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EXPLORING THE URBAN-RURAL LABOR INCOME GAP IN URUGUAY: A QUANTILE REGRESSION DECOMPOSITION

EXPLORANDO LA BRECHA DE INGRESOS LABORALES URBANO-RURAL EN URUGUAY: UNA DESCOMPOSICION DE REGRESION POR CUANTILES

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Abstract

This paper analyzes the differences in real hourly labor income (RHLI) distributions between urban and rural workers for Uruguay in 2006. A quantile regression decomposition technique is applied in order to examine the urban-rural gap across the entire RHLI distribution. The urban-rural gap was primarily explained by the differences in the distribution of covariates along the entire distribution. Differences in distribution of returns favored the rural workers in most of the RHLI distribution although its contribution decreased across quantiles. The resulting gap in returns was most relevant for the worst off rural workers compared to the urban counterparts in both Montevideo and the rest of the urban centers.

Keywords: *Urban-rural gap, labor income, quantile regression decomposition, Uruguay.*

JEL Classification: *C15, J31, O18.*

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Resumen

Este estudio analiza las diferencias en las distribuciones del ingreso real laboral horario (IRLH) entre trabajadores urbanos y rurales en Uruguay en 2008. Se aplica una técnica de descomposición por cuantiles para analizar la brecha urbano-rural a través de toda la distribución del IRLH. La brecha fue explicada principalmente por diferencias en la distribución de características. Las diferencias en la distribución de retornos favorecieron a los trabajadores rurales en la mayor parte de la distribución, aunque su contribución decreció con los cuantiles. Este diferencial fue más importante para los trabajadores rurales en peor situación comparados con los urbanos, tanto en Montevideo como en el resto de los centros urbanos.

Palabras Clave: *Brecha urbano-rural, ingreso laboral, descomposición por cuantiles, Uruguay.*

Clasificación JEL: *C15, J31, O18.*

I. INTRODUCTION

In recent years, regional inequality has become, for both researchers and policy makers, an important policy issue for reducing overall inequality in many developing countries due to its potential social and economic implications. Several studies have focused on differences in living standards across regions, such as the factors that contribute to urban-rural income inequality. In Latin America, one of the most unequal regions in the world, analysis of regional income inequality has received little attention in previous literature (Gasparini *et al.*, 2009). Given these factors, the study of urban and rural income differences is key to understanding regional development patterns (Kanbur, López Calva and Venables, 2005).

The aim of this paper is to investigate income inequality in Uruguay during 2006, focusing on the geographic dimension. For this purpose, the magnitude of the urban – rural gap across the real hourly labor income (RHLI) distribution and the main underlying factors have been studied[1]. Specifically, a quantile-based approach is used to decompose the distribution of the urban-rural gap in log RHLI into three components: one that is explained by differences in the distribution of observed workers characteristics in both regions, a second component explained by difference in the distribution of returns to those characteristics, and a third component due to differences in residuals. The data used to carry out the decomposition is the *Encuesta Nacional de Hogares Ampliada* (ENHA) for 2006. It is worth noting that 2006 was

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1 As in several studies on income inequality in Latin America, this analysis concentrates in labor income for both urban and rural regions in Uruguay it is the main source of household's income.

the first time that the Uruguayan official household survey covered small localities (less than 5000 inhabitants) and rural areas.

Even though Uruguay presents the lowest levels of inequality in the region, it is one of the most unequal countries in the ranking of more developed countries. Additionally, unlike most Latin American countries (LAC), which showed a persistent decline in inequality in the present decade (López-Calva and Lustig, 2010), uruguayan levels have remained relatively stable up to 2008, when it started to decrease.

Focusing on the urban-rural labor income gap is relevant in Uruguay for several reasons. First, labor income represents the main source of individual incomes in both urban and rural regions, as well as being the principal contributing factor to overall income inequality. Second, considering several socio-demographic groups, the regional disparities are the second most important source of relative share on overall income inequality after education attributes (Alves *et al*., 2009). Third, there are few studies in Uruguay which account for the regional differences that influence inequality (discussed in Section 2). Specifically, there are no previous studies that analyse the welfare urban-rural gap due to the fact that until 2006 the national household survey did not record information from rural areas. Finally, the findings that arise from this study may have policy implications, *e.g.* to what extent active policies regarding internal migration processes are necessary in Uruguay or if the policies designed to narrow the income gap must be focused on improving the endowments of rural workers or in the institutions of labor markets.

On the other hand, understanding the urban-rural gap in Uruguay may also have implications for other countries. Uruguay is a typical developing country with a high degree of geographic concentration of population and economic activity in urban areas[2]. This fact contrasts with other Latin American countries such as Bolivia, Ecuador and Paraguay where a high degree of ruralised population exists. Nevertheless, the study of regional disparities in Uruguay could be illustrative for other countries in the region such as Chile which has a similar urbanization rate, demographic transition stage and inequality levels, or even Argentina who also shares a comparable spatial distribution of urban and rural population and productive specialization. Moreover, at the beginning of the year 2000 both Argentina and Uruguay experienced a deep crisis and the later recovery was led by good primary exports which mainly favoured rural workers. In that sense, this paper contributes by presenting empirical evidence about the main forces that explain the urban-rural gap in Uruguay but it could also be useful for other countries in the region with similar characteristics, such as Argentina.

As documented by Gasparini *et al.* (2009) the urban-rural income gap in LAC is an important component in inequality, even though its contribution has decreased during the 2000s. Regional inequalities between urban and rural were addressed by Soto and Torche (2004) for Chile, Escobal and Torero (2005) for Peru and Araujo

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2 According to the UN Population Division estimates, Uruguay is one of the most urbanized countries in the world with a share of urban areas of over 90% (*i.e.* half of its population is concentrated in Montevideo, the capital city).

(2004), García-Verdú (2005) for Mexico. These studies showed the importance of spatial inequality in LAC, not only in terms of income but for other variables like education or infrastructure.

While those studies have analyzed the urban-rural gap focused on mean welfare outcomes (*e.g.* income, expenditure or wages) throughout cross tabulations or mean regressions, they did not investigate the difference in urban-rural welfare across the entire distribution. To overcome that issue this study explores the urban-rural gap focusing on the entire labor income distribution. This is particularly relevant in Uruguay (at least in 2006) due to the fact that the difference in labor income in urban and rural areas was greater at the top of the RHLI distribution than at the bottom (showed in Section 5).

Several steps were taken to explore the urban-rural gap in Uruguay. First of all, the difference in urban-rural RHLI is examined in the whole distribution and different patterns in individual and labor market covariates and returns to covariates are investigated across quantiles of the labor income distribution. Secondly, based on a quantile regression approach the returns are estimated for each percentile of the log RHLI distribution, which provides rich information obtained from a simple mean regression. Finally, a counterfactual exercise is applied to isolate the contribution of covariates, returns and residuals to the difference in urban-rural labor income across the entire distribution.

In order to estimate the effects of regional differences in covariates, returns and residuals the technique proposed by Autor, Katz and Kearney (2005) was applied to decompose the urban-rural gap at each quantile of distribution. This technique involves estimating counterfactual distributions of rural and urban RHLI throughout the urban and rural returns from quantile regression (on log RHLI) to the distribution of covariates. Unlike the Machado and Mata (2005) technique, the method proposed by Autor, Katz and Kearney (2005) while qualitatively similar provides a counterfactual measure of residual inequality. Isolating this component from "between-group" inequality is relevant in several studies because outcomes like labor income dispersion within groups (*e.g.* defined by gender or education) are significant, particularly at the top of the outcomes distribution. For Uruguay there is evidence that within-group inequality is important in both urban and rural areas and additionally, as shown in section 5.2.1, the log RHLI dispersion within educational or experienced groups seems to be relevant for urban areas but not for rural ones.

Finally, by comparing the estimated counterfactual distributions it is possible to decompose the urban-rural gap across the entire distribution, and thus isolate (adequately) the effects of the difference between urban and rural distribution of covariates from the difference in the returns to those covariates, and additionally obtains a component that captures the regional differences in dispersion of RHLI within demographics and skill groups.

To account for regional differences throughout the study focusing on examination of the urban-rural gap and considering seperately both the urban areas as a whole (named overall urban region), and Montevideo and the rest of the urban areas. Using separate samples should capture differences in incomes in an urban region with the highest concentrated population and economic activities regarding less concentrated geographic areas.

The main advantage of the quantile decomposition applied in this study over the traditional mean-based approach as the Oaxaca-Blinder method, is that the former explains the factors that contribute to the urban-rural gap across all quantiles of the log RHLI distribution. Meanwhile, a quantile-based decomposition has been used in a similar analysis in developing countries; this paper seems to be the first to apply the technique to explore the urban-rural gap in the LAC. Thus, it constitutes a relevant contribution to the literature in assessing the inequality in LAC. Additionally, this paper seems to represent the first application of a development issue to a quantile-based decomposition technique that isolated the residual component.

Finally, it is necessary to emphasize that this empirical strategy holds strong assumptions about the Data Generation Process so the estimation results do not allow for inference of causality and the parameter estimates will never be interpreted in that sense.

According to the results, using a sample of male workers of the new national household survey of Uruguay in 2006, a positive urban-rural gap was observed in most of the labor income distribution, which increased across the quantiles of distribution. The quantile decomposition reveals that differences in covariates are the primary component which explained the urban-rural gap across the whole distribution. This result is consistent with empirical evidence which suggests that the economic activities in urban areas require better individual attributes. The findings also reflect that the effect increased along the entire urban-rural gap distribution.

The decomposition exercise reveals that differences in returns to workers with similar attributes were larger in the rural labor market, indicating a relative advantage of residing in rural areas for those less paid workers (and worst endowed). This effect contrasts with the literature predictions and could be associated with some specificities on the economic characteristics of Uruguay in 2006.

Finally, the results reveal that future efforts to reduce regional income gaps may require different policies for rural areas than Montevideo and the rest of the urban area and must take into account differences of an individuals position throughout the distribution. Since the labor income gap is higher for Montevideo and the characteristics are mainly responsible for the gap, policies oriented to reduce regional inequality should improve rural workers' characteristics (*e.g.* education).

The rest of the paper is organized as follows. Section 2 presents some background on theoretical explanations and Uruguayan labor market and income distribution characteristics. Section 3 describes the data set and provides some descriptive statistics. Section 4 presents the decomposition procedure applied to assess the relevant factors that could explain the gap. In Section 5 the magnitude and distribution of the urban-rural gap, the estimates derived from quantile regression and decomposition technique, and the results of an exercise of price sensitivity analysis/exercise are presented. Section 6 gives concluding comments.

II. BACKGROUND: URBAN-RURAL INCOME GAP

2.1. Explanations and empirical findings in developing countries

Existing literature suggests that under free labor mobility and lower associated cost, in equilibrium, the welfare levels of households or individuals with the same observed and unobserved characteristics will be equalized across locations. According to this framework, welfare differences across locations will only be due to the locative "sorting" of individuals with different attributes (Shilpi, 2008; Bayer, Keohane and Timmins, 2009). Nevertheless, several studies for developing countries have found evidence of differences in returns to observed attributes across regions, even if there is no important barrier to factor mobility. The literature offers at least two possible explanations for the persistence of the spatial differences in observed returns[3].

The first explanation suggests that the returns to individual characteristics may differ significantly across locations if the unobserved heterogeneity across individuals and locations is not accurately controlled in the econometric estimation. The problem could be associated with selective migration process, where workers with better observed (*e.g.* education) and unobserved characteristics (*e.g.* ability) are "sorted" to specific areas, such as urban ones[4]. Additionally, spatial differences in observed returns may be the consequence of externalities produced in densely populated areas arising from agglomeration economies (*e.g.* labor market externalities and knowledge spillovers) or better public infrastructure and services (Overman, Rice and Venables, 2010; Jalan and Ravallion, 2002). The second approach has focused on the cost of migration. If migration is costly, differences in returns across regions may persist even in equilibrium (Kanbur and Rapoport, 2005). Therefore, individuals in urban areas could earn higher wages than their rural counterparts even if they have identical observational characteristics.

Those approaches have also emphasized that the returns to observed attributes will vary across individuals depending on their position in the welfare distribution and across regions depending on their relative proximity and location characteristics. Even in densely populated areas, a small percentage of economic activities are technology intensive or can internalize the externalities of the clustering activities (Fafchamps and Shilpi, 2005). Sorting of unobserved individual characteristics is likely to be more relevant for highly skilled workers which represent only a small fraction of the labor force. On the other hand, the selectivity of the migration process could vary between individuals according to their characteristics such as family background, the standard of living of migrants in their original locations or the risks they face (*e.g.* levels of vulnerability).

The majority of empirical studies which analyse the urban-rural income gap in developing countries have focused on summary measures of income distribution (Sicular *et al.*, 2007; Liu, 2005). Recent studies have adopted a more comprehensive

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3 For a comprehensive literature review of this issue see Shilpi (2008).

4 Negative selected process could also occur, however there is scarce evidence compared to positive self-selection that supports this prediction.

approach and decomposed the urban-rural gap focusing on the entire (specific) income distribution and not just on the average[5]. Nguyen *et al.* (2007) used a quantile regression method to analyse the urban-rural consumption expenditure inequality in Vietnam in 1993 and 1998. The authors found the gap in 1993 was primarily explained by differences in covariates, meanwhile, in 1998 it was due to differences in returns across regions, and for both years the returns to covariates were larger at the top of distribution. Likewise, Shilpi (2008) and Chamarbagwala (2010) for Bangladesh and India respectively, adopted a quantile decomposition approach to analyze the urban-rural inequality. These studies found evidence that both covariates and returns were relevant to explain the observed gap, although their behaviour was different across welfare distribution. To our knowledge, there are no studies for LAC that have analyzed the urban-rural inequality from a distributional approach.

In accordance with the above mentioned literature some facts should be expected regarding the urban-rural labor income gap observed in Uruguay (analyzed in Section 5). Firstly, this gap could be explained by both the difference in individual characteristics and returns to these characteristics across regional labor markets, even when in Uruguay there are no significant barriers to mobility. Second, the difference in returns is likely not to be constant throughout the labor income distribution and it is expected to be more relevant for the better off workers. However, the specific magnitude and directions of these factors will be an empirical matter.

2.2. Uruguay: inequality and the economic context

Uruguay has had lower levels of income inequality in relation to other Latin American countries. Alvez *et al* (2009) give a comprehensive description of its main trends since they have available data (1980s), pointing out that until the mid-nineties inequality remained relatively stable. Income inequality increased after 1999, due to the fact that 1999 was the starting point of one of the most important economic crisis in recent decades (reaching its lowest point in 2002), affecting the labor market markedly and negatively.

Since 2003 high international prices of commodities and an exceptional dynamism of agricultural production led Uruguayan economy to show signs of recovery (exports and production are highly concentrated on agriculture). In fact in the year 2006, after three years of intense growth, the GDP reached the maximum level of the past expansive cycle (in 1998). The fast recovery could be related to an expansion of agricultural productivity that took place after the crisis (Piñeiro and Moraes, 2008). This improvement in productivity could be partly attributed to changes in rural areas due to the introduction of technical change in agricultural activities. As a consequence, labor demand fell and this could have contributed to the displacement of workers to urban areas, reducing labor supply in rural ones, mainly in younger population

[5] This literature has adopted different specific methodologies to empirically address this issue. The most popular include the reweighting method (DiNardo, Fortin and Lemieux, 1996) and conditional quantile regressions and resampling approaches (Machado and Mata, 2005; Autor, Katz and Kearney, 2005; Melly, 2005).

(Dominguez and Durán, 2007). However, workers which remain in rural areas could benefit relatively more than others from this favorable context, given that they present lower unemployment rates than their urban counterparts and also due to the fact that in disperse rural areas an agricultural economically active population is predominant and directly receives spillovers from those activities.

Overall inequality does not decline until the year 2008, but over this period regional inequalities have been reduced considerably (Alvez *et al.*, 2009). Reduction was due to the growth of labor income being led by the high increase in income in the urban areas (different from Montevideo). Since the mid-2000s several institutional and economic reforms were carried out by the Uruguayan Government, with one of the most important being the 2005 reintroduction of the centralized collective bargaining through the wage councils (*Consejo de Salarios*) fixing different minimum wages and wage increases for each activity sector. Since urban workers were widely covered by wage councils in almost all economic sectors and occupations (Mazzuchi, 2009) and while it was the first time that collective bargaining was set up for rural workers (with relatively scarce achievements until 2006), potentially differential effects could been expected on wages for urban and rural workers. If minimum wages hold, and it is assumed that increases in minimum wages were higher in urban workers because of collective bargaining, the observed income gap between urban and rural workers would be higher at the bottom of the distribution than it would be without wage councils. In that sense, if urban workers could achieve higher bargaining wage increases the observed income gap would be greater along the labor income distribution.

Finally, it may be stressed that the only previous study based on regional disparities of labor income in Uruguay is Miles and Rossi (1999). The authors studied the geographic concentration effects on wage inequality in Uruguay during 1986-1997 using information that only covers urban population. They conclude that wages are higher in concentrated regions than in those more dispersed, which provides initial evidence of the existence of an income gap between concentrated and dispersed regions (in this case urban and rural ones).

III. DATA AND DEFINITIONS

The source of data is the *Encuesta Nacional de Hogares Ampliada* (ENHA) carried out by the National Institute of Statistic (*Instituto Nacional de Estadística*, INE). Information reflect data from the year 2006, since at that time Uruguay expanded the official household survey coverage including not only urban areas (more than 5000 inhabitants) but also small localities and rural dispersed areas. The sample frame consists of 85,316 households that represent the whole population of Uruguay, roughly 3.3 million people in 2006. This survey records individual and household incomes, as well as complete information about individual and socioeconomic characteristics.

For the purposes of the present study, we construct a sample of 40,666 full-time male workers between 18 and 60 years old, living 31,265 and 9,401 in urban and rural regions, respectively[6, 7]. Additionally, the urban sample was divided into two sub-samples representing Montevideo (workers) the capital city of Uruguay and the rest of the urban areas (RUA). These samples contain 12,659 and 18,606 workers, respectively.

The dependent variable used by the empirical analysis is log of real hourly labor income (log RHLI), which is the log of monthly earnings of a worker in his principal activity divided by the amount of monthly hours worked and deflated by the Consumer Price Index (CPI)[8, 9].

The explanatory variables reflect several socio-demographic and labor market characteristics of workers. These include an indicator of human capital measured by the number of years of schooling completed (*education*), a measure of years of experience in the labor market (*experience*) and experience squared (*experiencesq)*, and an interaction term between the measures of education and experience (*eduexp*)[10]. Regarding employment, the models include indicators on the firm and industry of the individuals employment. The firms were categorized by size and sector into private firm employed respectively, one person (*firmsize1* = 1), 2 up to 4 (*firmsize24* = 1), 5 up to 49 (*firmsize549* = 1), more than 49 (*firmsize50* = 1) and using the public firms (*public* = 1) as the omitted group. The industries were categorized as industry (*industry* = 1), agriculture (*agriculture* = 1), transport (*transport* = 1), services (*services* = 1), and other activities as public administration (*others* = 1), using trade activities as the omitted group (*trade*). Finally, regional dummies were used to indicate whether the worker is located in the Center-South (*Center-South* = 1), North (*North* = 1), Center-North (*Center-North* = 1) of Uruguay, the South region (*South* = 1) being the omitted group.

Table 1 in the Appendix presents summary statistics of those variables by urban (overall, Montevideo and RUA) and rural regions[11].

The data presents two main shortcomings. Firstly, the same CPI is used to define the labor income in real terms in both urban and rural regions, because it is the only one available from the Uruguayan statistical bureau (INE). If differences in prices between urban and rural areas were relevant, it could affect the results arising from the counterfactual analysis. To deal with this drawback, a sensitivity analysis/exercise is performed in Section 5.4 to analyze the robustness of the main results. Secondly,

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6 The INE classifies the urban region as towns with more than 5,000 inhabitants (Montevideo, the capital city is included) and small urbanized localities (with less than 5,000 inhabitants), while the rural one represents dispersed areas in the country.

7 Entrepreneurs, domestic workers and individuals enrolled in public programs have been excluded from the analysis.

8 Labor income includes salaried (private and public) and self-employed earnings.

9 The hourly labor income was valued in local currency units (Uruguayan Pesos) at constant prices in December 2006.

10 Currently, experience is measured as potential experience, *i.e.* calculated as age – education – 6.

11 Mean comparison tests between rural and urban regions were performed for all variables and it emerged that all differences were statically significant at 5% (except for regional variable Center-North). Additionally, mean tests were carried out between rural areas, Montevideo and the rest of the urban areas where in general differences were also found to be statically significant at 5%.

the survey does not contain enough information to adequately control for potential selective process, like migration. Indeed, if the econometric estimation does not control using non random sample selection the results will be biased. While it is a relevant issue, when the underlying selection model is unknown or there is not enough available information, the common practice has been for it not to be controlled[12]. Even though the focus of this study is not a causal analysis this issue will be taken into account to interpret the results.

IV. URBAN-RURAL LABOR INCOME GAP: A QUANTILE DECOMPOSITION METHOD

4.1. Counterfactual distributions

The framework applied in this paper follows the Autor, Katz and Kearney (2005) technique to construct counterfactual distributions. Like the Machado and Mata (2005) technique (the usual approach used by this literature) the method proposed by Autor, Katz and Kearney (2005) is based on conditional quantile model to construct counterfactual distributions, but in addition it enables us to separate the effect of coefficients into the effects of central tendency coefficients and residuals. Four basic steps must be followed in order to construct the desired counterfactual distribution.

First, a model for the conditional quantiles of outcome distribution of log RHLI is estimated. Let y be the log RHLI and x a set of covariates representing individual and regional characteristics. A quantile regression (QR) approach is used to characterize the entire conditional distribution of y given x as a linear function of covariates:

$$Q_\theta(y / x) = x'\beta(\theta) \tag{1}$$

where $Q_\theta(y / x)$ for $\theta \in (0.1,)$, denotes the θ^{th} quantile of the distribution of y given x. As Koenker and Bassett (1978) demonstrated, the quantile regression estimator of $\beta(\theta)$ solves the follow optimization problem[13]:

$$\min_{\beta(\theta)} = \sum_{i=1}^{N} \rho_\theta \left(y_i - x_i'\beta(\theta)\right), \text{ with } \rho_\theta(u) = \begin{cases} \theta u & \text{for} \quad u \geq 0 \\ (\theta - 1)u & \text{for} \quad u < 0 \end{cases}$$

While the (correctly specified) conditional quantile model offers a complete characterization of conditional distribution of y, it does not provide a marginal

[12] In fact, the vast majority of literature related to the issue addressed in this study was not controlled by self-selection.

[13] See also Buchinsky (1994) and Koenker and Hallock (2001). For details on asymptotic inference procedure about QR coefficients see Koenker and Basset (1978) and Koenker and Basset (1982).

distribution. This is because it depends on both, $\hat{\beta}(\theta)$ and the regional distribution of the covariates, *f(x)*.

Thus, the second step requires drawing rows of data *f(x)* and for each row x_i draw a random θ_i from the U(0,1) distribution. Hence, it is possible to derive a draw of the marginal density of *y* as a product of both vectors $\hat{y}_i \equiv x_i{}' \hat{\beta}(\theta_i)$. By applying this procedure repeatedly it is possible to draw large random samples from the desired distribution such as estimating the impact of differences in regional covariates or returns on the log RHLI distribution. For instance, the counterfactual distribution of log RHLI that would prevail if covariates were the observed in urban regions $f_u(x)$ but received rural returns to those covariates $\hat{\beta}_r(\theta)$ could be simulated[14].

However, as Autor, Katz and Kearney (2005) highlighted, $\hat{\beta}_r(\theta)$ describes the conditional distribution of log RHLI for given values of *x*, thus the counterfactual captures the "effect" of covariates on both, the between-group (urban-rural) inequality and the residual or within-group (urban and rural) inequality. For theoretical reasons, in several applications it is important to separate both components. To deal with the issue, Autor, Katz and Kearney (2005) suggested an extension of this simulation technique such as provided a counterfactual measure of residual inequality[15]. In particular, since the log RHLI dispersion within educational or experienced groups seems to be relevant for urban areas but not for rural areas, mainly in the lower and upper tail of distribution (see Section 5.2.1), that extension is applied in our study.

Thus, the third step requires us to define a coefficient vector of central tendency $\hat{\beta}^b$ as a measure of *between-group* inequality, and working on equation (1) express the quantile model as:

$$Q_\theta(y / x) = x'\hat{\beta}^b + x'\left[\hat{\beta}(\theta) - \hat{\beta}^b\right] = x'\hat{\beta}^b + x'\hat{\beta}^w(\theta) \qquad (2)$$

where $\hat{\beta}^w(\theta) = \left[\hat{\beta}(\theta) - \hat{\beta}^b\right]$ for $\theta \in (0.1,)$ is a (*within-group*) quantile coefficient matrix that is interpreted as a measurement of residual inequality. Notice that $x'\hat{\beta}^w(\theta)$ consistently estimates the residuals distribution conditional in *x* at the θ^{th} quantile.

In the final step, the desired simulated data, $g(\hat{y})$, could be drowning from the distribution $g(f(x), \hat{\beta}^b, \hat{\beta}^w)$ by applying $\hat{\beta}^b$ and $\hat{\beta}^w$ to $f(x)$.

In practice contrafactual distributions of log RHLI for urban (total urban region, and separating it in Montevideo and RUA) and rural workers were constructed using the Autor, Katz and Kearny procedure as follows. Denoting *u* and *r* as urban and rural values, first, for each percentile, $\theta =$ 0.01, 0.02,…,0.99, quantile regressions coefficients $\hat{\beta}_u(\theta)$ and $\hat{\beta}_r(\theta)$ were estimated using the urban (*u*) and rural (*r*) data.

[14] So far the procedure is like that applied by Machado and Mata (2005).

[15] See Melly (2005) decomposition procedure for a similar treatment of residual inequality.

Additionally, the OLS regression coefficients $\hat{\beta}_u{}^b$ and $\hat{\beta}_r{}^b$ were estimated such as provided the vector of central tendency or returns estimates. Third, the residual vectors $\hat{\beta}_u{}^w$ and $\hat{\beta}_r{}^w$ were calculated and then, $\hat{\beta}_r{}^w$ and $\bar{\beta}^w$ were obtained by averaging the urban and rural vectors of central tendency and residuals, respectively. Finally, using the equation (2) the desired counterfactuals distribution were constructed by applying the urban and rural data to $\bar{\beta}^b$ and $\bar{\beta}^w$.

In order to isolate the contribution of covariates, returns to those covariates and residual to the urban-rural gap were constructed using two pairs of counterfactuals distributions of log RHLI. First, the distributions of log RHLI, $g(f_u(x);\bar{\beta}^b,\bar{\beta}^w)$ and $g(f_u(x);\bar{\beta}^b,\bar{\beta}^w)$, the distribution that would exist if the urban (rural) workers received the same (average) returns to those characteristics and residuals coefficients than rural (urban) counterparts were constructed. Second, the distributions of log RHLI, $g(f_u(x),\hat{\beta}_u^b,\bar{\beta}^w)$ and $g(f_r(x),\hat{\beta}_r^b,\bar{\beta}^w)$, the distribution that would prevail if the urban (rural) workers received the returns to those characteristics in urban (rural) labor markets but residuals coefficients were the same (average) in both regions were constructed[16].

4.2. Isolating the effects of covariates, returns and residuals

To summarize the contribution of differences in the urban and rural covariate distributions, differences in returns to those covariates and differences in residuals to the urban-rural gap across the entire distribution a quantile version of the Juhn, Murphy and Pierce (1993) procedure is computed. Defining the counterfactuals distributions obtained earlier and the empirical urban, $Q_\theta(g_u(y))$, and rural, $Q_\theta(g_r(y))$, distributions at θ^{th} - percentile, the urban-rural gap at the θ^{th} - percentile of log RHLI distribution is given by $\Delta Q_\theta = Q_\theta(g_u(y)) - Q_\theta(g_r(y)) = \Delta Q_\theta^X + \Delta Q_\theta^b + \Delta Q_\theta^w$, where

$$\Delta Q_\theta^X = Q_\theta(g(f_u(x);\bar{\beta}^b,\bar{\beta}^w)) - Q_\theta(g(f_r(x),\bar{\beta}^b,\bar{\beta}^w)) \tag{3}$$

represents the *covariates effect*, and measures the contribution of different covariate values to the urban-rural gap at the θ^{th} - percentile.

$$\Delta Q_\theta^b = Q_\theta(g(f_u(x),\hat{\beta}_u^b,\bar{\beta}^w)) - Q_\theta(g(f_r(x),\hat{\beta}_r^b,\bar{\beta}^w)) - \Delta Q_\theta^X \tag{4}$$

16 Taking averages of estimated coefficients is a procedure used for the literature to deal with the connection between the decomposition estimates and choice of a base model (*path dependence*).

reflects the *returns effect*, which measures the contribution of differences in the returns to the urban-rural gap at the θ^{th} - percentile.

$$\Delta Q_\theta^w = Q_\theta(g(f_u(x), \hat{\beta}_u^b, \hat{\beta}_u^w)) - Q_\theta(g(f_r(x), \hat{\beta}_r^b, \hat{\beta}_r^w)) - \Delta Q_\theta^X - \Delta Q_\theta^b \qquad (5)$$

represents *the residual effect*, and measures the contribution of differences in residuals to the urban-rural gap at each percentile.

V. RESULTS

The results discussed in this section follow the methodological issues explained in Section 4. First, quantile regressions are estimated under the three urban samples and the rural sample and then counterfactuals of the conditional distributions of the RHLI are constructed. Then, in each case the estimated gap is decomposed to estimate the contribution of the covariates and returns on the difference in the urban (total, Montevideo and RUA) and rural labor income distribution.

5.1. Magnitude and distribution of the urban-rural income gap in Uruguay

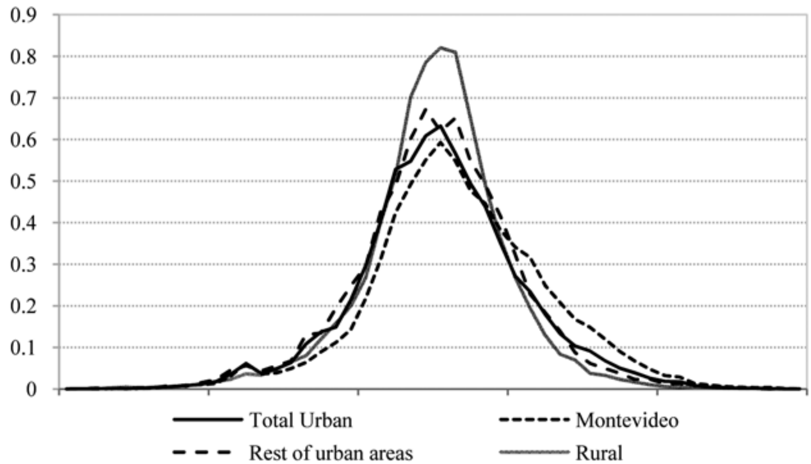
Table 1 in the Appendix shows that average labor income was different for urban and rural workers, reflecting a gap in RHLI of roughly 40% on average. Considering Montevideo and RUA separately, the average RHLI differences with rural areas are accentuated for Montevideo as it reaches 74% and substantially lower regarding the RUA, closer to 17%. Figure 1 depicts the log RHLI for urban (total, Montevideo and RUA) and rural regions through a Kernel density estimation. It can be seen that a larger labor income dispersion exists in the urban workers than in the rural counterparts, whose earnings were concentrated around the mean values of the distribution. Furthermore, even if there were no significant differences at the bottom of both distributions, labor income certainly differed at the medium and top ranges. Inside urban areas, Montevideo is the most unequal region and shows important relative differences mainly at the top of the labor income distribution.

Figure 2 shows the difference in the log RHLI between urban (total, Montevideo and RUA) and rural regions for quantiles of distribution[17]. The urban-rural gap is positive and increases along the entire distribution. In other words, the urban workers earned higher incomes than rural counterparts in all percentiles of distribution and this gap is higher between the richest workers than between the poorest ones. When decomposing the urban region in Montevideo and RUA similar patterns in the gaps

[17] The gap is calculated as the difference in log of the median RHLI for each percentile of the distributions. The corresponding confidence intervals were calculated through the bootstrap technique on 150 replications.

FIGURE 1

(LOG) HOURLY LABOR INCOME DENSITIES FOR URBAN (TOTAL, MONTEVIDEO AND RUA) AND RURAL REGIONS



Source: Authors' calculations based on INE (ENHA, 2006).

arise regarding rural areas. Both lines have positive slopes, although the Montevideo-rural gap is larger than shown by the RUA-rural one and this difference is especially relevant at the top of the distribution. For the overall urban-rural region at the 10th percentile the gap in RHLI is roughly 15% while it is about 7% and 28% for RUA-rural and Montevideo-rural region, respectively. Meanwhile, at the 90th percentile the gaps reach about 62%, 21% and 121%, respectively.

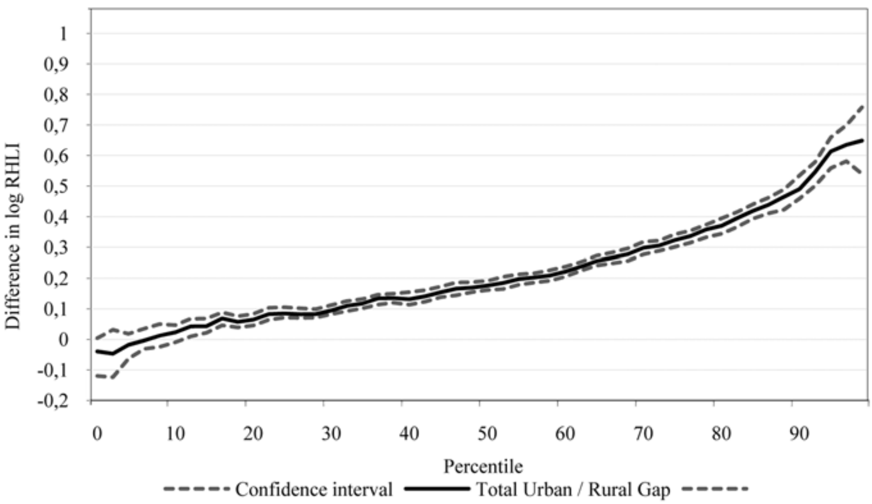
Table 2 in the Appendix presents the averages of variables used in the study for urban (total, Montevideo and RUA) and rural regions and by selected quantiles of RHLI distribution. As expected, the years of schooling within each region, as well as the educational urban-rural gap increase across the quantiles of distribution. On the contrary, the rural workers had more years of experience than urban counterparts and this gap was greater at the lowest RHLI quantiles. Regarding the employment sector, the rural workers were clearly employed in agricultural activities and the relative share remains almost unchanged up to three-quarters of the distribution. In urban areas, both for the average and for Montevideo and RUA, the individuals engaged principally in trade and services, although they were better-off in the latter.

For Uruguay there is evidence of differences in covariates across the labor income distribution in urban and rural regions.

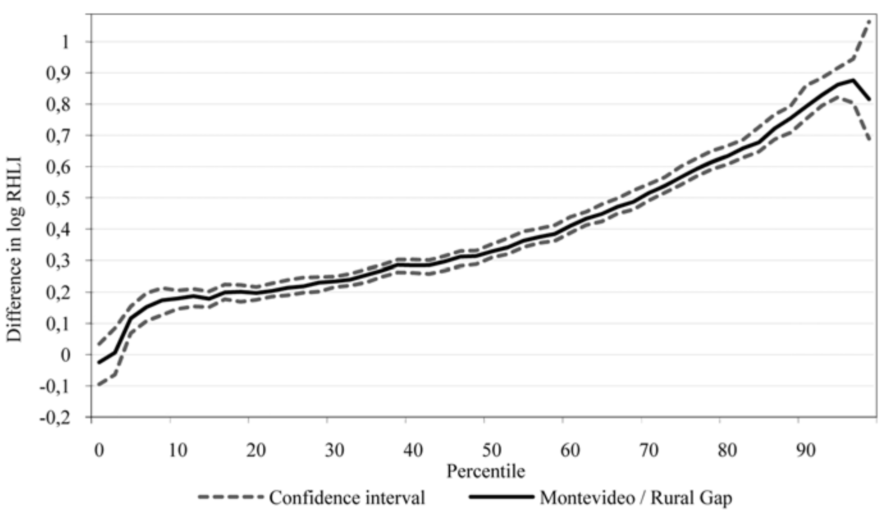
FIGURE 2

URBAN (TOTAL, MONTEVIDEO AND RUA) – RURAL RHLI GAPS (LOG)

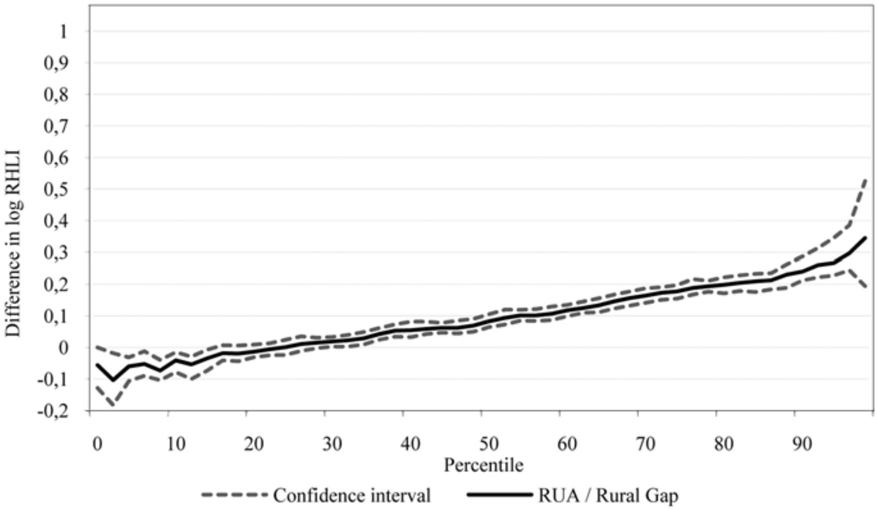
PANEL A – TOTAL URBAN – RURAL RHLI GAP (LOG)



PANEL B – TOTAL MONTEVIDEO – RURAL RHLI GAP (LOG)



PANEL C – TOTAL RUA – RURAL RHLI GAP (LOG)



Source: Authors' calculations based on INE (ENHA, 2006).
Note: Confidence intervals at 95% are obtained using the bootstrap technique on 150 replications. In each region, the observed gap is calculated for the percentiles of real hourly labor income distribution as the difference of logarithm of median income at θ^{th} quantile.

5.2. Quantile regression

The QR model includes the socio-demographic and employment controls stressed in Section 3 and it is estimated for urban (as a whole) and rural regions, as well as for the two urban samples, Montevideo and RUA respectively. The estimation is conducted for percentiles 1-99 of the distribution[18]. Tables 3 and 4 in the Appendix present the quantile regression coefficients and standard errors for the 10th, 25th, 50th, 75th and 90th percentiles for all surveys. Additionally, these tables present OLS estimates in order to compare with the quantile estimation. For all the samples and selected percentiles the estimated coefficients are statistically significant at the 1% level (the majority) or at the 5% level. In general, the QR coefficient estimates seem to differ across the selected quantiles and also seem to be different from the OLS estimates. Unlike the urban areas, the QR coefficient estimates for the rural sample do not seem to be different across the quantile distribution, at least regarding relevant variables as education or experience.

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[18] For the sake of space the same specification is used along the empirical section. In Bérgolo and Carbajal (2008) other specifications were proved but the general results hold.

In order to explore these specific patterns, the returns to key labor market characteristics (*i.e.* education, experience, and sector of employment) are examined in more detail. Figures 3 and 4 in the Appendix illustrate the returns to those characteristics across the conditional quantile of the distribution of log RHLI in each region (total urban, rural, Montevideo and RUA)[19].

5.2.1. *Returns to education and experience*

Figure 3 plots the returns associated with an additional year of education and experience (estimated as difference in log RHLI) in the vertical axis and in the horizontal axis the percentile of log RHLI distribution[20]. The solid line represents the quantile estimates of returns while the dotted line depicts the OLS estimates showed for comparison purposes.

Not surprisingly, the urban-rural gap in returns to education was almost positive in the entire quantile distribution, and this fact is seen both when the urban region is considered as a whole as well as if it is separated in Montevideo and RUA. This probably indicates that in urban areas the productivity of educated workers is improved as a consequence of economic agglomeration typical of densely populated areas. In Montevideo, the main economic centre of Uruguay, the differential in returns (regarding rural areas) was higher relative to the RUA.

Some interesting issues arise when the analysis is focused on the patterns across the distribution. At the lowest and highest percentiles, the urban-rural gap in returns to education was greater than in the central part of labor income distribution. This pattern is due to the U-shape and flat-shape form showed by the returns to education across the quantiles in urban (total, Montevideo and the RUA) and rural regions, respectively[21]. Thus, as was expected, education pays off more for urban than rural labor at the highest percentiles of distribution. This may reflect a "positive" selective migration process, especially for Montevideo where the opportunities for superior education and qualified jobs are more relevant than in rural areas. On the other hand, it is surprising that a similar pattern is observed but in the lower part of the labor income distribution. However, this finding is quite similar to that found in Miles and Rossi (1999) for a long time span, thus this behavior does not seem to be cyclical or specific to this study.

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[19] The figures plot the returns to those covariates against log RHLI distribution for percentiles from the 5th to the 95th in 1% increments.

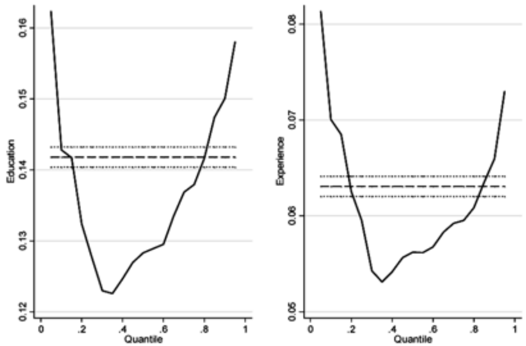
[20] The return to years of education in all the samples is the sum of the coefficient on the covariate and the coefficient on the interaction of the education covariate with the experience covariate for a base case. Regarding the return to experience, it is the coefficient on the covariate plus the coefficient of quadratic term of that covariate. For space reasons, the figures only plot the estimated coefficients on education and experience covariates. Tables 3 and 4 in the Appendix show that even if "the interaction and quadratic" coefficients are statistically significant their magnitude is closest to zero. Thus, the pattern and magnitude of estimated coefficients on education and experience covariates remains basically unchanged if these are added or not.

[21] Note that in rural region the pattern of returns to education is stable and is not statically different to the OLS estimate almost across the quantiles.

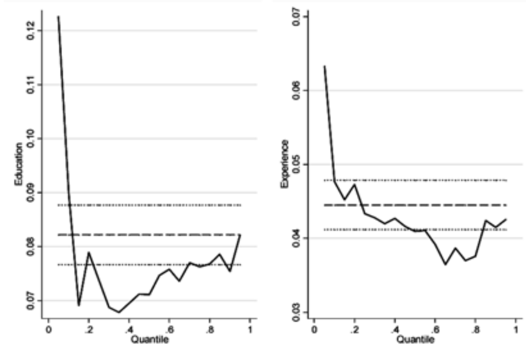
FIGURE 3

QR AND OLS ESTIMATES FOR EDUCATIONAL AND EXPERIENCE VARIABLES

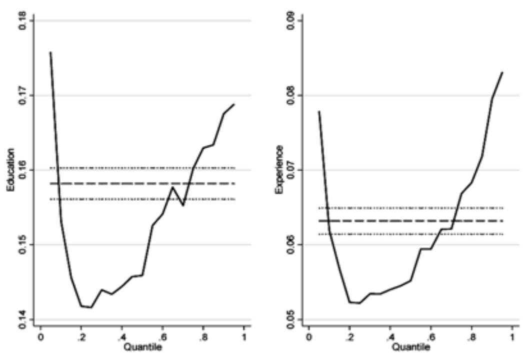
PANEL A - TOTAL URBAN AREA



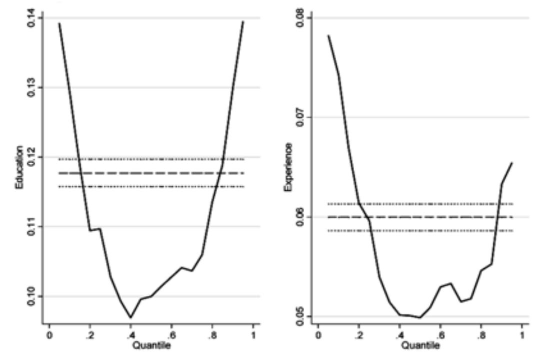
PANEL B - RURAL AREA



PANEL C – MONTEVIDEO



PANEL D – REST OF URBAN AREAS (RUA)



Source: Authors' calculations based on INE (ENHA, 2006).
Note: Quantile regression estimates (solid line) and least squares (dotted line) coefficients for education and experience variables.

Analyzing experience, it can be shown that a similar picture is observed although the differences in the gaps were smaller. In general, the returns in urban areas were greater than rural returns across the quantiles, although the positive difference was greater at the lowest and highest percentiles of the distribution. However, unlike the returns to education, the experience pay off was better for Montevideo than rural areas at the upper part of the labor income distribution while for RUA the same has occurred but at the lower part of quantiles.

5.2.2. *Returns to sector of employment*

Figure 4 depicts the returns to employment in agriculture and services. Individuals in rural areas engaged in agriculture received positive and stable returns up to around the 60^{th} percentile, after which they showed a sharp decrease up to the top of the distribution where they were not statically significant. In the urban region these returns presented the reversal tendency. These patterns generated a large negative urban-rural gap in returns to the agricultural sector at the lower part of distribution which narrowed substantially up to the 80^{th} percentile, and changed to positive at the high end of quantiles. This picture is particularly relevant for Montevideo regarding rural areas, where the negative differential in returns to agricultural employment was greater at the low end of the distribution.

Returns to service sectors increased across the distribution for the overall urban region, and this tendency was seen in both Montevideo and RUA (it was negative up to the 40^{th} percentile). Meanwhile, for rural areas these returns were negative for the top and especially the bottom of distribution. Thus, unlike agriculture, the urban-rural gap in returns for the service sector was positive across quantiles (at least up to 40^{th} percentile and after 60^{th} percentiles). However, the better off workers enjoyed higher differentials in returns to services than the worst off workers in all urban areas.

The above results suggest that individuals employed in the agricultural sector in rural areas (the main economic activity) may have benefited from spillover effects generated by the sharp growth of this activity after the 2003 crisis. Further, this effect seems to be more relevant for the worse off workers. On the contrary, the urban workers engaged in services employment probably received the benefits of the growth after activities after the crisis (*e.g.* financial intermediation, R+D and tourism) were concentrated in urban areas (mainly in Montevideo). Not surprisingly, due to the characteristics of the activities that this sector encompasses the urban differential in returns was accentuated at the top of the labor income distribution.

5.3. Behind the urban-rural labor income gap: a decomposition analysis

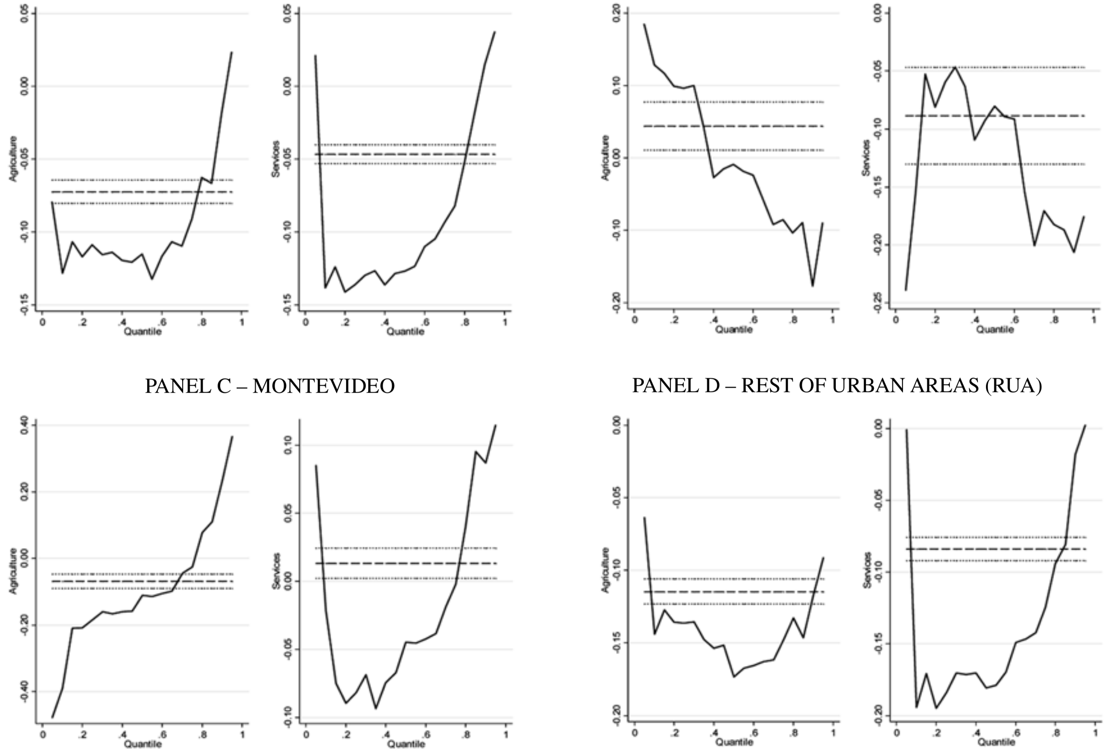
Previous sections have shown evidence of differences in covariates across the labor income distribution in urban and rural workers and the returns to those covariates. Additionally, it has been documented that the returns to certain covariates vary across the conditional quantiles in the distribution of log RHLI (basically in urban areas) and that the urban-rural gap in returns to those covariates was not constant along the entire distribution. This section summarises the main results by applying the decomposition

FIGURE 4

QR AND OLS ESTIMATES FOR AGRICULTURE AND SERVICES ACTIVITY SECTORS VARIABLES

PANEL A - TOTAL URBAN AREA

PANEL B - RURAL AREA



Source: Authors' calculations based on INE (ENHA, 2006).
Note: Quantile regression estimates (solid line) and least squares (dotted line) coefficients for agriculture and services variables.

procedure detailed earlier for the ENHA 2006 sample. This implies decomposing the urban-rural gap into components attributable to urban-rural differences in distribution of workers' covariates (called covariates effect), and the urban-rural difference in the distribution of returns to those covariates (called returns effect). Finally, a residual component is computed which reflects the contribution to the gap unaccounted for by the estimation method (residual effect).

Figure 5 on the left-side presents the covariates effect, the returns effect and the residual effect for the urban-rural model, Montevideo-rural and RUA-rural models. Those effects are plotted for percentiles 5-95 of distribution with 95% confidence bounds[22, 23]. Certain interesting features stand out on Figure 5.

The covariates effect was always positive and larger at higher percentiles, although the slope seems to be steeper for the RUA-rural regions than for Montevideo-rural regions. Surprisingly, the returns effect was negative in almost all of the distribution for all models, although its magnitude was reduced at higher quantiles. While for RUA-rural regions the returns effect is negative for the entire distribution, for Montevideo-rural regions the reversal of returns effects from negative to positive occurred at around the 70th percentile of the distribution. On the other hand, the residual effect is more or less constant and not relevant (relatively) up to the middle of the distribution but increasing after around the 60th percentile for the urban-rural sample[24]. In Montevideo-rural regions that behaviour at the higher quintiles was steeper compared to RUA-rural regions.

Another feature to highlight is the patterns regarding the contribution of those effects across the distribution, considering both the urban region as a whole and Montevideo and RUA regions separately. Figure 5, on the right-side, shows the relative contribution of the covariates, returns and residual effects (in absolute values) for the three samples[25]. For the total urban-rural gap a dominance of the covariate effect was observed and it increased across the distribution. However, at the bottom of the distribution, both returns (negative) and covariate effects were relevant to explain the overall-urban gap, meaning the returns played a compensating role in favour of rural workers. On the other hand, this "compensatory effect" became smaller at greater quantiles due to the sharp decrease of the contribution of returns effects across distribution. Thus, for the total urban-rural sample both greater relative contribution

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22 Bootstrapped standard errors are calculated from 150 replications.

23 Table 5 in the Appendix present the point estimates for the 10th, 25th, 50th, 75th and 90th percentiles in Panel A, B and C for urban-rural, Montevideo-rural and RUA-rural regions, respectively. The panels present small discrepancies between the observed and estimated urban-rural gap, which reflect a simulation error due to the quantile simulation which does not capture the observed distribution perfectly. These differences are quite small, so it was decided not to make adjustments for them.

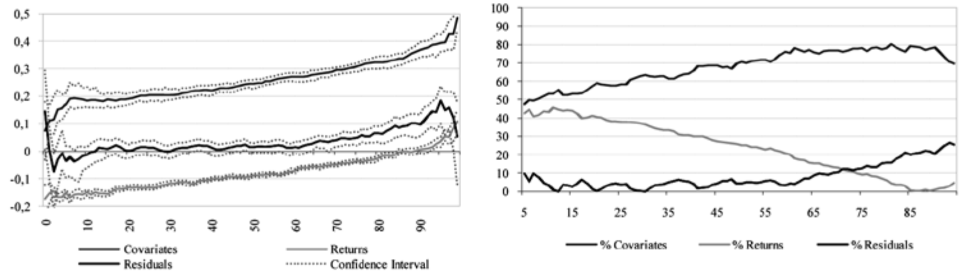
24 Autor, Katz and Kearny (2005) in their study found similar pattern of residual effect at the top of the wage distribution.

25 For each sample the contributions were calculated as a percentage of the overall estimated urban-rural gap. Since the returns effect was negative in almost the distribution, for the sake of exposition the contribution was computed taken the estimates in absolute values such as the contribution of each effect were positive. However, the relationship between each effect and the overall gap estimated across quantiles remains unchanged.

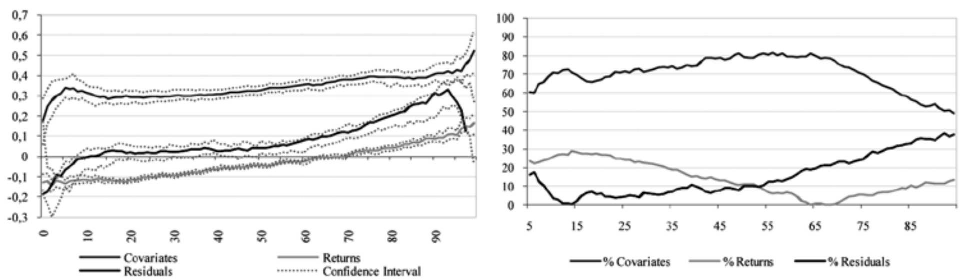
FIGURE 5

COVARIATES, RETURNS AND RESIDUALS EFFECTS: MAGNITUDE AND CONTRIBUTION

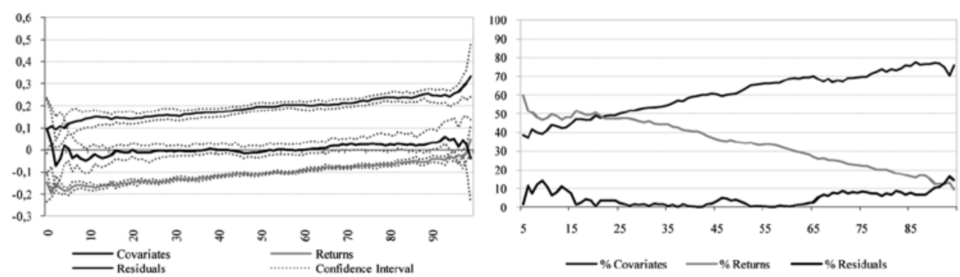
PANEL A – TOTAL URBAN – RURAL RHLI GAP (LOG)



PANEL B – TOTAL MONTEVIDEO – RURAL RHLI GAP (LOG)



PANEL C – TOTAL RUA – RURAL RHLI GAP (LOG)



Source: Authors' calculations based on INE (ENHA, 2006).

of covariate effect and smaller contribution of returns were mainly responsible for the widening of the urban-rural gap at higher quantiles.

This figure is steeper for the RUA-rural sample where the returns showed greater contribution to the gap at the bottom of the distribution, which is negative up to roughly the 25th percentile. For the Montevideo-rural sample the picture is quite different, for the bottom half of the distribution the covariate effect explained most of the gap, but roughly from the 60th percentile its contribution decreased dramatically while the returns effect (positive in this part of distribution) and mainly the residual effect became relevant to explain the increase in the gap at higher quantiles.

Analysis of the decomposition results shows a positive effect for all the samples of covariates on the urban-rural gap that increases along the quantiles and a "compensatory effect" of the returns relevant at the bottom of the distribution. One possible interpretation of this result is that given the same attributes, the rural labor market compensated their workers beyond their characteristics. On the other hand, urban labor market behaves as usual, paying more to those workers that have better attributes. Decomposition also reveals different patterns for the three samples across the distribution. In the Montevideo-rural regions covariates and returns explain the gap at the bottom of the distribution, but in upper quantiles (from the 60th) returns and residuals effects explain the increasing gap. The explanatory power of covariates and returns in the RUA-rural sample widen along quantiles in opposite directions: while the covariates increase their explanatory power, the contribution of gap returns decreases. Meanwhile the residuals do not have a significant contribution.

5.4. Sensitivity analysis/exercise

The above results were obtained under the assumption of equal levels of CPI between urban and rural regions. In this section a sensitivity analysis/exercise is carried out to analyze the extent to which the main findings depend on this assumption. Specifically, three scenarios are proposed where the rural labor incomes are rescaled in such a way that the rural region shows 5%, 10% and 15% lower levels of prices than the urban ones. Then, the counterfactual decomposition is subsequently performed.

Empirically, in each scenario this analysis produces two main changes. On the one hand, it reduces the labor income gaps between regions. On the other hand, the proportional increase in the rural labor incomes supposes an effect on the rural income equation throughout a change in the constant. Therefore, the main changes produced by this exercise would be observed in the return effect. Given the "compensating" role of parameters for the rural region in all the models estimated earlier, it might be expected that this effect would be stronger (weaker when the price effect is positive) for every decrease in prices of rural areas.

Table 6 shows the results for every level of prices by selected quantiles and for the three models. For space reasons, only the return effect estimates are reported[26]. Not surprisingly, for every reduction in rural prices in each model the labor income

[26] However, as was stated earlier the main impact of the exercise is observed in this component.

gap decreases (increases) and the price effect increases (decreases) in magnitude when it favors the rural (urban) workers, however these effects remain unchanged in the direction of the price effect in most of the quantiles.

If prices in rural areas were lower than the urban ones it would have generated a widening negative urban-rural gap in returns and thus narrowed the urban-rural gap across the labor income distribution. And this effect might have produced a negative urban-rural gap at the bottom of distribution (perhaps steeper for RUA-rural areas compared to the overall overall-rural gap). Therefore, despite not having regional prices this robustness exercise strengthens the main findings of the study.

VI. CONCLUDING COMMENTS

This paper analyzes the labor income differences between urban and rural workforce for Uruguay in 2006, taking into account the whole distribution. A quantile regression approach was applied using the Autor, Katz and Kerney (2005) technique to isolate the sources that contribute to the observed urban-rural gap. Some interesting findings emerge from this exercise.

The covariates effect was positive and increased along quantiles. It is the most important effect in explaining the income gap for all regions. Montevideo-rural gap and RUA-rural gap showed different patterns in 2006. In other words, the fact that urban workers were much better endowed than rural counterparts, holding all else constant, explained most of the observed urban-rural gap in Uruguay. Meanwhile, the returns effect was negative up to the 70th quantile for the Montevideo-rural sample and negative along the whole RHLI distribution for RUA-rural regions, showing a "compensatory effect" on the observed income labor differences. On the other hand, the residual effect only had an important impact at the top of the distribution for the former and showed a small effect for the latter.

Results are consistent with the decreasing trend observed on regional income differences in Uruguay. Rural workers appear to receive a better return on their remuneration than the urban counterparts, mainly at the lower end of the distribution. This may be related to the exceptional economic growth period since 2003 in Uruguay, led by agricultural production. Since roughly 70% of rural workers are employed in the agricultural sector they could have directly benefited from spillovers from the high dynamism and employment requirements of this activity. Another interpretation is related with rural jobs characteristics, in which some individual characteristics (such as education) do not necessarily have the strong influence as is the case in urban activities implying returns to the rural activities are beyond the individual rural workers' attributes. This picture is (in part) supported by the positives and great returns to agricultural employment found in rural areas at the bottom of the RHLI distribution.

The magnitude and the sign of covariates effect is consistent with the empirical evidence that points out that the economic activities in urban areas require better individual attributes, but this did not explain the diminishing observed trend of disparities between urban and rural incomes. In the upper tail of the labor income distribution urban workers were better paid in the labor market. Richer urban workers are mostly employed in services (especially in Montevideo) and those activities could demand high labor qualification requirements, both observable and unobservable (*e.g.*, ability). In addition, Montevideo is not only the main economic center but also concentrates on higher educational opportunities, particularly the provision of tertiary education. Thus, this pattern in returns likely reflects (at least in part) a self-selective behavior of more educated individuals from rural areas to urban ones (mainly Montevideo).

Some policy recomendation can be drawn from these results. Policy interventions could be divided according to improving individual endowments and returns to individual characteristics. Given that covariates explain most of the wage gap in all regions and along distribution, policies targeted towards improving the level of education for rural population (significantly lagged compared urban workers), would be one of the most effective measures to reduce the labor income gap. Moreover, since around 80% of rural workers are employed in small firms (less than 50 employees) improving labor opportunities for small rural firms or family farmers would have positive impacts. Institutional efforts to upgrade benefits from wage councils for rural workers could prompt the situation in that direction. This remains an important policy issue according to the high levels of informality associated with small firms, and thus the government should support rural workers with social protection policies. In that sense, this paper could have important implications for several developing economies since the urban-rural labor income gap and its determinants have had an outstanding role in the income distribution and levels of informality are important. Last but not least, investments in rural areas (*e.g.* in infrastructure and public services) oriented towards requirements of potential migrant population could encourage an increase in labor productivity in this area.

Additionally, it must be highlighted that the urban-rural gap could also be diminished with policies oriented toward workers at the top of the distribution could improve returns to their characteristics, encouraging in rural areas those sector activities that provide the best labor market returns. On the other hand, policies affecting returns for poorer workers may be oriented to enhance labor conditions stimulating and attracting rural areas. However, it must be considered that if the compensation was only on the returns but the distribution of attributes remains unchanged to rural workers, it could increase disparities between urban and rural labor income.

Finally, should be noted that some variables in the model may be endogenous. Even thought it could be seems as an important caveat, the aim of this paper is not to estimate causal effects, *e.g.* of regional covariates on log RHLI. Therefore, while the focus of this study is not a causal interpretation it even to allows provide relevant evidence about which is the behavior of urban-rural inequality across the entire labor income distribution in Uruguay and to what to extent it varies by certain individual and regional labor market characteristics.

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VIII. APPENDIX

TABLE 1

DESCRIPTIVE STATISTICS

	URBAN						RURAL	
	Total		Montevideo		Rest of Urban Areas (RUA)			
	Mean	Standard deviation	Mean	Standard deviation	Mean	Standard deviation	Mean	Standard deviation
RHLI	*46.62*	49.46	*57.90*	62.85	*38.83*	35.48	*33.31*	26.81
RHLI (log.)	3.52	0.78	*3.70*	0.83	*3.40*	0.71	*3.31*	0.62
Education	*9.11*	3.40	*10.01*	3.64	*8.49*	3.07	*6.78*	2.69
Experience	*23.86*	11.94	*23.35*	11.74	*24.21*	12.07	*27.14*	12.81
Firm size								
Public	*0.17*	0.38	*0.15*	0.36	*0.19*	0.39	*0.05*	0.21
Firmsize1	*0.16*	0.37	*0.15*	0.36	*0.17*	0.37	*0.21*	0.41
Firmsize24	*0.18*	0.38	*0.15*	0.35	*0.20*	0.40	*0.45*	0.50
Firmsize549	*0.27*	0.45	*0.28*	0.45	*0.27*	0.44	*0.23*	0.42
Firmsize50	*0.21*	0.41	*0.27*	0.44	*0.18*	0.38	*0.06*	0.23
Industry sector								
Agriculture	0.09	0.29	*0.02*	0.15	*0.14*	0.35	*0.76*	0.43
Industry	*0.18*	0.39	*0.19*	0.40	*0.18*	0.38	*0.08*	0.27
Trade	*0.21*	0.41	*0.24*	0.43	*0.19*	0.39	*0.05*	0.21
Transport	*0.09*	0.28	*0.12*	0.32	*0.07*	0.26	*0.02*	0.13
Services	*0.28*	0.45	*0.32*	0.47	*0.26*	0.44	*0.07*	0.25
Others	*0.14*	0.35	*0.11*	0.31	*0.16*	0.37	*0.03*	0.18
Regional variables								
South	*0.69*	0.46	*1.00*	0.00	*0.48*	0.50	*0.43*	0.50
Center–South	*0.09*	0.29	*0.00*	0.00	*0.15*	0.36	*0.18*	0.38
North	*0.11*	0.31	*0.00*	0.00	*0.19*	0.39	*0.19*	0.39
Centher–North	0.11	0.31	*0.00*	0.00	*0.18*	0.39	*0.20*	0.40
Sample	**31265**		**12659**		**18606**		**9401**	

Source: Authors' calculations based on INE (ENHA, 2006).

Note: Sample of full-time male workers between 18 and 60 years old is considered. The definition of variables is the following: RHLI (real hourly labor income of salaried and self-employed workers); education (measured in single years), experience (measured in single years and calculated as age – education – 6); variables categorize by size and private firm (public sector, *public*; one person, *firmsize1*; firm with 2-4 employees, *firmsize24*; firm with 5-49 employees, *firmsize549* and; firm with 50 or more employees, *firmsize50*); the industry sector (Agriculture and fishing, *agriculture*; Manufacturing industry, *industry*; Wholesale and retail trade, *trade*; Transport, *transport*; Services - Hotels and Rest., Real Estate and Financial Institutions, others and, Other sectors - Construction, electricity, gas and water, mining, *others*) and; regional variables (which divides Uruguay in four non-administrative big geographic areas: *South*, *Center-South, North, Center-North*).

TABLE 2

MEAN OF VARIABLES CONDITIONED BY HOURLY LABOR INCOME QUANTILES

	10th QUANTILE				25th QUANTILE				50th QUANTILE			
	Urban				Urban				Urban			
	Total	Monte-video	Rest of Urban Areas (RUA)	Rural	Total	Monte-video	Rest of Urban Areas (RUA)	Rural	Total	Monte-video	Rest of Urban Areas (RUA)	Rural
RHLI	21.47	23.73	19.92	18.60	27.97	32.17	25.07	25.57	38.90	44.90	34.73	30.61
RHLI (log.)	2.94	3.05	2.86	2.80	3.20	3.35	3.10	3.15	3.52	3.65	3.42	3.33
Education	7.17	7.50	6.95	5.76	7.92	8.17	7.74	6.01	8.51	9.14	8.07	6.38
Experience	24.06	22.77	24.95	31.04	22.87	22.26	23.29	28.03	24.25	25.94	23.07	28.82
Firm size												
Public	0.17	0.13	0.20	0.05	0.16	0.10	0.21	0.05	0.18	0.16	0.20	0.05
Firmsize1	0.22	0.24	0.21	0.25	0.13	0.07	0.17	0.19	0.15	0.16	0.14	0.19
Firmsize24	0.21	0.13	0.27	0.48	0.25	0.21	0.28	0.38	0.16	0.11	0.19	0.48
Firmsize549	0.28	0.31	0.25	0.16	0.29	0.39	0.22	0.32	0.26	0.30	0.24	0.22
Firmsize50	0.12	0.19	0.07	0.06	0.17	0.23	0.12	0.07	0.25	0.27	0.23	0.05
Industry sector												
Agriculture	0.13	0.02	0.20	0.72	0.12	0.01	0.19	0.77	0.09	0.02	0.15	0.76
Industry	0.16	0.21	0.13	0.06	0.18	0.24	0.14	0.08	0.20	0.21	0.20	0.08
Trade	0.21	0.26	0.18	0.06	0.25	0.28	0.22	0.04	0.22	0.21	0.22	0.03
Transport	0.03	0.04	0.02	0.00	0.09	0.09	0.09	0.03	0.09	0.16	0.04	0.02
Services	0.25	0.26	0.23	0.12	0.22	0.24	0.20	0.06	0.24	0.26	0.23	0.07
Others	0.22	0.20	0.23	0.03	0.15	0.13	0.16	0.03	0.16	0.14	0.17	0.03
Regional variables												
South	0.63	1.00	0.37	0.41	0.64	1.00	0.39	0.44	0.72	1.00	0.52	0.45
Center–South	0.09	0.00	0.15	0.18	0.11	0.00	0.19	0.10	0.07	0.00	0.12	0.19
North	0.15	0.00	0.25	0.23	0.14	0.00	0.23	0.24	0.13	0.00	0.22	0.14
Centher–North	0.14	0.00	0.23	0.18	0.11	0.00	0.19	0.22	0.08	0.00	0.14	0.22

TABLE 2 (cont.)

MEAN OF VARIABLES CONDITIONED BY HOURLY LABOR INCOME QUANTILES

	75th QUANTILE				90th QUANTILE			
	Urban				Urban			
	Total	Montevideo	Rest of urban Areas (RUA)	Rural	Total	Montevideo	Rest of urban Areas (RUA))	Rural
RHLI	56.00	69.04	47.02	39.81	77.32	105.58	57.77	47.71
RHLI (log.)	3.85	4.07	3.70	3.54	4.17	4.51	3.93	3.74
Education	10.05	11.63	8.96	7.00	11.90	13.93	10.50	7.12
Experience	25.35	24.15	26.19	27.46	23.12	20.95	24.62	27.48
Firm size								
Public	0.25	0.21	0.28	0.04	0.22	0.23	0.21	0.06
Firmsize1	0.16	0.11	0.18	0.20	0.16	0.12	0.18	0.18
Firmsize24	0.14	0.15	0.14	0.42	0.11	0.09	0.12	0.43
Firmsize549	0.23	0.26	0.20	0.29	0.28	0.27	0.28	0.24
Firmsize50	0.23	0.27	0.19	0.06	0.24	0.29	0.21	0.09
Industry sector								
Agriculture	0.05	0.01	0.08	0.79	0.04	0.04	0.04	0.66
Industry	0.15	0.13	0.17	0.07	0.13	0.10	0.15	0.15
Trade	0.22	0.19	0.24	0.05	0.18	0.14	0.20	0.05
Transport	0.12	0.18	0.07	0.04	0.12	0.16	0.09	0.04
Services	0.37	0.42	0.33	0.03	0.38	0.49	0.30	0.06
Others	0.10	0.07	0.11	0.03	0.16	0.06	0.22	0.03
Regional variables								
South	0.71	1.00	0.52	0.39	0.76	1.00	0.59	0.55
Center–South	0.09	0.00	0.16	0.26	0.07	0.00	0.13	0.19
North	0.08	0.00	0.13	0.12	0.09	0.00	0.15	0.14
Centher–North	0.11	0.00	0.19	0.23	0.08	0.00	0.14	0.12

Source: Authors' calculations based on INE (ENHA, 2006).

Note: Sample of full-time male workers between 18 and 60 years old. For definition of variables see note in Table 1. Comparison means tests were performed at the 5% significance level for all variables. The null hypothesis of equality among the mean of the variables between urban and rural regions is rejected for all variables except for the C*enter-North* variable of the regional variables' group. Additionally, mean tests were carried out between Montevideo and the rest of urban areas, and rural regions where in general differences were also found statically significant at 5%.

TABLE 3

QUANTILE ESTIMATES: TOTAL URBAN AND MONTEVIDEO

	TOTAL URBAN					
	Q = 10th	Q = 25th	Q = 50th	Q = 75th	Q = 90th	OLS
Education	0.1428 (0.0012)**	0.12769 (0.0008)**	0.12829 (0.0006)**	0.13795 (0.0008)**	0.15009 (0.0013)**	0.14179 (0.0008)**
Eduexp	–0.002 (0.0001)**	–0.00147 (0)**	–0.00118 (0)**	–0.00103 (0)**	–0.00108 (0.0001)**	–0.00141 (0)**
Experience	0.07004 (0.0009)**	0.05954 (0.0006)**	0.0562 (0.0004)**	0.05951 (0.0006)**	0.06598 (0.0009)**	0.06306 (0.0005)**
Experiencesq	–0.00078 (0)**	–0.00065 (0.000)**	–0.00059 (0.000)**	–0.00063 (0.000)**	–0.0007 (0)**	–0.00068 (0.000)**
Firmsize1	–0.82888 (0.006)**	–0.66955 (0.0042)**	–0.50376 (0.003)**	–0.36659 (0.0038)**	–0.22544 (0.0058)**	–0.49786 (0.0038)**
Firmsize24	–0.60856 (0.0062)**	–0.50023 (0.0043)**	–0.39287 (0.003)**	–0.3345 (0.0038)**	–0.27309 (0.0058)**	–0.40341 (0.0036)**
Firmsize549	–0.29101 (0.0058)**	–0.20338 (0.004)**	–0.16649 (0.0028)**	–0.14096 (0.0035)**	–0.09491 (0.0053)**	–0.16777 (0.0032)**
Firmsize50	–0.14144 (0.006)**	–0.01148 (0.0041)**	0.06331 (0.0028)**	0.09595 (0.0036)**	0.13879 (0.0055)**	0.02861 (0.0035)**
Agriculture	–0.1282 (0.0074)**	–0.10871 (0.005)**	–0.11511 (0.0033)**	–0.09102 (0.0041)**	–0.01814 (0.0063)**	–0.07238 (0.0043)**
Industry	0.01927 (0.006)**	–0.05819 (0.0041)**	–0.09238 (0.0028)**	–0.10085 (0.0035)**	–0.07318 (0.0053)**	–0.03612 (0.0035)**
Trade	–0.11504 (0.0058)**	–0.15197 (0.004)**	–0.1701 (0.0027)**	–0.1654 (0.0033)**	–0.12678 (0.005)**	–0.11694 (0.0034)**
Transport	0.04767 (0.0071)**	0.00507 –0.0049	–0.01391 (0.0033)**	–0.01195 (0.0041)**	0.03428 (0.0063)**	0.04026 (0.0042)**
Services	–0.13824 (0.0056)**	–0.13607 (0.0039)**	–0.12665 (0.0027)**	–0.08207 (0.0034)**	0.01484 (0.0052)**	–0.04657 (0.0034)**
Center–South	–0.07983 (0.006)**	–0.10428 (0.0041)**	–0.11744 (0.0028)**	–0.13436 (0.0034)**	–0.1732 (0.0051)**	–0.11719 (0.0031)**
North	–0.21064 (0.0056)**	–0.22906 (0.0038)**	–0.22749 (0.0026)**	–0.22742 (0.0031)**	–0.2385 (0.0047)**	–0.22791 (0.0031)**
Centher–North	–0.159 (0.0056)**	–0.18166 (0.0038)**	–0.18613 (0.0026)**	–0.19133 (0.0032)**	–0.1876 (0.0047)**	–0.1775 (0.0031)**
Constant	1.26304 (0.0164)**	1.76193 (0.0114)**	2.03724 (0.0079)**	2.16314 (0.0105)**	2.20372 (0.0171)**	1.79339 (0.01)**

TABLE 3 (cont.)

QUANTILE ESTIMATES: TOTAL URBAN AND MONTEVIDEO

	MONTEVIDEO					
	Q = 10th	Q = 25th	Q = 50th	Q = 75th	Q = 90th	OLS
Education	0.15315 (0.0015)**	0.14164 (0.0011)**	0.1459 (0.001)**	0.16021 (0.0011)**	0.16751 (0.0011)**	0.15821 (0.0011)**
Eduexp	–0.00182 (0.0001)**	–0.00127 (0)**	–0.00111 (0)**	–0.00131 (0)**	–0.00139 (0)**	–0.00142 (0)**
Experience	0.0619 (0.0012)**	0.05222 (0.0009)**	0.05522 (0.0008)**	0.06685 (0.0009)**	0.07954 (0.0009)**	0.06319 (0.0009)**
Experiencesq	–0.0007 (0)**	–0.00053 (0)**	–0.00055 (0)**	–0.00069 (0)**	–0.00087 (0)**	–0.00066 (0)**
Firmsize1	–0.70945 (0.0078)**	–0.57981 (0.0059)**	–0.41395 (0.0057)**	–0.31413 (0.0062)**	–0.16026 (0.0057)**	–0.42933 (0.0062)**
Firmsize24	–0.55865 (0.0081)**	–0.45147 (0.0061)**	–0.40311 (0.0058)**	–0.37167 (0.0063)**	–0.26908 (0.0058)**	–0.41308 (0.006)**
Firmsize549	–0.21913 (0.0075)**	–0.15986 (0.0055)**	–0.16273 (0.0052)**	–0.15745 (0.0056)**	–0.08237 (0.0051)**	–0.1707 (0.0052)**
Firmsize50	–0.06993 (0.0074)**	–0.00007 –0.0054	0.03403 (0.0051)**	0.07156 (0.0054)**	0.10276 (0.005)**	0.01605 (0.0052)**
Agriculture	–0.38937 (0.0151)**	–0.18523 (0.0114)**	–0.11086 (0.0106)**	–0.02509 (0.0112)*	0.234 (0.0103)**	–0.06819 (0.0139)**
Industry	0.09006 (0.008)**	–0.0298 (0.0059)**	–0.0207 (0.0056)**	–0.01943 (0.0059)**	0.01767 (0.0055)**	0.025 (0.0059)**
Trade	–0.06881 (0.0078)**	–0.14466 (0.0058)**	–0.11327 (0.0053)**	–0.09194 (0.0056)**	–0.03072 (0.0052)**	–0.07047 (0.0058)**
Transport	0.13363 (0.0089)**	0.01125 –0.0066	0.02587 (0.0062)**	0.05569 (0.0065)**	0.10018 (0.0061)**	0.08493 (0.0066)**
Services	–0.02149 (0.0075)**	–0.0819 (0.0056)**	–0.04484 (0.0053)**	–0.00235 –0.0057	0.08685 (0.0052)**	0.01324 (0.0057)*
Center–South	–	–	–	–	–	–
North	–	–	–	–	–	–
Centher-North	–	–	–	–	–	–
Constant	1.12944 (0.0213)**	1.62098 (0.0157)**	1.79817 (0.0149)**	1.84111 (0.0166)**	1.83897 (0.0165)**	1.57661 (0.0157)**

Source: Authors' calculations based on INE (ENHA, 2006).

Note: The regressions are computed using QR and OLS framework. The dependant variable used is RHLI (real hourly labor income, in logs.). For a detailed definition of variables see note in Table 1. Each regression includes a constant term, education (E*ducation*), experience (*Experience*) and its square (*Experiencesq*), an interaction between education and experience (*Eduexp*), a set of characteristics of workers' firms (size of the firm and the industry sector) and regional variables. The omitted group is the male working in the *public* sector, in the *south* region and in *other* sector. In parenthesis are the standard errors: * significant at 5%; ** significant at 1%.

TABLE 4

QUANTILE ESTIMATES: REST OF URBAN AREAS (RUA) AND RURAL

	REST OF URBAN AREAS (RUA)					
	Q = 10th	Q = 25th	Q = 50th	Q = 75th	Q = 90th	OLS
Education	0.12933	0.1097	0.09999	0.10597	0.12989	0.11772
	(0.0014)**	(0.0009)**	(0.0006)**	(0.0008)**	(0.0013)**	(0.0011)**
Eduexp	–0.00214	–0.00139	–0.00085	–0.00064	–0.00109	–0.00118
	(0.0001)**	(0)**	(0)**	(0)**	(0.0001)**	(0)**
Experience	0.07426	0.05962	0.04988	0.05181	0.06329	0.05998
	(0.0009)**	(0.0006)**	(0.0004)**	(0.0005)**	(0.0008)**	(0.0007)**
Experiencesq	–0.00082	–0.00067	–0.00054	–0.00058	–0.0007	–0.00068
	(0)**	(0)**	(0)**	(0)**	(0)**	(0)**
Firmsize1	–0.8893	–0.7325	–0.56035	–0.40209	–0.29526	–0.5431
	(0.0059)**	(0.0042)**	(0.0025)**	(0.0033)**	(0.0053)**	(0.0048)**
Firmsize24	–0.64814	–0.53163	–0.3982	–0.32413	–0.24667	–0.4055
	(0.0061)**	(0.0042)**	(0.0025)**	(0.0033)**	(0.0053)**	(0.0045)**
Firmsize549	–0.31871	–0.23179	–0.17369	–0.1309	–0.09699	–0.17089
	–0.0057	(0.004)**	(0.0023)**	(0.0031)**	(0.0049)**	(0.0042)**
Firmsize50	–0.15108	–0.02039	0.06848	0.11872	0.17378	0.0331
	(0.0063)**	(0.0043)**	(0.0025)**	(0.0034)**	(0.0054)**	(0.0048)**
Agriculture	–0.14405	–0.13632	–0.17332	–0.1478	–0.11669	–0.11454
	(0.0063)**	(0.0043)**	(0.0024)**	(0.0031)**	(0.0048)**	(0.0047)**
Industry	–0.01043	–0.07103	–0.14105	–0.14393	–0.116	–0.0661
	–0.0058	(0.004)**	(0.0023)**	(0.0029)**	(0.0046)**	(0.0044)**
Trade	–0.0946	–0.13566	–0.20003	–0.19199	–0.18332	–0.12928
	(0.0056)**	(0.0039)**	(0.0022)**	(0.0028)**	(0.0043)**	(0.0042)**
Transport	0.02374	0.00222	–0.01462	–0.0153	0.00955	0.02796
	(0.0073)**	–0.0051	(0.0029)**	(0.0038)**	–0.0059	(0.0056)**
Services	–0.19434	–0.18409	–0.17875	–0.1244	–0.01793	–0.08383
	(0.0053)**	(0.0038)**	(0.0023)**	(0.003)**	(0.0048)**	(0.0043)**
Center–South	–0.05944	–0.09261	–0.09535	–0.10229	–0.11674	–0.09701
	(0.0049)**	(0.0034)**	(0.0019)**	(0.0024)**	(0.0038)**	(0.0034)**
North	–0.20602	–0.21697	–0.216	–0.20484	–0.18302	–0.20908
	(0.0046)**	(0.0032)**	(0.0018)**	(0.0023)**	(0.0035)**	(0.0033)**
Centher–North	–0.13408	–0.17329	–0.16919	–0.15812	–0.1337	–0.15595
	(0.0046)**	(0.0031)**	(0.0018)**	(0.0023)**	(0.0035)**	(0.0033)**
Constant	1.36767	1.94912	2.36409	2.49778	2.40577	2.04063
	(0.0169)**	(0.0116)**	(0.0069)**	(0.0095)**	(0.0162)**	(0.0134)**

TABLE 4 (cont.)

QUANTILE ESTIMATES: REST OF URBAN AREAS (RUA) AND RURAL

	RURAL					
	Q = 10th	Q = 25th	Q = 50th	Q = 75th	Q = 90th	OLS
Education	0.08968 (0.0049)**	0.07386 (0.0025)**	0.07112 (0.0024)**	0.0763 (0.0025)**	0.07541 (0.0044)**	0.08221 (0.003)**
Eduexp	–0.00107 (0.0002)**	–0.00088 (0.0001)**	–0.00064 (0.0001)**	–0.00021 (0.0001)*	0.00017 –0.0002	–0.0006 (0.0001)**
Experience	0.04767 (0.0029)**	0.04335 (0.0015)**	0.04094 (0.0015)**	0.03701 (0.0015)**	0.04149 (0.0025)**	0.04453 (0.0018)**
Experiencesq	–0.00056 (0)**	–0.00053 (0)**	–0.00051 (0)**	–0.00043 (0)**	–0.00051 (0)**	–0.00054 (0)**
Firmsize1	–0.81956 (0.0325)**	–0.61523 (0.0173)**	–0.36019 (0.0165)**	–0.27719 (0.0167)**	–0.09965 (0.027)**	–0.44063 (0.0203)**
Firmsize24	–0.59096 (0.0324)**	–0.43807 (0.0172)**	–0.25997 (0.0164)**	–0.24011 (0.0166)**	–0.15692 (0.0268)**	–0.33846 (0.0196)**
Firmsize549	–0.32441 (0.0329)**	–0.2832 (0.0174)**	–0.17165 (0.0166)**	–0.15671 (0.0169)**	–0.08922 (0.0277)**	–0.22151 (0.0198)**
Firmsize50	–0.18686 (0.0382)**	–0.02268 –0.0198	0.09659 (0.0187)**	0.12389 (0.0188)**	0.21166 (0.0308)**	0.03134 –0.0231
Agriculture	0.12841 (0.0294)**	0.0963 (0.0155)**	–0.00887 –0.0143	–0.08499 (0.0135)**	–0.17704 (0.022)**	0.0442 (0.0189)*
Industry	0.01232 –0.0335	0.03387 –0.0178	–0.02305 –0.0166	–0.13323 (0.0157)**	–0.24741 (0.0257)**	–0.03469 –0.0212
Trade	–0.05872 –0.036	–0.03617 –0.0192	–0.16645 (0.018)**	–0.16646 (0.0171)**	–0.14427 (0.0281)**	–0.09082 (0.0237)**
Transport	0.28022 (0.0459)**	0.21714 (0.0248)**	0.1256 (0.0233)**	0.03786 –0.0224	0.02627 –0.0363	0.1437 (0.0284)**
Services	–0.15453 (0.0343)**	–0.0594 (0.0187)**	–0.0803 (0.0181)**	–0.17049 (0.0182)**	–0.20629 (0.0296)**	–0.08849 (0.0236)**
Center–South	0.04729 (0.0142)**	0.09154 (0.0076)**	0.09428 (0.007)**	0.09028 (0.0068)**	0.10099 (0.0112)**	0.09076 (0.0084)**
North	–0.05984 (0.014)**	–0.03752 (0.0074)**	–0.04235 (0.0069)**	–0.05352 (0.0066)**	–0.03666 (0.0109)**	–0.04148 (0.0081)**
Centher–North	–0.01069 –0.0138	0.07314 (0.0074)**	0.04376 (0.0068)**	0.03851 (0.0066)**	0.0243 (0.0109)*	0.03622 (0.0081)**
Constant	1.87012 (0.0643)**	2.26544 (0.0336)**	2.54396 (0.0327)**	2.83098 (0.0342)**	3.00246 (0.0589)**	2.39222 (0.0404)**

Source: Authors' calculations based on INE (ENHA, 2006).

Note: The regressions are computed using QR and OLS framework. The dependant variable used is RHLI (real hourly labor income, in logs.). For a detailed definition of variables see note in Table 1. Each regression includes a constant term, education (E*ducation*), experience (*Experience*) and its square (*Experiencesq*), an interaction between education and experience (*Eduexp*), a set of characteristics of workers' firms (size of the firm and the industry sector) and regional variables. The omitted group is the male working in the *public* sector, in the *south* region and in *other* sector. In parenthesis are the standard errors: * significant at 5%; ** significant at 1%.

TABLE 5

QUANTILE DECOMPOSITION OF LOG RHLI INTO COVARIATES, RETURNS AND RESIDUAL COMPONENTS

PANEL A – URBAN-RURAL LOG RHLI GAP

	Q = 10th	Q = 25th	Q = 50th	Q = 75th	Q = 90th
Observed Gap	0.012	0.084	0.169	0.315	0.465
	(–0.024–0.05)	(0.067–0.105)	(0.155–0.188)	(0.293–0.331)	(0.423–0.489)
Estimated Gap	0.012	0.084	0.169	0.315	0.465
	(–0.025–0.046)	(0.058–0.102)	(0.147–0.181)	(0.296–0.333)	(0.426–0.492)
	0.188	0.202	0.246	0.305	0.363
Covariates Effect	(0.159–0.229)	(0.178–0.217)	(0.231–0.26)	(0.289–0.316)	(0.334–0.382)
	–0.159	–0.134	–0.092	–0.039	0.001
Returns Effect	(–0.177-–0.15)	(–0.14-–0.125)	(–0.102-–0.085)	(–0.045-–0.031)	(–0.011-–0.011)
	–0.017	0.015	0.015	0.048	0.102
Residual Effect	(–0.072–0.016)	(–0.012–0.039)	(–0.009–0.03)	(0.023–0.069)	(0.05–0.137)

PANEL B - MONTEVIDEO - RURAL LOG RHLI GAP

	Q = 10th	Q = 25th	Q = 50th	Q = 75th	Q = 90th
Observed Gap	0.174	0.207	0.314	0.552	0.754
	(0.127–0.213)	(0.185–0.237)	(0.288–0.332)	(0.524–0.584)	(0.709–0.793)
Estimated Gap	0.174	0.207	0.314	0.552	0.754
	(0.142–0.21)	(0.182–0.232)	(0.292–0.329)	(0.527–0.576)	(0.723–0.798)
	0.323	0.294	0.325	0.391	0.399
Covariates Effect	(0.288–0.373)	(0.261–0.322)	(0.304–0.346)	(0.362–0.414)	(0.363–0.439)
	–0.116	–0.104	–0.043	0.031	0.088
Returns Effect	(–0.13-–0.092)	(–0.115-–0.095)	(–0.05-–0.035)	(0.019–0.042)	(0.073–0.104)
	–0.033	0.018	0.032	0.131	0.267
Residual Effect	(–0.077–0.023)	(–0.024–0.047)	(–0.001–0.051)	(0.104–0.169)	(0.194–0.306)

PANEL C - RUA - RURAL LOG RHLI GAP

	Q = 10th	Q = 25th	Q = 50th	Q = 75th	Q = 90th
Observed Gap	–0.076	–0.005	0.069	0.175	0.231
	(–0.104-–0.039)	(–0.027–0.019)	(0.05–0.091)	(0.156–0.195)	(0.189–0.263)
Estimated Gap	–0.076	–0.006	0.069	0.175	0.231
	(–0.114-–0.026)	(–0.034–0.018)	(0.04–0.088)	(0.153–0.196)	(0.189–0.274)
	0.141	0.151	0.195	0.223	0.254
Covariates Effect	(0.101–0.175)	(0.13–0.172)	(0.175–0.212)	(0.202–0.237)	(0.218–0.276)
	–0.166	–0.146	–0.112	–0.072	–0.050
Returns Effect	(–0.18-–0.153)	(–0.153-–0.137)	(–0.121-–0.106)	(–0.081-–0.064)	(–0.061-–0.035)
	–0.050	–0.011	–0.013	0.025	0.028
Residual Effect	(–0.106–0.003)	(–0.057–0.019)	(–0.037–0.018)	(0–0.061)	(–0.004–0.092)

Source: Authors' calculations based on INE (ENHA, 2006).

Note: Estimated gap is the sum of three components: Covariates Effect, Returns Effect and Residual Effect. Those are estimated as a difference in logs for selected quantiles of observed and simulated labor income distributions. Selected quantiles are presented in columns. For each component in the rows the first cell corresponds to their values and the second entry is the confidence interval at 95% using bootstrap technique with 150 replications.

TABLE 6

PRICE SENSITIVITY ANALYSIS/EXERCISE

Quantiles	Reduction in the level of Rural prices	Urban – Rural Sample		Montevideo – Rural Sample		RUA – Rural Sample	
		Returns Effect	Estimated Gap	Returns Effect	Estimated Gap	Returns Effect	Estimated Gap
Q = 10th	0%	–0.155	0.033	–0.120	0.189	–0.167	–0.060
	5%	–0.206	–0.018	–0.172	0.138	–0.219	–0.111
	10%	–0.260	–0.073	–0.226	0.084	–0.273	–0.165
	15%	–0.317	–0.130	–0.283	0.026	–0.330	–0.223
Q = 25th	0%	–0.132	0.089	–0.097	0.213	–0.148	–0.001
	5%	–0.183	0.037	–0.148	0.161	–0.199	–0.053
	10%	–0.238	–0.017	–0.202	0.107	–0.254	–0.107
	15%	–0.295	–0.074	–0.259	0.050	–0.311	–0.164
Q = 50th	0%	–0.089	0.173	–0.043	0.320	–0.109	0.075
	5%	–0.140	0.122	–0.094	0.269	–0.161	0.024
	10%	–0.194	0.068	–0.148	0.215	–0.215	–0.030
	15%	–0.251	0.011	–0.206	0.158	–0.272	–0.088
Q = 75th	0%	–0.039	0.316	0.030	0.558	–0.073	0.175
	5%	–0.091	0.265	–0.021	0.506	–0.125	0.124
	10%	–0.145	0.211	–0.076	0.452	–0.179	0.070
	15%	–0.202	0.153	–0.133	0.395	–0.236	0.013
Q = 90th	0%	–0.001	0.465	0.086	0.753	–0.049	0.234
	5%	–0.053	0.414	0.035	0.702	–0.100	0.183
	10%	–0.107	0.360	–0.019	0.648	–0.154	0.129
	15%	–0.164	0.302	–0.076	0.591	–0.211	0.072

Source: Authors' calculations based on INE (ENHA, 2006).

Note: To perform analysis three scenarios were considered: rural labor incomes were rescaled in such a way that the rural region shows 5%, 10% and 15% lower levels of prices than the urban one. Calculations are based on the median value at θ^{th} quantile.