.1668)	(0.3122)	(0.1476)	(0.1644)	(0.1759)	(0.2830)	(0.3597)
Northeast	−0.5293*	−0.4808*	−0.3418*	−0.5313*	−0.6105*	−0.1645*	−0.4230*	−0.5190*	−0.2192	−0.4028
	(0.1149)	(0.1104)	(0.0950)	(0.1351)	(0.2454)	(0.0446)	(0.0875)	(0.1031)	(0.1962)	(0.3180)
Center-West	−0.0180	0.0611	0.1155	−0.0748*	−0.6450*	−0.2530*	−0.1082	−0.1785	0.2084	0.0511
	(0.1186)	(0.1318)	(0.1344)	(0.2375)	(0.3559)	(0.1658)	(0.1680)	(0.1976)	(0.3248)	(0.4848)
Southeast	0.0039	0.0422	−0.1246	−0.3181*	−0.7094*	−0.0931*	−0.0991	−0.2255*	0.1467	−0.0648
	(0.0894)	(0.1072)	(0.1009)	(0.1523)	(0.2649)	(0.0457)	(0.0892)	(0.1116)	(0.2197)	(0.3564)
South	0.1085	0.0437	−0.1526	−0.4850*	−0.8937*	−0.0495	0.0290	−0.0671	0.1162	−0.1579
	(0.0928)	(0.1108)	(0.1110)	(0.1549)	(0.2502)	(0.0380)	(0.0799)	(0.1083)	(0.2146)	(0.3430)
Constant	0.1830	0.7217*	0.9913*	1.4000*	1.9748*	1.3725*	1.3504*	1.5430*	1.2469*	1.8477*
	(0.2122)	(0.1929)	(0.1958)	(0.2618)	(0.3916)	(0.1541)	(0.1921)	(0.2331)	(0.3691)	(0.5236)
N	562	562	562	562	562	355	355	355	355	355
R^2	0.2432	0.2286	0.2513	0.2458	0.2246	0.0651	0.2137	0.2375	0.1735	0.1113
F	0.0000	0.0000	0.0000	0.0000	0.0000	0.0191	0.0000	0.0000	0.0000	0.0013

Note(s): *statistically significant at 5%. Standard errors in parentheses
Source(s): Prepared by the authors based on data from the 2005 and 2015 PNA

Table A4.
RIF rural–rural worker: when estimated in relation to the rural–urban worker

	2005					2015				
Variables	q10	q25	q50	q75	q90	q10	q25	q50	q75	q90
Years in school	0.0433*	0.0409*	0.0312*	0.0607*	0.1033*	0.0338*	0.0330*	0.0248*	0.0465*	0.0762*
	(0.0141)	(0.0086)	(0.0050)	(0.0066)	(0.0154)	(0.0127)	(0.0097)	(0.0052)	(0.0066)	(0.0110)
Experience	−0.0262*	−0.0151*	−0.0052	0.0243*	0.0596*	−0.0153	−0.0143	−0.0096	0.0127*	0.0355*
	(0.0131)	(0.0087)	(0.0051)	(0.0061)	(0.0113)	(0.0152)	(0.0122)	(0.0070)	(0.0085)	(0.0113)
Experience^2	0.0004*	0.0002*	0.0001	−0.0003*	−0.0007*	0.0002	0.0002	0.0001	−0.0001	−0.0003*
	(0.0002)	(0.0001)	(0.0001)	(0.0001)	(0.0002)	(0.0002)	(0.0002)	(0.0001)	(0.0001)	(0.0002)
Female	−0.7126*	−0.4334*	−0.1449*	−0.0161	0.0381	−0.7712*	−0.8406*	−0.3611*	−0.2830*	−0.2019*
	(0.1489)	(0.0743)	(0.0370)	(0.0445)	(0.0828)	(0.1361)	(0.0954)	(0.0437)	(0.0490)	(0.0748)
Nonwhite	−0.0696	−0.0012	−0.0265	−0.1038*	−0.1981*	−0.0650	−0.0973	−0.1004*	−0.1473*	−0.1771*
	(0.1015	(0.0583)	(0.0312)	(0.0371)	(0.0662)	(0.1008)	(0.0768)	(0.0428)	(0.0506)	(0.0775)
Industry	−0.6326*	−0.1280	−0.0285	−0.0029	−0.1526	−0.0364	0.0471	0.1470*	0.0843	−0.0375
	(0.2346	(0.1174)	(0.0608)	(0.0787)	(0.1136)	(0.2045)	(0.1457)	(0.0677)	(0.0815)	(0.1238)
Construction	0.7964*	0.7416*	0.3637*	0.0130	−0.3702*	0.6743*	0.8811*	0.5665*	0.2108	0.1598
	(0.1157)	(0.1219)	(0.1312)	(0.1582)	(0.1562)	(0.1210)	(0.1380)	(0.1041)	(0.1451)	(0.2154)
Commerce	0.6266*	0.4083*	0.0243	0.0868	−0.1133	0.4686*	0.3611*	0.2360*	0.1947*	0.0790*
	(0.2659)	(0.1961)	(0.1086)	(0.1189)	(0.1932)	(0.2278)	(0.1826)	(0.0930)	(0.1024)	(0.1414)
Transportation	0.4422*	0.5740*	0.4054*	0.8602*	0.8271	0.8269*	1.0417*	0.7041*	0.9626*	1.0610
	(0.1533)	(0.1162)	(0.1028)	(0.2055)	(0.6422)	(0.0971)	(0.1629)	(0.1380)	(0.2178)	(0.4375)
Education	1.3699*	0.9672*	0.6192*	0.4363*	0.2798	1.4000*	1.7199*	0.9330*	1.0049*	0.2536*
	(0.1729)	(0.1458)	(0.0893)	(0.1611)	(0.3386)	(0.1531)	(0.1618)	(0.1308)	(0.2036)	(0.2549)
Northeast	−1.3076*	−0.8172*	−0.4215*	−0.4112*	−0.3512*	−0.7100*	−0.7981*	−0.4705*	−0.4553*	−0.5034*
	(0.0898)	(0.0759)	(0.0459)	(0.0595)	(0.0933)	(0.1076)	(0.0931)	(0.0501)	(0.0587)	(0.0948)
Center-West	−0.1416*	−0.0875	0.0255	0.0590	0.1159	0.2535*	0.6319*	0.3976*	0.5100*	0.0765
	(0.0782)	(0.0947)	(0.0638)	(0.0888)	(0.1683)	(0.0862)	(0.0798)	(0.0734)	(0.1142)	(0.1907)
Southeast	−0.1859*	−0.0670	−0.0717	−0.1711*	−0.0921	0.1518*	0.3911*	0.1440*	−0.0424	−0.3189*
	(0.0856)	(0.0853)	(0.0569)	(0.0744)	(0.1303)	(0.1015)	(0.0942)	(0.0634)	(0.0801)	(0.1218)
South	−0.2634*	0.0632	0.1312*	0.2570*	0.5532*	0.1660	0.4577*	0.3261*	0.2700*	0.1194
	(0.1002)	(0.0819)	(0.0530)	(0.0729)	(0.1407)	(0.1252)	(0.1058)	(0.0675)	(0.0941)	(0.1610)
Constant	0.7283*	0.8641*	1.1412*	0.9606*	0.6174*	0.1660*	1.1207*	1.6023*	1.5052*	1.5851*
	(0.2456)	(0.1791)	(0.1059)	(0.1212)	(0.2259)	(0.2868)	(0.2335)	(0.1356)	(0.1683)	(0.2374)
N	3,689	3,689	3,689	3,689	3,689	2,621	2,621	2,621	2,621	2,621
R^2	0.0976	0.1422	0.1620	0.1793	0.1060	0.0916	0.2101	0.2332	0.1810	0.0924
F	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000

Note(s): *statistically significant at 5%. Standard errors in parentheses
Source(s): Prepared by the authors based on data from the 2005 and 2015 PNA

Effects	q10	q25	q50	q75	q90	Mean
Differential	0.1825*	0.1807*	0.1820*	0.3317*	0.4423*	0.2499*
Composition effect	0.1535*	0.1708*	0.1372	0.1693*	0.1647*	0.2029*
	(84.10%)	(94.56%)	(75.36%)	(51.05%)	(37.25%)	(81.19%)
Wage structure effect	0.0290*	0.0098*	0.0448*	0.1623*	0.2775*	0.0470*
	(15.90%)	(5.44%)	(24.64%)	(48.95%)	(62.75%)	(18.80%)
Detailed composition effect						
Years in school	0.1109*	0.1177*	0.1572*	0.2272*	0.3347*	0.2294*
Experience	−0.0127*	−0.0122*	−0.0209*	−0.0293*	- 0.0365*	−0.0337*
Discrimination	0.0075	0.0120	−0.0009	0.0001	−0.0118	−0.0015*
Activity	−0.0021	−0.0065*	−0.0160	−0.0339*	−0.0495*	−0.0183*
Region	0.0498*	0.0598*	0.0178	0.0053	−0.0720*	0.0271*
Detailed wage structure effect						
Years in school	−0.1081	0.0642	0.2988*	0.6373*	1.0146*	0.2385*
Experience	−0.1218	0.0742	−0.0121	0.0424	0.2098	−0.0298*
Discrimination	−0.0698*	−0.0408	0.0175	0.0012	−0.0760	−0.0498*
Activity	−0.2148*	−0.1030*	−0.0210	0.0916	0.2207	−0.0039
Region	0.1688*	0.1598*	0.3012*	0.4730*	0.8089*	0.2259*
Constant	0.3748*	−0.1446	−0.5396*	−1.0832*	−1.9005*	−0.3337*

Note(s): * statistically significant at 5%. Standard errors in parentheses
Source(s): Prepared by the authors based on data from the 2005 and 2015 PNA

Table A5.
Results of the decomposition of the income differential: rural–urban, urban–urban, 2005

Effects	q10	q25	q50	q75	q90	Mean
Differential	0.1021*	0.2282*	0.2266*	0.3150*	0.5135*	0.2842*
Composition effect	0.0129*	0.0586*	0.0714*	0.1517*	0.1515*	0.1642*
	(12.60%)	(25.66%)	(31.51%)	(48.15%)	(29.50%)	(57.77%)
Wage structure effect	0.0893*	0.1696*	0.1552*	0.1634*	0.3620*	0.1200*
	(87.40%)	(74.34%)	(68.49%)	(51.85%)	(70.50%)	(42.23%)
Detailed composition effect						
Years in school	0.0013*	0.0269*	0.0409*	0.0946*	0.0997*	0.1320*
Experience	0.0002	0.0032	0.0043*	0.0080	0.0074	0.0128
Discrimination	−0.0007	−0.0042	−0.0108	−0.0072	0.0011	−0.0140*
Activity	0.0150*	−0.0012	0.0095	−0.0090	−0.0280	0.0074
Region	−0.0029	0.0337*	0.0276	0.0653*	0.0712*	0.0258*
Detailed wage structure effect						
Years in school	0.2780*	0.2877*	0.5609*	0.8799*	1.2849*	0.4875*
Experience	0.0860	0.0603	0.1689*	0.1740	0.2936*	0.1992*
Discrimination	−0.0009	−0.0560*	−0.0572*	−0.1574*	−0.3198*	−0.0913*
Activity	0.1426	0.0751	−0.0552	−0.0554	0.0620	−0.0223
Region	0.2031*	0.2691*	0.3690*	−0.0174	0.2614	0.2401*
Constant	−0.6196*	−0.4666*	−0.8312*	−0.6604*	−1.2201*	−0.6931*

Note(s): *statistically significant at 5%. Standard errors in parentheses
Source(s): Prepared by the authors based on data from the 2005 and 2015 PNA

Table A6.
Results of the decomposition of the income differential: rural-urban, urban-urban, 2015

Table A7.
Results of the decomposition of the income differential: rural–urban, rural–rural, 2005

Effects	q10	q25	q50	q75	q90	Mean
Differential	1.4049*	0.9554*	0.7492*	0.6660*	0.6897*	0.6599*
Composition effect	0.5360*	0.5507*	0.3613*	0.3837*	0.3588*	0.3937*
	(38.15%)	(57.64%)	(48.22%)	(57.62%)	(52.02%)	(59.66%)
Wage structure effect	0.8689*	0.4047*	0.3879*	0.2823*	0.3310*	0.2662*
	(61.85%)	(42.36%)	(51.78%)	(42.38%)	(47.98%)	(40.33%)
Detailed composition effect						
Years in school	0.2009*	0.1900*	0.1450*	0.2817*	0.4795*	0.5193*
Experience	0.0559	0.0302	0.0211	−0.1057*	−0.2362*	−0.2011*
Discrimination	−0.0866*	−0.0562*	−0.0165*	0.0069	0.0221*	−0.0259*
Activity	0.0954	0.2028*	0.1214*	0.1276*	0.0127	0.0362*
Region	0.2703*	0.1839*	0.0903*	0.0733*	0.0807*	0.0651*
Detailed wage structure effect						
Years in school	0.0660	0.1132	0.3536*	0.3765*	0.4346*	0.2154*
Experience	0.6850*	0.4096*	0.5418*	0.2582*	−0.1430	0.4513*
Discrimination	0.2059*	0.4096	0.5418*	−0.1417*	−0.1263	−0.0476*
Activity	0.1046	−0.1156	−0.1535*	−0.3669*	−0.5163*	−0.0059
Region	0.3526*	0.1140	−0.0722	−0.2832*	−0.6754*	0.1568*
Constant	0.3526*	−0.1423	−0.1499	0.4394	1.3574*	−0.5038*

Note(s):*p < 0.10;*p < 0.05; *p < 0.01
Source(s): Prepared by the authors based on data from the 2005 and 2015 PNA

Table A8.
Results of the decomposition of the income differential: rural–urban, rural–rural, 2015

Effects	q10	q25	q50	q75	q90	Mean
Differential	1.4670*	0.8972*	0.5318*	0.4380*	0.2788*	0.6660*
Composition effect	0.6301*	0.8220*	0.5752*	0.4711*	0.2998*	0.4849*
	(42.95%)	(91.62%)	(108.16%)	(107.56%)	(107.53%)	(72.81%)
Wage structure effect	0.8369*	0.0752*	−0.0434*	−0.0331*	−0.0210*	0.1811*
	(57.05%)	(8.38%)	(-8.16%)	(-7.56%)	(-7.53%)	(27.18%)
Detailed composition effect						
Years in school	0.1454*	0.1417*	0.1067*	0.1997*	0.3274*	0.2915*
Experience	0.0207	0.0541	0.0397*	−0.0996*	−0.2410*	−0.1105*
Discrimination	−0.0558*	−0.0578*	−0.0181*	−0.0064	0.0036	−0.0179*
Activity	0.3602*	0.4460*	0.3079*	0.2729*	0.1406*	0.2373*
Region	0.1596*	0.2380*	0.1391*	0.1045*	0.0691*	0.0845*
Detailed wage structure effect						
Years in school	−0.3269*	−0.1590	0.0086	0.1278	−0.1350	0.1537*
Experience	0.1937	0.3559*	0.3225*	0.1321	−0.3150	0.4190*
Discrimination	0.2237*	0.2509*	0.0681*	0.0630	0.1988*	0.0394
Activity	−0.2391*	−0.4336*	−0.1241	−0.1745	−0.0491	0.0068
Region	0.0305	−0.1687*	−0.2591*	0.0768	0.0167	0.2000*
Constant	0.9550*	0.2297	−0.0593	−0.2583	0.2626	0.2000*

Note(s): *statistically significant at 5%. Standard errors in parentheses
Source(s): Prepared by the authors based on data from the 2005 and 2015 PNA