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Labor informality: choice or sign of segmentation?
A Quantile Regression Approach at the Regional Level for Colombia

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Abstract

The labor market in developing countries is remarkably heterogeneous with a small productive formal sector, enjoying high wages and attractive employment conditions and another large informal sector with low productivity and volatile wages. The informal sector is particularly diverse. In this paper we examine the heterogeneity of the informal sector at regional level in Colombia. In general, our findings suggest that, both voluntary and involuntary informal employment co-exist by choice and as a result of labor market segmentation. We also find that there are striking differences in labor market characteristics between cities, in particular in the traditional informal segment. In less developed cities this segment represents roughly 70% of informal total informal employment, while in more developed cities it represents around 40%. Regarding decomposition of the formal/informal wage gap by groups of cities, the results show that at the bottom of the distribution coefficient effects explain most of the wage gap regardless of the group of cities. This evidences the marked labor segmentation at this point of the distribution. Conversely, the positive wage gap at the top of the distribution is mainly explained by characteristics effects in more developed cities, while in less developed cities the wage gap declines to zero since the coefficient effects compensate the differential in characteristics in favor of formal workers. These results indicate that informal workers who are located at the top of the distribution choose working in the informal sector for the wage (and non-wage) benefits that they would not have in such sector.

Keywords: Informality, local labor markets, quantile regression, selection bias, formal/informal wage gap decomposition
***JEL Classification*:** O17, J42, J31, C21

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1. Introduction

One of the features that stands out in developing countries is the great heterogeneity in their urban labor markets. It is common to observe the coexistence of a small productive formal sector, which offers attractive labor conditions and relatively high wages, with a large informal sector which uses unskilled labor, with low earnings and productivity, and does not fully comply with established legal regulations (Dickens and Lang, 1985; Maloney, 1999 and 2004; Jütting and De Laiglesia, 2009). Nevertheless, within this large informal sector, there is a considerable variety of workers.

But why is there such diversity in the informal sector? Are there different kinds of informal workers; ones who are voluntarily informal and others who end up in this sector because they do not have any other alternative form of employment? Is labor informality a choice or the result of labor market segmentation?

The segmented labor markets theory considers informality as a survival alternative to escape involuntary unemployment for those disadvantaged or rationed out of formal employment opportunities (Dickens and Lang, 1985). The result is a dualism in earnings for individuals with similar characteristics which depend on the sector in which they work. In the formal sector there are internal markets that constrain the labor supply and produce high wages, while in the informal sector there is no institutional or efficiency-wage basis that regulates the wages. In addition the few entry barriers and an abundant supply of unskilled workers lead to low wages. Thus, wages depend on the sector in which workers are employed and not on their skills *per se* (Uribe *et al*., 2007).

On the contrary, the orthodox neoclassical view of the human capital theory postulates that, like in any another market, price flexibility and free labor mobility lead to a full employment equilibrium with equal remuneration for the same kind of work (De Soto, 1987; Saavedra and Chong, 1999; Maloney, 1999). Due to this competitive market framework, being part of the informal sector may be a desirable choice for workers and firms, as it is based on the private cost-benefit calculations of belonging to the sector. Being informal can have desirable non-wage features and therefore individuals maximize their utility rather than their earnings. Alternatively, certain workers have a comparative advantage in the informal sector that they would not have in the formal sector (Gindling, 1991).

These two polarized views can be combined if the informal sector is very heterogeneous and contains elements of each scenario; namely if the informal sector has its own internal duality. Recent literature has recognized the existence of "upper" and “lower” tiers or “voluntary” and “involuntary” entry of informal employees or firms (Fields, 1990 and 2005; Cunningham and Maloney, 2001; Maloney, 2004). In such a scenario the upper-tier employees are those who are voluntarily informal because, given their specific characteristics, they expect to earn more than they would in the formal sector. On the contrary, the lower-tier employees are those disadvantaged workers that see informality as a last resort.

Nevertheless, from the empirical stance this more recent view on dualism within the informal sector has not been satisfactory treated. For example, Magnac (1991) when testing for competitiveness or segmentation in the labor market of Colombia in the 1980’s, found evidence of a competitive labor market structure. Similarly, Gindling (1991) and Pratap and Quintin (2006) found evidence of segmentation in Costa Rica and of a competitive structure in Argentina, respectively. However, in all the above papers the authors assume homogeneity of the informal sector, thus limiting their analysis.

Among the few studies that have tried to model the heterogeneous structure of the informal sector, we can list Cunningham and Maloney (2001), and Günther and Launov (2012). The former model the informal sector as a mixture of “upper-tier” and “lower-tier” enterprises and using econometric techniques of factor and cluster analysis they allow for the segmentation of the market. However, despite finding evidence of segmentation, Cunningham and Maloney (2001) considered only informal firms, so that the alternative of being a formal firm does not exist in their model. Further, they do not take into account the selection bias induced by the type of employment decision of individuals.

The work of Günther and Launov (2012) analyzes the possible heterogeneous structure of the informal sector, estimating a finite mixture model which allows determining the number and size of segments that could compose the informal sector. This model uses minimal *a priori* assumptions to determine the segments and provides a new method to identify the size of voluntary and/or involuntary employment in the informal sector. The empirical analysis uses data from the Ivory Coast at the end of the 1990s. Among their findings, the authors report that the informal sector consists of two segments: a high-paid and a low-paid segment. They also found that 45% of informal employment is not voluntary and is mainly located in the lower-paid informal segment, while the remaining 55% of informal employment is voluntary and is situated in the higher-paid informal segment.

In this paper we analyze the heterogeneity of the informal sector decomposing the wage differential between the formal and informal sector throughout the entire distribution of wages. This methodology is conceptually similar to Günther and Launov's (2012) approach, except it accounts for a wider variety of informal employees as well as formal ones. Our method advances beyond the studies based on the workers' mean-earnings which are incapable of distinguishing if there are different behaviors throughout the entire distribution of wages.

Our research focuses on the regional labor markets of Colombia. Given the geographic, demographic, social conditions and economic dynamics, Colombia provides rich evidence from a large, heterogeneous informal sector. Furthermore, there are marked differences in the structures and dynamics of the local labor markets. In Colombia roughly six out of ten employees work in the informal sector[1] and cities such as Cúcuta or Montería have informality rates of around 75%. Others such as Medellín or Bogotá, have rates of about 50% (García, 2011; Galvis, 2012).

In order to analyze the different motivations to join the informal sector we decompose the formal/informal wage gap. Such decomposition allows us to distinguish what proportion of the wage gap is due to differences in prices related to individual characteristics and what proportion is due to characteristics which differ between the formal and informal sector. If the wage gap is mainly attributable to the first factor it indicates that individuals in the informal sector earn less because they get lower returns for their skills and therefore they are part of the disadvantaged sector of a segmented market. On the other hand, if the wage gap is primarily explained by the second factor, the labor segmentation is not as strong as in the above case and the differences in wages between sectors are due to differences in endowments. In this latter situation, being an informal worker is a choice, because these individuals can get non-wage benefits or earn more than they would not earn in the formal sector.

To carry out the decomposition, we estimate earnings functions for informal and formal workers using quantile regression taking into account the possibility of self-selection into those sectors. We follow the method of Machado and Mata (2005) and the extension proposed by Albrecht, Vuuren and Vroman (2009) to account for selection, which is based on Buchinsky (1998) who uses semi-parametric methods.

[1] According to International Labor Organization (ILO, 2011) estimates, Colombia is the fourth country with the highest informality rate in South America after Paraguay (70.4%), Perú (70.3%) and Bolivia (69.5%).

Following this introduction, Section 2 proceeds with the description of the data. In Section 3 we discuss the estimation procedure. Section 4 describes the empirical findings, and finally conclusions are drawn in Section 5.

2. Data and descriptive evidence

The data used in this paper come from the Great Integrated Household Survey (GIHS) for 2009, carried out by the National Administrative Statistics Department (DANE). This cross-section survey has information at micro-data level on labor force, unemployment and informality of thirteen major cities with their metropolitan areas of Colombia.[2]

The sample considered in this work is composed of individuals between 12 and 65 years old and we further excluded agriculture workers. Our final sample is composed of 62,278 individuals.[3] The main variable of analysis is the real hourly wage, computed as the monthly wage divided by the effective number of hours worked during that month and adjusted for the price level using the consumer price index (base year 2008) of each city as deflator.[4]

As regards informality, we define informal workers as those workers who are not covered by the social security system. More precisely, informal workers are those workers who are not covered by the health insurance and the pension system. Applying this condition, we have 36,293 (58.3%) formal workers and 25,985 (41.7%) informal workers. In Table 1, we give some descriptive statistics for the key variables for formal and informal workers.

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[2] Namely, Barranquilla, Bogotá, Bucaramanga, Cali, Cartagena, Cúcuta, Ibagué, Manizales, Medellín, Montería, Pasto, Pereira, and Villavicencio. These metropolitan areas represent 45% of total population and about 60% of urban population according to 2005 Population Census.

[3] Note that we excluded government employees, employers and self-employed. Given this exclusion the informality rate may differ from that reported by ILO.

[4] Consumer price indices for the biggest cities in Colombia were obtained from DANE. Since each one of these cities is the core of a metropolitan area, we applied the consumer prices index of the city to the whole metropolitan area. To Ibagué the consumer prices index is no calculated by DANE, so we decided to use the consumer prices index of Pereira given the similarities in population and social and cultural characteristics, as well as proximity between theses cities.

Table 1. Descriptive statistics

	Formal workers	**Informal workers**	**Total**
Real hourly wage	3269.2	2311.9	2927.4
Age (years)	34.3	32.9	33.8
Education (years)	11.0	8.6	10.2
Tenure at job (years)	4.7	2.8	4.0
Education levels			
Up to primary school	11.9	28.1	17.7
Lower secondary school	14.3	26.4	18.6
Higher secondary school	62.2	42.3	55.1
Bachelor/Master	11.6	3.2	8.6
Male	55.6	48.7	53.1
Head of household	43.0	35.4	40.3
Married	53.5	46.1	50.8
Firm size			
1 – 10 employees	17.9	76.6	38.9
11 – 50 employees	22.3	14.1	19.3
More than 51 employees	59.8	9.3	41.8
Sample size	36,293	25,985	62,278

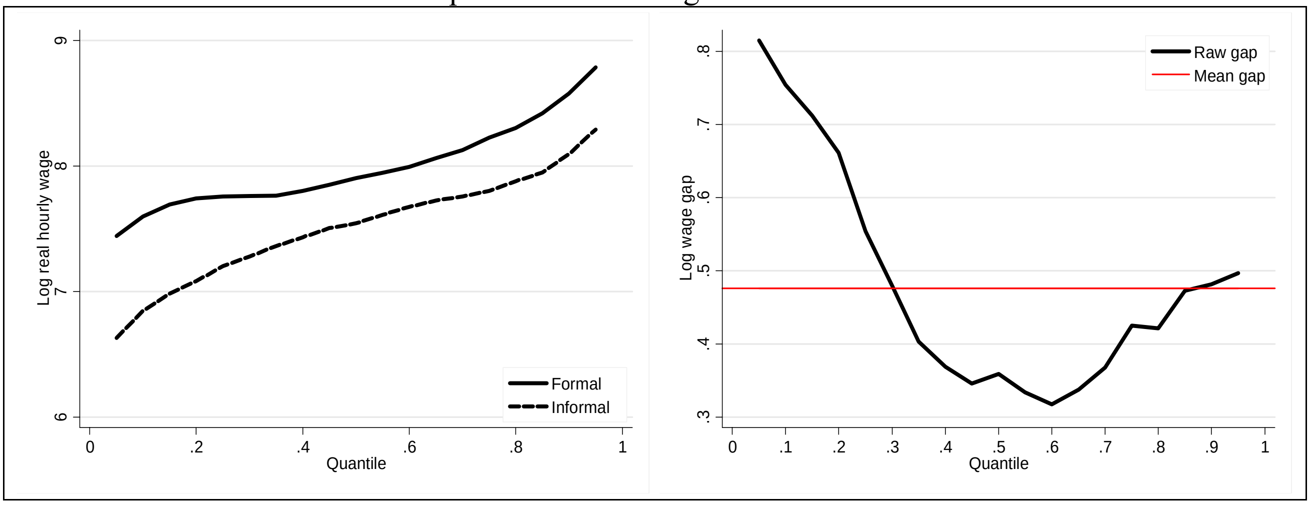
Note: We used person sampling weight available in the database. The wages are in Colombian pesos (in December 2009 the exchange rate was 2935 Colombian pesos per euro).

As can be seen from Table 1, the average wage among formal workers is higher than the corresponding average among informal workers: a formal worker earns on average 30% more than an informal worker. In terms of the variables that we can use to explain variation in wages, there are also some important differences between kinds of employees. Formal workers have on average similar age than informal workers, and years of tenure at job are higher for formal workers than informal workers. Turning to education we can see that formal workers are consistently more educated than informal. The informal sector has a higher percentage of individuals with primary and less secondary school (54%), while the formal sector has a much higher percentage of individuals with secondary and bachelor/master certificate (74%). As regards other personal characteristics, we can see that the informal workers are less likely being men, head of household and married than formal workers. Finally, informal workers are more likely to work in firms between 1 and 10 employees (77%), while formal workers are employed in firms of more than 51 employees (60%).

Figure 1 depicts the estimated kernel densities of formal's and informal's wages. Wage disparities between sectors are clearly visible, as wage distribution for formal workers is shifted to the right. The distribution of formal and informal sector wage and wage gap between sectors by quantile, i.e., the difference in log wages between formal workers and informal workers at each quantile of their respective distributions, is plotted in Figure 2. We can see that wage differential between sectors is positive along the whole wage distribution with a large wage gap within low-paid occupations. Its size ranges between 54% at the bottom end of the distribution to 30% at the median, then increasing to roughly 39% at the top end of the distribution. There are marked differences between formal and informal workers especially within low-paid and high-paid occupations, which may be due to very different human capital endowments and job opportunities in these points of the earnings distribution.

Figure 1. Kernel density of log real hourly wage by formal and informal sector

Figure 2. Wage differentials between formal and informal sector over different quantiles of the wage distribution



At the city level we can see that there are also positive wage differences between sectors along the whole distribution and there are different patterns between cities (see Figure A1 in the Appendix). Pasto, Montería and Cartagena present the largest wage gaps, with particularly large wage gap within low-paid occupations. The common characteristic in these cities is that they present the highest levels of informality in Colombia (see Table A1 in the Appendix) and therefore there is an important heterogeneity of employments and workers in the informal sector. In these cities the relative abundance of informal jobs is an important determinant to join the informal sector. Turning to the biggest and most developed cities, such as Bogotá, Medellín, and Cali, we can see that the wages differentials between sectors are smaller than in the first cities.

In order to simplify the presentation of the results of the empirical exercise we define two groups of cities. In the following section we describe these groups and present some descriptive statistics of their labor markets.

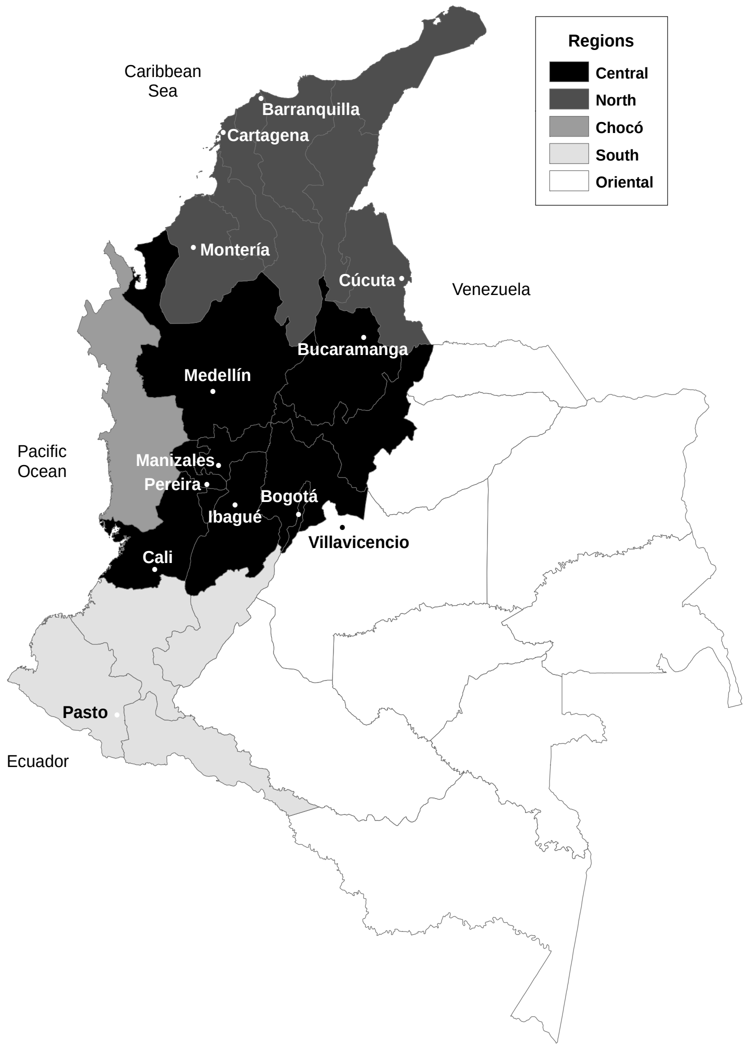
2.1 Group of cities and their labor markets

Although there are different set of cities that can be considered, we follow the regional grouping formulated by Galvis (2007). To our knowledge, only Galvis undertakes a study identifying the economic regions for Colombia at city level.[5] The author carries

[5] Barón (2002) also identifies the economic regions of Colombia but his grouping is at the department level.

out an analysis of the intensity of economic activity[6] and using spatial econometrics techniques evaluate the existence of spatial dependence in the sub-regions conformed by cities where economic activity is more concentrated. The author identifies five sub-regions: central, north, *Chocó*, south and oriental. Highlighting only regions containing our cities analyzed, in the first region are included Bogotá, Medellín, Cali, Bucaramanga, Manizales, Pereira and Ibagué. In the second region are all Caribbean coast cities, such as Cartagena, Barranquilla and Montería, and the cities of the department of *Norte de Santander* which has as capital Cúcuta. Pasto and Villavicencio, which are other of the cities in our analysis, are located in the south region and oriental region, respectively. The map in Figure 3 shows the economic regions proposed by Galvis (2007).

Figure 3. Economic regions proposed by Galvis (2007)



6 Given that there are not figures on GDP at the city level in Colombia, Galvis (2007) uses the bank deposits and the local tax collections per capita as measures of economic activity of the cities. According to Bonet and Meisel (1999) there is a correlation between GDP and bank deposits of around 0.8.

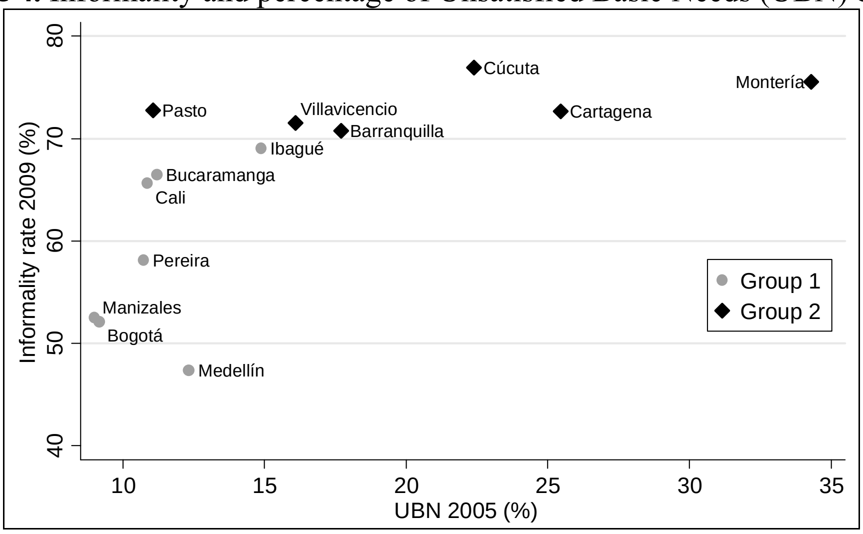
Since Pasto and Villavicencio are not located in the central or north region, we regrouped these with the north region. Although, these cities are not geographically close to the north region, they have socioeconomic characteristics that can make them closer beyond the geographic distance. In this regards, Sánchez and España (2012) state that Pasto, Villavicencio, the Caribbean coast cities and Cúcuta are part of the same group of intermediate urban centers in Colombia. This group is composed by cities which are usually capitals and have low levels of economic concentration and diversification. It is important to note that Pasto and Cúcuta are border cities, the first one shares border with Ecuador and the second one with Venezuela, which is a common characteristic that can influence the type of activity and of employment generated, in particular those related with the commerce (legal and illegal) and currency exchange (Bonet, 2007; García, 2005 and 2011). Villavicencio also has important similarities with the Caribbean coast cities, especially with Montería. These cities are the capitals of the two main cattle farming regions of the country and therefore their economies are based mainly on this activity. Furthermore, these two regions are considered conflict zones due to the paramilitaries, guerrillas and drug traffickers active, which influence not only the activity economic but also the social, political and cultural aspects of the regions (Vilore de la Hoz, 2009; Sánchez *et al*., 2012).

We therefore define two groups of cities. The first one is composing by Bogotá, Medellín, Cali, Manizales, Bucaramanga, Pereira and Ibagué (Group 1); and the second one by Cúcuta, Montería, Pasto, Cartagena, Barranquilla and Villavicencio (Group 2). Consequently, the selection of these groups of cities was undertaken in such a way so as to intensify similarities within groups and differences across groups. The first group is composed of the largest industrial and the most dynamic cities in Colombia. These cities represent 0.7% of the national territory and according to the 2005 Population Census concentrated around 45% of urban population. Galvis (2007) reports that the region formed between Bogotá, Cali, Medellín and Bucaramanga, called by the author as *Trapecio Andino*, generates 80% of total economic activity of the country and their provision of infrastructure, measure as the number of telephone lines per capita, is higher than national level (276 lines versus 219 lines per 1000 inhabitants[7], see Figure A2 in the Appendix).

[7] We calculated this based on *Sistema Único de Servicios Públicos de Colombia* data for 2007 (www.siu.gov.co).

The second group is composed of lagging cities, located in peripheral areas and with less dynamic economic. Although Barranquilla and Cartagena are among most urban cities of Colombia, are the most important seaports of the country and have an important industrial cluster associated with the plastics and petrochemical sector[8], their socioeconomic and labor market indicators are unfavorable. These cities show one of the highest poverty, inequality and informality levels among the main cities of Colombia (Bonilla, 2008; Galvis, 2009). In Figure 4 we show the relationship between informality and the percentage of Unsatisfied Basic Needs (UBN) as indicator of poverty. We can see that Cartagena and Barranquilla along with Montería and Cúcuta, present the highest levels of informality, as well as of UBN. The tourist vocation of the Caribbean region and the relatively low capacity to create jobs in the highly productive sectors (such as chemical, plastic and petrochemical sectors), due to these are mostly composed by big companies with high capital intensity and export activities, it has led to a process of tertiarization of the economy, where the service sector has little impact on the competitiveness of the other sectors and generates a lot of jobs but of low quality (Bonet, 2005 and 2007; Bonilla, 2010; Cepeda, 2011; Acosta, 2012).

Figure 4. Informality and percentage of Unsatisfied Basic Needs (UBN) by city



Source: UBN: 2005 Population Census – DANE; Informality rate: Table A1 in the Appendix.

In Table 2 we show some descriptive statistics of the labor markets that form the two groups of cities. As expected, there are a higher percentage of informal wage

[8] In the industrial zone of *Mamonal* in Cartagena is located the second oil refinery of Colombia which is integrated with petrochemical, chemical and plastic industries. Barranquilla is highly specialized in the food and beverages, chemicals, non-metallic mineral products and basic metallurgy sectors. A more detailed economic characterization of Barranquilla and Cartagena can be found in Bonilla (2010) and Acosta (2012), respectively.

workers in less developed cities (53%) than in more developed ones (35%). We also can see that the formal workers earn more and are more educate than the informal workers, and the differences are more severe into the group of cities 2. While the wage differences between sectors is 26% in the group of cities 1, in the group 2 the wage difference is around 40%. Regarding education we can note that on average there is a difference between sectors of 2.3 and 3 years of education in the group 1 and 2, respectively. These results may suggest that there is a process of labor segmentation more marked in less developed cities than more developed cities, which can be associated to low creation of jobs in the most productive sectors in the first group of cities.

Table 2. Descriptive statistics by groups of cities

	Group 1			**Group 2**		
	Formal workers	**Informal workers**	**Total**	**Formal workers**	**Informal workers**	**Total**
Real hourly wage	3273.1	2408.5	2989.5	3241.1	1988.7	2601.3
Age (years)	34.2	33.0	33.8	34.9	32.8	33.8
Education (years)	10.9	8.6	10.2	11.6	8.6	10.1
Tenure at job (years)	1.9	1.4	1.8	2.1	1.5	1.8
Education levels						
Up to primary school	12.4	27.8	17.5	7.9	29.0	18.7
Lower secondary school	14.9	27.2	18.9	10.1	24.0	17.2
Higher secondary school	61.8	42.1	55.4	65.3	43.0	53.9
Bachelor/Master	10.9	2.9	8.3	16.7	4.0	10.2
Male	55.1	48.3	52.9	58.7	50.2	54.4
Head of household	43.0	35.8	40.7	43.1	33.8	38.4
Married	52.3	45.7	50.1	61.6	47.7	54.5
Firm size						
1 – 10 employees	18.5	77.3	37.7	13.5	74.3	44.6
11 – 50 employees	22.2	13.6	19.4	22.9	15.4	19.1
More than 51 employees	59.3	9.1	42.9	63.5	10.3	36.3
Sample size	25,368	13,723	39,091	10,925	12,262	23,187

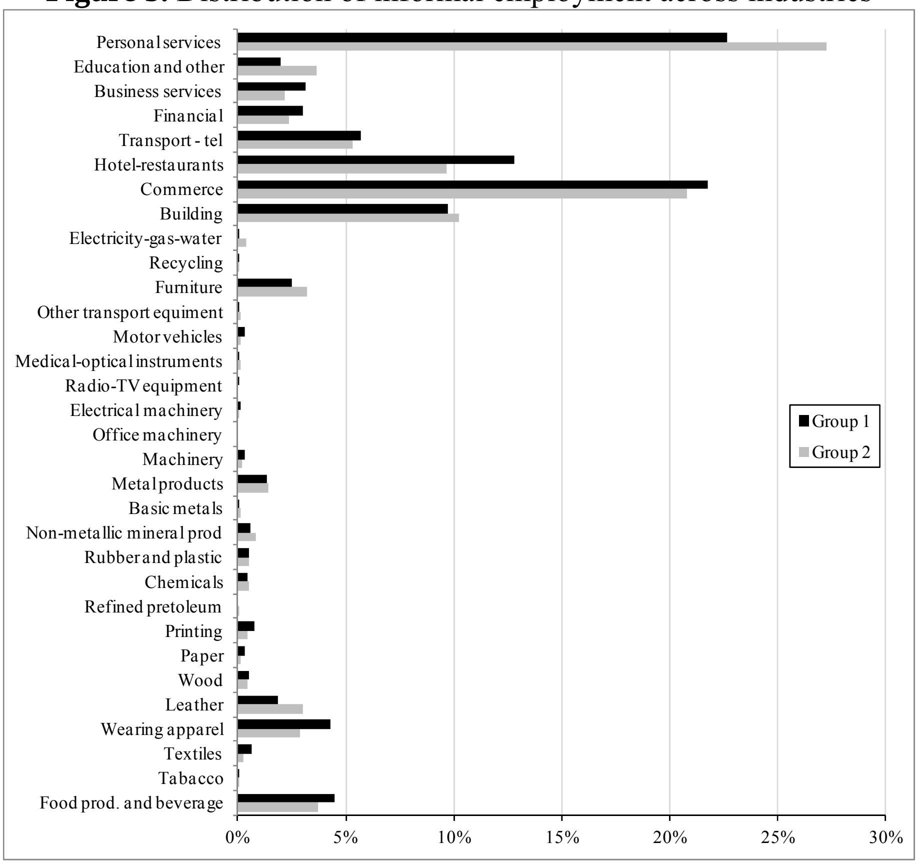
Note: We used person sampling weight available in the database. The wages are in Colombian pesos (in December 2009 the exchange rate was 2935 Colombian pesos per euro).

An important point to highlight in the regional differences in the labor markets, is the fact that the formal workers in less developed cities are more educated and earn similar wages that the formal workers in more developed cities. In the first cities the average years of education is 11.6 while in the second cities is 10.9. There are also striking differences in the percentage of workers with tertiary education: around 17% of formal workers in less developed cities have a bachelor o master degree, while only

11% of formal workers in more developed cities have such degree. The reason for these results may be associated with higher degree of specialization of less developed cities, in particular Cartagena and Barranquilla. According to Acosta (2012), these cities are among the most specialized cities of Colombia and the industrial sectors of chemicals, refinery, petroleum products, rubber and plastic are leading such specialization. These industries are technically complex and therefore require highly skilled labor. In this regards, Arango (2011), who studies the differences of main variables of the labor markets of the major cities of Colombia in the period from 2001 to 2011, find that indeed Cartagena and Barranquilla (along with Bogotá) are cities characterized by having the highest worker education rates in Colombia.

Figure 5 shows the distribution of informal sector employment across 2-digit industries by group of cities. Most informal sector employment in both groups of cities is in the service sector (around 71%), being the personal services and commerce sectors where is concentrated the greater share of informal employment: 23% and 22% in more developed cities and 27% and 21% in less developed cities, respectively. Within the industrial sector, again for both groups of cities, the informal employment is in food and beverages and wearing apparel, followed by furniture, leather and metal products.

Figure 5. Distribution of informal employment across industries



In order to measure the degree of modernity of the informal sector for each industry we calculate an index based on the location and size of firms where the worker performs his activity. This measure is suggested by Ranis and Stewart (1999) and they argue that the modern informal segment is capital-intensive, usually larger in size, dynamic in technology and often organized outside their owners' homes.[9] Hence, we defined our measure of modernity of informal sector as the log ratio between the number of workers perform their activity in enterprises with more than 10 workers and with a local fixed such as offices or plants but outside of the household, and the number of workers perform their activity in enterprises with 10 or fewer workers and located in the household, without local fixed or outside of a office or plant (such as kiosks, vehicles, among others). We calculated this index for each 2-digit industry and city.

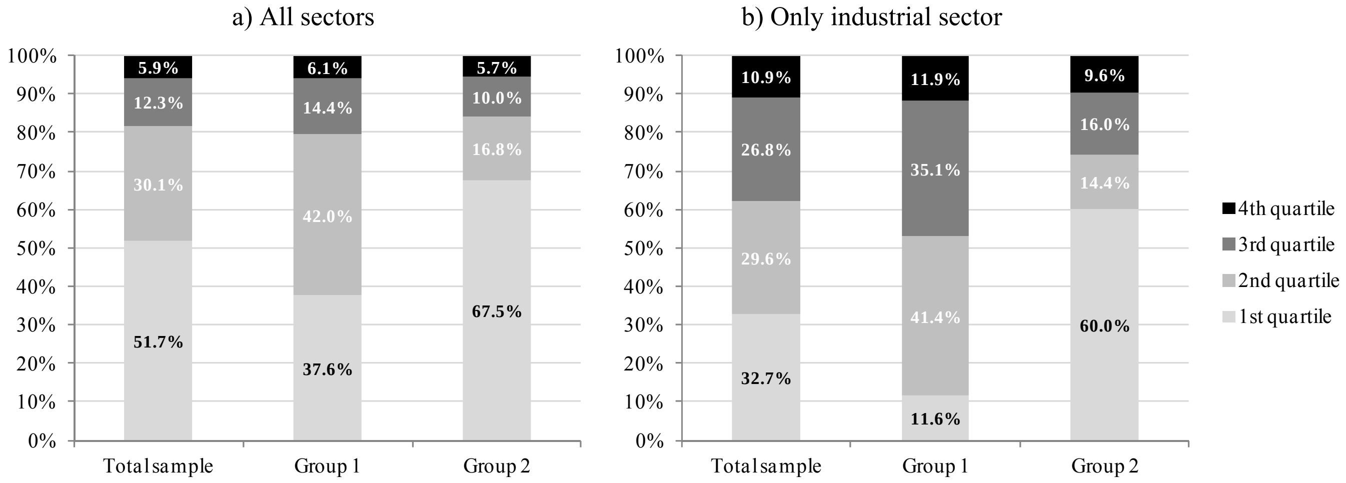
Figure 6 displays the distribution of informal employment across modernity quartiles for the total sample and by group of cities. As shown in panel a) in Figure 6 for all sectors, less than 6% of informal employment for the total sample is in industries in the top quartile of the modernity index distribution, that is, where the majority of workers perform their activity in large firms and with a fixed location. In fact, more than half of informal employment (52%) remains in the most traditional activities.

By group of cities the results show that more developed cities have higher degree of modernity of the informal sector than less developed cities, although the difference is marginal: 6.1% versus 5.7% of total informal employment is in the top quartile of the modernity index distribution. On the contrary, as expected, in less developed cities most of informal employment is in the less modern activities (68%).

When we only take into account the industrial sector, which represents a more modern sector, the differences in the modernity of the informal sector between groups of cities are reinforced. Panel b) in Figure 6 shows the latter. Again, the main differences between groups of cities are at the bottom of the distribution. While in less developed cities 60% of informal industrial employment is concentrated in the most traditional activities, in more developed cities only 12% is in such activities. In contrast, at the top quartile of the modernity index distribution the difference between groups of cities is only around 2 percentage points.

[9] See Moreno-Monroy *et al.*, (2012) for an application of this index for the case of India.

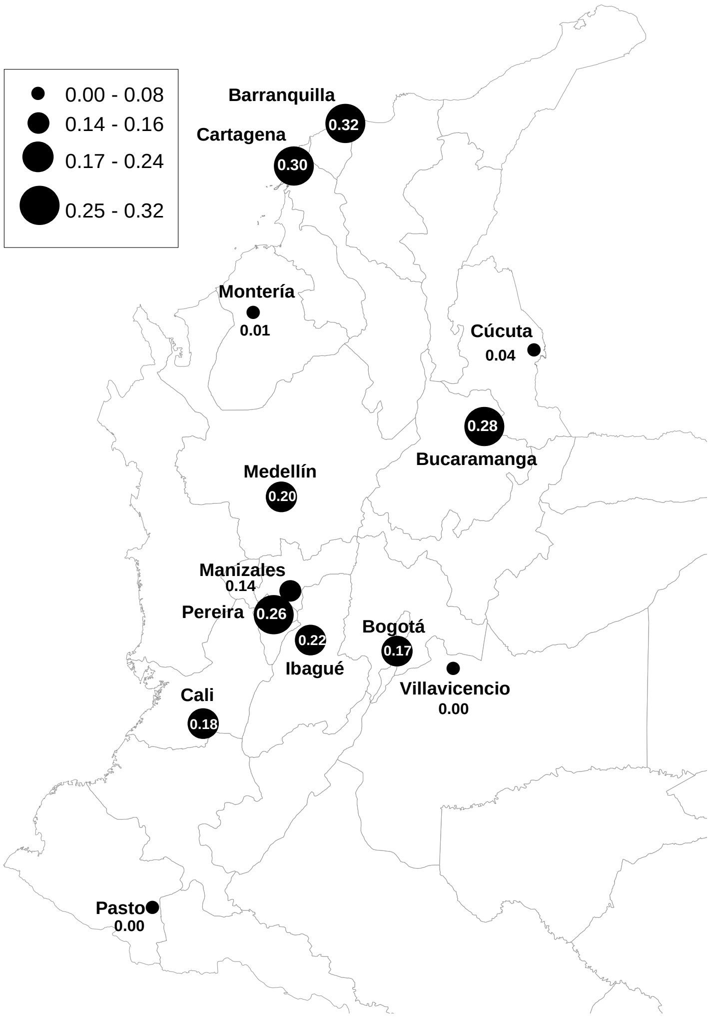
Figure 6. Informal sector employment by modernity quartile



Part of the answer to the low difference between groups of cities at the top of the distribution may be due to higher size of the informal modern segment in some cities of the group of less developed cities. In Figure 7 we show the size of modern informal segment by each city calculated as the share of informal industrial employment in relatively modern industries. As can be seen from data in figure, Barranquilla and Cartagena present the highest share of informal modern employment, around 31%. This higher size of the informal modern segment in these cities may be associated with the greater capacity of productive linkages between the formal and informal sector in the most productive and moderns sectors. This is the case of sectors such as chemicals, rubber and plastic which have an important contribution to the value added of these cities (Bonilla, 2010; Acosta, 2012).[10] As pointed out by Ranis and Stewart (1999) higher intermediate linkages (e.g. through subcontracting) between the formal and informal sector can lead to the expansion of the modern informal segment.

[10] In fact, these sectors have the highest index of modernity when they are compared with the indexes of other cities (see Figure A3 in the Appendix, comparing these two cities to Bogotá)

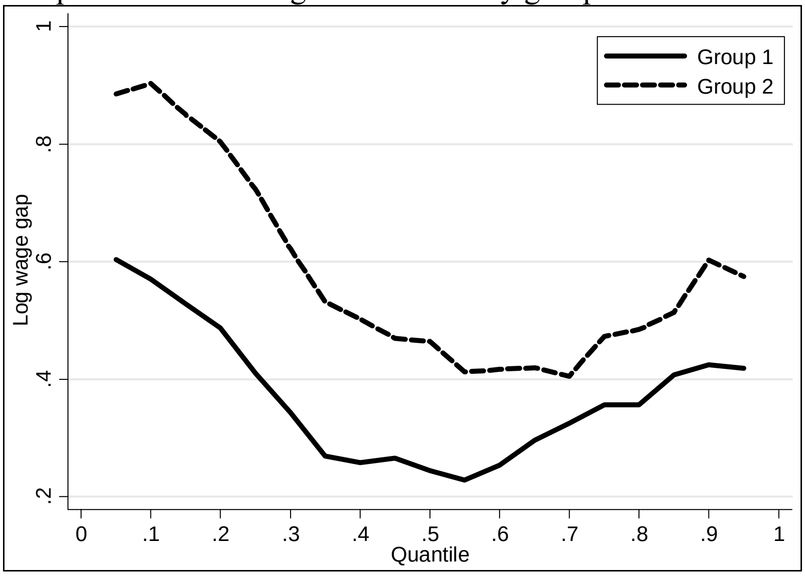
Figure 7. Share of informal industrial employment in relatively modern industries



Note: The relatively modern industries are those with an index above the average index of modernity.

Turning now to the wage gap between sectors, in Figure 8 we presents this at each quantile of their respective distributions by groups of cities. From the figure we can see that the wage differentials by sectors are considerably greater in less developed cities and especially at the bottom end of the distribution. In more developed cities, the wage differential ranges between 45% of the relevant gap at the bottom of the wage distribution to roughly 35% at the top the distribution. While in less developed cities, its size ranges from a very high around 60% at the bottom of the distribution to 45% at the top end of the distribution. These marked differences between groups of cities may reflect the fact that a greater variety of activities and jobs opportunities in more developed cities can reduce the wage gap between the formal and informal sector.

Figure 8. Wage differentials between formal and informal sector over different quantiles of the wage distribution by group of cities



3. Estimation procedure

In order to determine what factors influence the wage gap between the formal and informal sector taking into account the heterogeneity of workers along of the distribution, as well as the differences that can exist between groups of cities, we make use of the quantile decomposition methodology. Quantile regression methods are particularly useful to analyze the decomposition of the wages gap at different points of the distribution in situations where disparities are large, as is the case of a country like Colombia (Bonilla, 2008 and 2009). Furthermore, this methodology allows takes into account the wage heterogeneity between group of individuals and the different impact that could have the determinants of wages and their gaps by type of employment at different points of the distribution (Machado and Mata, 2005). Thus, the results are more complete than those obtained by OLS.

The decomposition methods have been extensively used to analyze the gender and union wage gap, and temporal change in wage.[11] In recent years this approach also has been used to study the wage differences by race (Bucheli and Porzecanski, 2011), ethnicity (Atal *et al.*, 2009), native/immigrant (Simón *et* al., 2008; Nicodemo and Ramos, 2012) and type of workers such as private/public (Lucifora and Meurs, 2006; Bargain and Melly, 2008), full/part-time (Hardoy and Schone, 2006; Wahlberg, 2008), permanent/temporary (Bosio, 2009; Comi and Grasseni, 2009) and formal/informal (Bargain and Kwenda, 2010; Arabsheibani and Staneva, 2012).

[11] A more detail literature review of this methodology can be found in Fortin *et al*. (2011)

We now present a brief description of the estimation procedure of the Machado and Mata decomposition with sample selection adjustment. We follow the adaptation of the Machado-Mata procedure introduced by Albrecht *et al*. (2009) based on Buchinsky (1998), which is a non-parametric method to account for selection for quantile regression.

In our analysis, the potential selection bias in the estimation of wage equations may result from a self-selection of individuals into different employment types: formal or informal. There are several observable and unobservable factors which may affect whether a worker is part of the formal or informal sector. In order to correct this selection bias, as a first step we could follow Heckman (1979) and estimate a probit model to calculate the probabilities of workers being in the formal and informal sector. However, the methodology proposed by Buchinsky (1998) does not impose the restriction of normality and instead uses a semi-parametric method developed by Ichimura (1993), which makes no assumptions about the distribution of the residuals.

Following Buchinsky (1998), we thus let I_i be the variable that indicates the sector in which worker i is employed and takes the values: 1 for the informal and 0 for the formal. For this binary model we have the following equation for the latent or index variable:

$$I_i^* = z_i^{'}\gamma + v_i , \tag{1}$$

where z_i is a set of observable characteristics that influence the probability that a worker i is employed in the informal sector; and γ is a vector of coefficients to estimate. The employment sector is determined by:

$$I_i = \begin{cases} 1 \text{ if } I_i^* > 0 \\ 0 \text{ if } I_i^* \leq 0 \end{cases} \tag{2}$$

Now, let X_{inf} and X_{for} be the stochastic vectors of characteristics for informal (*inf*) and formal (*for*) workers which have distribution functions $G_{X_{inf}}$ and $G_{X_{for}}$, respectively. The realizations of these stochastic vectors are given by x_{inf} and x_{for}. The endogenous variable that represents the log wage is Y_{inf} for the group of informal workers and Y_{for} for the group of formal workers and have unconditional distribution functions $F_{Y_{inf}}$ and $F_{Y_{for}}$, respectively. The quantile regression can be written for each sector as:

$$Q_\theta(Y_{for} \mid X_{for} = x_{for}) = x_{for}^{'}\beta^{for}(\theta) \tag{3}$$

and

$$Q_\theta(Y_{inf} \mid X_{inf} = x_{inf}) = x'_{inf}\beta^{inf}(\theta), \tag{4}$$

where $Q_\theta(Y \mid X = x)$ is the conditional quantile at θ^{th} quantile. The Machado-Mata procedure consists in generating a random sample of size *m* from a uniform distribution $U[0,1]: u_1, u_2, ..., u_m$, and calculating the conditional quantile regression for each group which yields *m* estimates of the quantile regression coefficients $\hat{\beta}^{inf}(u_m)$ and $\hat{\beta}^{for}(u_m)$. Then we use the estimated result and a random sample of size *m* of the vectors of covariates *x* to predict simulated values of both $\hat{y}_{for} = \tilde{x}'_{for}\hat{\beta}^{for}(u)$ and the counterfactual wage distribution $\hat{y}_{inf} = \tilde{x}'_{inf}\hat{\beta}^{for}(u)$, that is, the wage distribution of the informal sector resulting from assigning the returns of the formal sector but keeping the observed characteristics of the informal sector unaltered. These steps are repeated *m* times. Finally, the difference between the log wages of formal workers and the log wage given in the counterfactual distribution at the θ^{th} quantile can be decomposed as:

$$\begin{aligned} Q_\theta(Y_{for} \mid X_{for} = \tilde{x}_{for}) - Q_\theta(Y_{inf} \mid X_{inf} = \tilde{x}_{inf}) &= \underbrace{\left[Q_\theta(\tilde{x}'_{for}\hat{\beta}^{for}(u)) - Q_\theta(\tilde{x}'_{inf}\hat{\beta}^{for}(u)) \right]}_{characteristics\ effects} \\ &+ \underbrace{\left[Q_\theta(\tilde{x}'_{inf}\hat{\beta}^{for}(u)) - Q_\theta(\tilde{x}'_{inf}\hat{\beta}^{inf}(u)) \right]}_{coefficient\ effects} \end{aligned} \tag{5}$$

The first term of the right hand side of expression (5) refers to the characteristics effects. This term shows the contribution of the differences in the distribution of endowments between formal and informal workers to the wage gap at the θ^{th} quantile. The second term computes the counterfactual value of the wage gap if the informal workers retained their observed characteristics but were paid for them like the formal workers. This term represent the coefficient effects. We use a bootstrap procedure to estimate standard errors for the reported components of the decomposition.

Since we only observe the wages of those workers who actually work in the informal or formal sector, these workers are not draw randomly from the distribution of individuals and therefore there can be a selection bias when we estimate the wage equations. Consequently, in order to correct for selection and to get unbiased estimates of β in the quantile wage equations, Buchinsky (1998) proposes to introduce an extra term in the quantile regressions, namely,

$$Q_\theta(Y_{for} \mid Z = z) = x'_{for}\beta^{for}(\theta) + h_\theta(z'\gamma) \tag{6}$$

and

$$Q_\theta(Y_{inf} \mid Z = z) = x'_{inf}\beta^{inf}(\theta) + h_\theta(z'\gamma)\,. \tag{7}$$

The vector Z includes also the set of observable characteristics that influence wages (i.e., the X's), but for identification Z must contain at least one variable that is not included in X and should be uncorrelated with the log wage. The term $h_\theta(z'\gamma)$ plays the same role as Mill's ratio in the usual Heckman (1979) procedure, but it is quantile-specific and more general so as not assume normality. Buchinsky (1998) suggests the following power series approximation to the term $h_\theta(z'\gamma)$

$$\hat{h}_\theta(z'\gamma) = \sum_{k=1}^{K} (\lambda(\hat{\mu}' + \hat{\sigma} z'\hat{\gamma}))^{k-1} \hat{\delta}_k(\theta)\,, \tag{8}$$

where $\lambda(\cdot)$ represents the usual inverse Mill's ratios, and $\hat{\mu}$ and $\hat{\sigma}$ are scaling parameters which are estimates of the constant and slope coefficients from the probit regression of I_i on the index $z'\hat{\gamma}$.

In order to estimate the coefficients γ in equation (1), Buchinsky (1998) proposes to use the semi-parametric least-squares (SLS) method proposed by Ichimura (1993). Since we estimate a semi-parametric sample selection model, the intercept in the wage equation is not identified. When k=1 in equation (8), $\delta_1(\theta)$ is equal to one and therefore it cannot be separately identified from the constant term in $\beta(\theta)$. To identify the constant term in the wage equation, we first remove the k=1 term from the power series expansion and estimate the resulting quantile model; and then we estimate the constant term in the wage equation without adjusting for selection by using a subsample of observations such that the probability of informal sector participation is close to one.

In summary, the extension of the Machado-Mata algorithm to adjust for selection proposed by Albrecht *et al*. (2009) is the following:

1. Estimate γ using a semi-parametric least-squares (SLS) method (Ichimura, 1993).
2. Sample u from a standard uniform distribution.
3. Compute $\hat{\beta}^{inf}(u)$ and $\hat{\beta}^{for}(u)$ using the Buchinsky technique.
4. Sample x_{inf} and x_{for} from the empirical distribution $\hat{G}_{X_{inf}}$ and $\hat{G}_{X_{for}}$, respectively.
5. Compute $\hat{y}_{for} = \tilde{x}'_{for}\hat{\beta}^{for}(u)$ and $\hat{y}_{inf} = \tilde{x}'_{inf}\hat{\beta}^{for}(u)$.

6. Repeat steps 2 – 5 *m* times. [12]
7. Compare the simulated distributions to decompose the estimated wage gap between sectors.

4. Results

In this section we present the results of the quantile decomposition formal/informal wage gap. The conditional quantile regression approach proposed by Machado and Mata (2005) allows decomposing the difference between the formal and informal workers log wage distributions and identifying how much of the wage gap estimated at different quantiles of the wage distribution can be attributed to differences in characteristics and how much can be attributed to differences in returns to those characteristics.

4.1 SLS estimation and the quantile regression models

As mentioned in Section 3, in the first step we estimate the semi-parametric least squares (SLS) model for the probability of being informal, and in the second step we estimate the quantile regression models for the wage equation including the power series expansion to deal with selection. In both the probability and the quantile regression models we included variables for education levels, gender, and dummies for size of firm, industry and occupation. In order to identify the probability models we included variables for presence of children between 0 and 12 years old at home, presence of other relatives working as formal workers, the average number of years of education of members of the household as a measure of the educational environment of the household, if the individual is head of household, marital status, and if the worker has a labor contract. Table 2 shows results for the probit and SLS probability models for the total and group of cities.

In order to test if in effect the probability of being informal relies on the normality assumption for the residuals, we performed a Hausman test. As pointed out by Buchinsky (1998), the SLS estimate is consistent and independent of the distribution of the residuals, while the probit estimate is efficient under normally distributed residuals, and therefore a Hausman type test can be performed. Test statistics for Hausman's test reported at the bottom of Table 2 clearly indicate that for the total and

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[12] Our estimations are based on m=1000.

by groups of cities the null hypothesis of normal errors is rejected at the 5% significance level. Therefore we use the estimates from the SLS models in the quantile regression models.

Table 2. Estimates of the informal employment models
(y = 1 informal; 0 formal)

	Total			Group 1		Group 2	
	Probit	Probit[a]	SLS	Probit	SLS	Probit	SLS
Constant	2.468***	2.474***	2.474	2.652***	2.652	2.761***	2.761
	(60.96)	(51.13)	(·)	(49.12)	(·)	(41.38)	(·)
Age	-0.018***	-0.018***	-0.018	-0.019***	-0.019	-0.020***	-0.020
	(-25.10)	(-20.52)	(·)	(-19.16)	(·)	(-16.13)	(·)
Education levels							
Lower secondary education	-0.136***	-0.132***	-0.142***	-0.113	-0.119***	-0.211***	-0.186***
	(-6.33)	(-5.15)	(-4.82)	(-4.07)	(-3.29)	(-5.50)	(-4.19)
Higher secondary education	-0.471***	-0.452***	-0.480***	-0.458***	-0.534***	-0.644***	-0.608***
	(-23.74)	(-19.10)	(-16.56)	(-17.42)	(-12.69)	(-18.84)	(-12.87)
Bachelor/Master	-0.708***	-0.700***	-1.028***	-0.722***	-1.074***	-0.993***	-1.174***
	(-20.58)	(-17.05)	(-16.84)	(-14.73)	(-11.27)	(-18.20)	(-11.87)
Male	-0.124***	-0.119***	-0.179***	-0.148***	-0.197***	-0.109***	-0.093***
	(-7.96)	(-6.42)	(-8.45)	(-7.11)	(-6.45)	(-4.17)	(-3.06)
Head of household	-0.046***	-0.057***	-0.140***	-0.165***	-0.244***	-0.143***	-0.166***
	(-2.82)	(-2.90)	(-6.54)	(-7.61)	(-6.46)	(-5.25)	(-4.50)
Married	-0.101***	-0.094***	-0.145***	-0.098***	-0.105***	-0.127***	-0.150***
	(-6.85)	(-5.34)	(-6.60)	(-4.93)	(-3.49)	(-5.21)	(-4.68)
Presence of children at home	0.036**	0.043**	0.115***	-0.018	-0.009	0.046*	0.054**
	(2.47)	(2.44)	(6.08)	(-0.91)	(0.34)	(1.94)	(1.97)
Other relatives working as formal	-0.278***	-0.272***	-0.293***	-0.215***	-0.287***	-0.405***	-0.387***
	(20.51)	(16.80)	(12.77)	(10.70)	(8.42)	(-15.48)	(-9.54)
Education of household	-0.019***	-0.022***	-0.036***	-0.009**	-0.021***	-0.021***	-0.010*
	(-7.10)	(-6.72)	(-8.68)	(-2.45)	(-3.58)	(-4.33)	(-1.82)
Size of firm							
11 - 50 employees	-0.985***	-0.995***	-1.083***	-0.967***	-1.260***	-1.052***	-1.079***
	(-58.03)	(-49.05)	(-22.16)	(-42.01)	(-14.48)	(-37.74)	(-13.10)
More than 51 employees	-1.616***	-1.608***	-1.934***	-1.552***	-2.180***	-1.766***	-2.025***
	(-98.15)	(-81.80)	(-23.36)	(-69.15)	(-14.44)	(-65.06)	(-13.66)
Contract	-1.147***	-1.157***	-1.664***	-1.242***	-2.241***	-0.901***	-1.254***
	(-60.52)	(-50.82)	(-22.03)	(-48.26)	(-14.20)	(-27.64)	(-12.49)
Observations	62,278	43,595		39,091		23,187	
Hausman test		216.1		198.6		315.2	
p-value		[0.000]		[0.000]		[0.000]	

Note: ***, **, *, denotes significance at 1%, 5% and 10%, respectively. ( ) z-statistics. The constant and the coefficient on variable age in the SLS models were normalized, they are equal to their values in the probit models, so that the probit and SLS models are comparable. All models include industry dummies and occupation dummies. Up to primary school and 1-10 employees are the excluded categories in education and size of firm variables, respectively.
[a] Given computational restrictions on the total sample we take a sample randomly selecting 70% of the observation in each metropolitan area. The resulting sample is 43,595 observations.

Results presented in Table 2 indicate that younger, less educated, females, non-head of household and non-married individuals are more likely to work in the informal sector. These higher probabilities of individuals in less important positions into family may indicate that the secondary incomes of household are made in informality. We also can see that having a child at home has a positive impact on the propensity to work in the informal sector but this variable is not significant in more developed cities. The presence at home of other relatives working in the formal sector has a negative impact on the probability of being informal and this effect is greater in less prosperous cities. This effect can reflect that the medical benefits program covers a worker's entire family, therefore in households whose principal breadwinner works in the formal sector there may not be reason to additional members to be formally employed (Maloney, 1999; Jütting *et al.*, 2008).

Turning to the education of household variable, the results show that a household with a higher education level implies a negative effect on the likelihood of being an informal worker. The size of firm variables are significant and show that as the size of firm increases, the probability of being part of the informal sector decreases and this effect is higher in more developed cities than less developed ones. Finally, having a labor contract shows a strong negative effect on the probability of being informal, which is higher in more developed cities.

As described above, in the second step we use the estimates from the SLS to calculate the power series expansion and introduce this term in the quantile regression models to correct for selectivity. To calculate this correction term we included two terms of orthogonal polynomials in the series expansion.[13] On the other hand, to implement the identification of the constant term in the wage equations, we used a subsample of workers with a high probability of being informal, namely, those who are younger or older, less educated (up to primary school), with presence of children at home and other relatives working in the informal sector. In Tables A2 to A4 in the Appendix we present results for corrected quantile regressions for the 5th, 10th, 25th, 50th, 75th, 90th and 95th quantiles.

It can be seen from data in Tables A2 to A4 that in less developed cities as well as in the total sample most of the selection terms are statistically significant, while in more developed cities not all such terms are significant. These results indicate the presence of sample selection bias for individuals across the whole wage distribution in the former two groups, but not in the latter group. Given these results we use the estimations of wage equation for more developed cities without correcting for selectivity in the decomposition. Table 3 summarizes the results for corrected and uncorrected quantile regressions at three representative quantiles. The results obtained from OLS and other quantiles for more developed cities are shown in Table A5 in the Appendix.

[13] In fact we tested including a third term of polynomials in the series expansion, but the estimations presented severe multicollinearity problems. This problem was also mentioned by Buchinsky (1998).

From Table 3 we can see that the formal workers in more prosperous cities receive higher returns to high levels of education than similar individuals in the formal sector living in less developed cities and the highest differences in returns are found within low-paid occupations. Additionally, the returns to a primary and secondary school certificate are higher for informal workers in less developed cities than more developed cities, especially for individuals with more than a secondary school certificate and within highly-paid occupations. At low quantiles, informal workers in less developed cities benefit more than informal workers in more developed cities from going to college. Another interesting pattern within less prosperous cities is that the informal workers consistently receive higher returns to education than formal ones and there is a marked difference within more educated individuals and high-paid occupations.

Results regarding the other basic human capital variables, such as experience and job tenure, show that more experience has a positive and decreasing impact on wages and this effect is particularly higher within low-paid occupations in the informal sector and similar in magnitude in both groups of cities. An extra year of tenure in a job has a positive impact on wages and it is relatively constant across the distribution in the formal sector independently of the group of cities. Meanwhile, in the informal sector an extra year of tenure also has a positive effect but this decreases across the distribution.

These findings of relatively higher informal sector returns to human capital variables, in particular in less developed cities and within highly-paid occupations, indicate the heterogeneous nature of the informal sector. At high quantiles, informal workers can have similar or higher skills and training requirements than formal workers and therefore returns to education, experience and tenure would matter more in the informal sector. In this upper segment the informal sector can be indistinguishable from formal workers in small or medium firms and even may be competitive with the formal sector.

Regarding the gender variable, results display that there is a strong discrimination against women in the informal sector in less developed cities. This is more severe at high quantiles of the distribution: a woman's expected earnings at the 90^{th} percentile is approximately 14% lower than a man's. Similar results are found in the formal sector in more developed cities where the difference in wage between a woman and a man is 10%.

Table 3. Quantile regressions with corrections for selectivity
(y = Log real hourly wage)

	Total						Group 1						Group 2					
	Formal			Informal			Formal			Informal			Formal			Informal		
	10%	50%	90%	10%	50%	90%	10%	50%	90%	10%	50%	90%	10%	50%	90%	10%	50%	90%
Constant	7.453***	7.556***	7.689***	6.525***	7.169***	7.619***	7.245***	7.525***	7.662***	6.702***	7.287***	7.719***	7.494	7.605***	7.640***	6.389***	7.002***	7.463***
	(282.55)	(385.98)	(190.59)	(244.24)	(467.5)	(293.46)	(412.1)	(709.99)	(262.73)	(203.86)	(475.94)	(250.72)	(144.6)	(220.34)	(101.09)	(221.78)	(364.92)	(234.51)
λ	0.177***	0.024***	0.026	-0.049***	-0.024*	-0.073***							0.197***	0.062***	0.025**	-0.043	-0.063***	-0.185***
	(11.91)	(2.16)	(1.07)	(-2.23)	(-1.87)	(-3.47)							(7.44)	(3.55)	(2.19)	(-1.29)	(-2.86)	(-5.30)
Education levels																		
Lower secondary education	0.059***	0.041***	0.087***	0.083***	0.096***	0.095***	0.067***	0.038***	0.091***	0.071***	0.089***	0.091***	0.086***	0.054***	0.108***	0.103***	0.090***	0.109***
	(4.81)	(4.46)	(4.56)	(4.67)	(9.29)	(5.67)	(5.30)	(4.84)	(4.20)	(3.38)	(8.75)	(4.50)	(3.69)	(3.45)	(3.23)	(5.40)	(6.92)	(5.29)
Higher secondary education	0.141***	0.116***	0.274***	0.215***	0.210***	0.239***	0.164***	0.119***	0.296***	0.179***	0.196***	0.216***	0.155***	0.118***	0.278***	0.219***	0.231***	0.281***
	(11.19)	(12.51)	(14.62)	(10.71)	(18.75)	(13.07)	(13.21)	(15.72)	(14.20)	(7.82)	(18.35)	(10.27)	(6.59)	(7.52)	(8.37)	(9.90)	(15.95)	(12.34)
Bachelor/Master	0.320***	0.497***	0.647***	0.508***	0.551***	0.630***	0.406***	0.536***	0.666***	0.388***	0.547***	0.765***	0.296***	0.476***	0.648***	0.629***	0.645***	0.764***
	(18.20)	(39.85)	(25.25)	(11.10)	(21.29)	(14.72)	(22.41)	(51.48)	(22.74)	(7.38)	(21.49)	(15.11)	(9.30)	(23.53)	(14.98)	(13.18)	(19.71)	(14.94)
Experience	0.002***	0.004***	0.006***	0.015***	0.010***	0.009***	0.002***	0.004***	0.006***	0.012***	0.010***	0.005**	0.001	0.004***	0.008***	0.015***	0.012***	0.012***
	(2.35)	(5.74)	(4.48)	(8.72)	(10.80)	(5.38)	(2.37)	(7.42)	(3.58)	(6.64)	(10.42)	(2.55)	(0.36)	(3.64)	(3.57)	(8.02)	(10.24)	(6.33)
Experience^2	-0.0001***	-0.0001***	-0.0001***	-0.0002***	-0.0001***	-0.0001***	-0.0001**	-0.0001***	-0.0001**	-0.0002***	-0.0002***	-0.00005	-0.00003	-0.0001***	-0.0001**	-0.0002***	-0.0002***	-0.0002***
	(-3.63)	(-5.29)	(-2.45)	(-6.61)	(-7.68)	(-3.03)	(-2.50)	(-6.66)	(-1.96)	(-6.46)	(-8.25)	(-1.29)	(-0.90)	(-3.08)	(-2.03)	(-6.16)	(-7.79)	(-4.20)
Tenure	0.010***	0.012***	0.016***	0.031***	0.020***	0.020***	0.011***	0.011***	0.019***	0.045***	0.019***	0.026***	0.007***	0.009***	0.010***	0.027***	0.021***	0.018***
	(6.79)	(11.29)	(7.47)	(9.09)	(9.64)	(5.96)	(7.04)	(11.92)	(7.64)	(10.25)	(8.55)	(5.86)	(2.93)	(5.39)	(2.74)	(7.77)	(8.44)	(5.07)
Tenure^2	-0.0002***	-0.0001**	-0.0001	-0.001***	-0.001***	-0.001***	-0.0002***	0.00001	-0.0002**	-0.002***	-0.001***	-0.001***	-0.0001	-0.00001	0.0001	-0.001***	-0.0005***	-0.0004***
	(-2.77)	(-2.11)	(-1.25)	(-7.41)	(-5.99)	(-3.65)	(-3.36)	(0.29)	(-1.98)	(-10.61)	(-5.15)	(-4.02)	(-0.84)	(-0.14)	(0.46)	(-5.06)	(-4.44)	(-2.88)
Male	-0.001	0.041***	0.094***	0.091***	0.094***	0.130***	0.016***	0.052***	0.112***	0.083***	0.094***	0.105***	-0.031***	0.018***	0.067***	0.108***	0.128***	0.143***
	(-0.13)	(8.39)	(9.75)	(5.80)	(10.49)	(8.87)	(2.24)	(12.16)	(9.96)	(4.72)	(10.79)	(6.21)	(-2.85)	(2.47)	(4.35)	(6.31)	(11.15)	(7.60)
Size of firm																		
11 – 50 employees	0.012	0.049***	0.064***	0.272***	0.162***	0.175***	0.100***	0.059***	0.072***	0.205***	0.130***	0.134***	0.023	0.029*	0.063*	0.294***	0.191***	0.217***
	(0.99)	(5.31)	(3.43)	(12.84)	(13.18)	(8.7)	(10.14)	(9.52)	(4.31)	(9.70)	(12.07)	(6.31)	(1.04)	(1.91)	(1.92)	(12.20)	(11.90)	(8.71)
More than 51 employees	0.020	0.091***	0.150***	0.392***	0.248***	0.342***	0.151***	0.106***	0.151***	0.189***	0.125***	0.221***	-0.011	0.044***	0.142***	0.454***	0.365***	0.503***
	(1.38)	(8.59)	(6.81)	(11.50)	(12.83)	(11.06)	(17.45)	(19.75)	(10.46)	(7.17)	(9.47)	(8.69)	(-0.39)	(2.27)	(3.31)	(9.70)	(12.44)	(11.20)
Observations		25,392			18,203			18,018			8304			6325			7974	

Note: ***, **, *, denotes significance at 1%, 5% and 10%, respectively. ( ) t statistics. Experience is calculated as (age-year of education-6). All models include industry dummies and occupation dummies. Up to primary school and 1-10 employees are the excluded categories in education and size of firm variables, respectively.

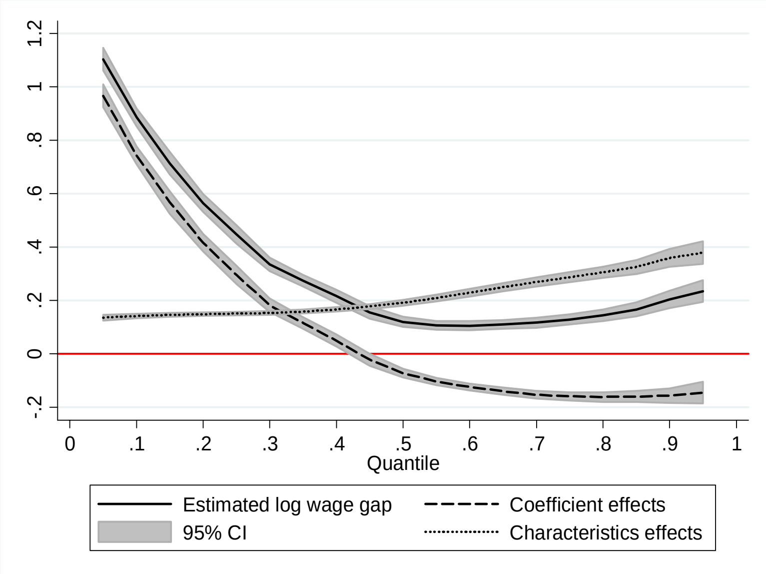
4.2 Decomposition results

In this section we present the results of the decomposition. Figures 9, 10 and 11 plot the wage gap that remains after we take into account the difference in the returns of observed characteristics between sectors and correcting for selection for the total and by group of cities.[14]

As can be seen from Figure 9, for the total sample a significant positive wage gap across the whole distribution remains with a large gap at the bottom of the distribution. Regarding the contribution of each set of factors (coefficients and characteristics), we can see that the coefficient effects is positive at the bottom of the distribution and explains most of the wage gap. After the 40th quantile of the distribution the coefficient effects is negative, but the positive characteristics effects largely exceeds such a negative effect, mainly at the top. These results indicate that low-pay informal workers earn less because not only are they less skilled, but they also get lower returns to such skills. This suggests that these workers are part of the disadvantaged sector of a segmented market. Meanwhile, high-pay informal workers, despite receiving better returns to their characteristics than formal workers, earn less because formal workers have much better skills. In this case, although informal workers earn less than formal workers, informality can arise of a voluntary decision of the worker because the benefits to become formal cannot be attractive. For instance, at the 90th quantile of the distribution the wage gap between sectors is around 18%, and the costs associated with the formal sector (such as taxes or social security contributions) may exceed such amount.

[14] In order to check the sensitivity of the our results to choice of a different set of cities, we also carried out the decomposition using an alternative grouping: the first group is composed by the four most developed cities and with the lowest informality rates (Bogotá, Medellín, Manizales and Cali), and in the second group are the four less developed cities and with the highest informality rates (Cúcuta, Montería, Pasto and Cartagena). We find that our results remain unchanged (see Figure A4 in the Appendix).

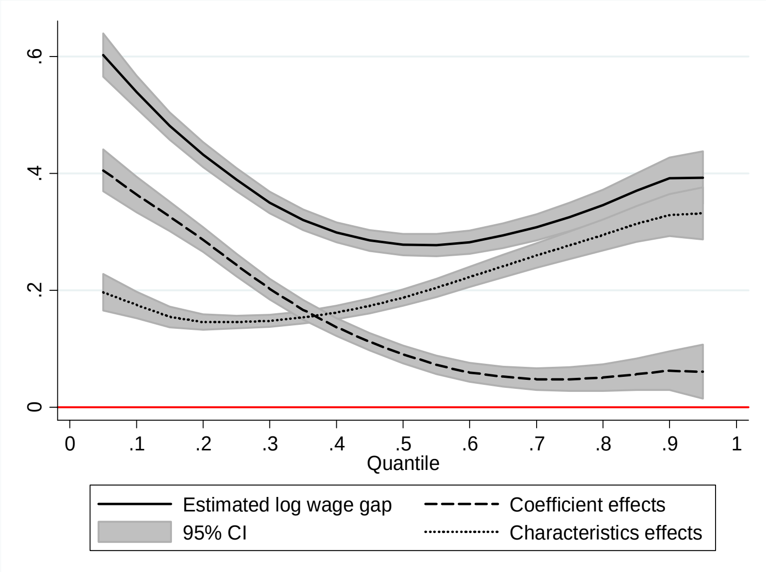
Figure 9. Quantile decomposition of wage gaps between the formal sector and informal sector for total sample



Source: Table A6 in the Appendix

At the groups of cities level we can see different patterns in the wage gap and their determinants. In less developed cities the gap between the log wages of formal workers and the log wage given in the counterfactual distribution is smaller over the whole distribution; indeed this gap tends to zero at median and higher quantiles of the distribution (see Figure 11). On the contrary, in more developed cities a significant positive formal/informal wage gap across the whole distribution remains (see Figure 10). The decomposition results show that for the first group of cities, at low quantiles the coefficient effects are positive and largely exceed the effect of characteristics, while at high quantiles the decline in the wage gap are attributable to the negative sign of the coefficient effects. As regards the second group of cities, the findings show that both the coefficient effects and characteristics effects contribute positively to the wage gap in favor of the formal sector. This wage gap at the low end of the distribution is mainly explained by the coefficient effects, while the characteristics effects explain most of the wage gap in the rest of the distribution, particularly at the top end.

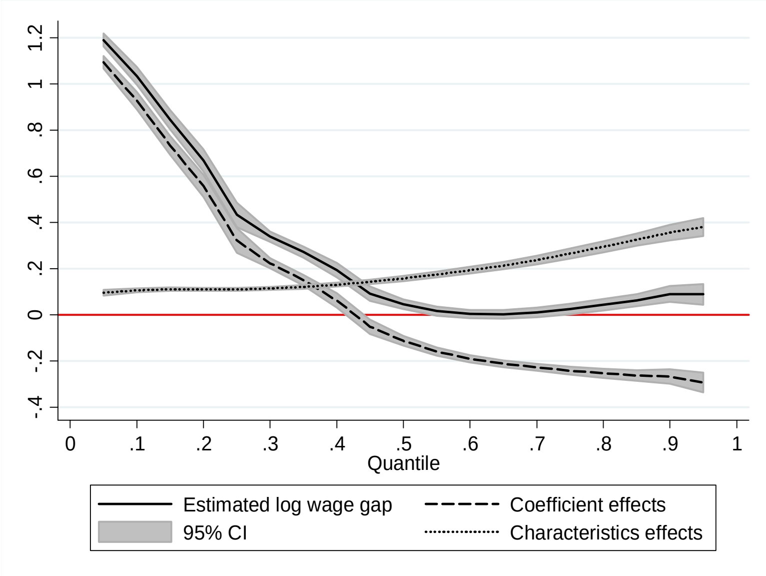
Figure 10. Quantile decomposition of wage gaps between the formal sector and informal sector for regions with low informality



Source: Table A6 in the Appendix

Overall, at very bottom of the distribution there is a common pattern between the groups of cities: the wage gap between sectors is due not only to the fact that informal workers are less skilled, but primarily because they get lower returns to such skills. This seems to confirm that at these points of the wages distribution there is no room for these workers in the formal sector and informality is a last resort option to escape unemployment. In this part of the distribution is located the traditional or more disadvantaged segment of the informal sector. This segment is characterized by low- or un-skilled labor, little o no physical capital, and therefore weak complementarity between these factors, their activities are small scale, easy entry, carry out in non-fixed location, with very low value added and low capacity to create productive linkages. These kinds of workers are concentrated in activities such as retail sales and personal services.

Figure 11. Quantile decomposition of wage gaps between the formal sector and informal sector for regions with high informality



Source: Table A6 in the Appendix

At very top of the distribution the differences between groups of cities are more evident. While in more developed cities the size of the estimated wage differential is 32% at the 95th quantile, being the characteristics effects that explain most of this differential, in less developed cities the size of the estimated wage gap is only 8% at the same quantile and, although the characteristics effects account for a much higher percentage of the wage gap, the negative sign of the coefficient effects is also important. Such differences between groups of cities can be explained in part by the degrees of specialization and modernity of the productive structures of the cities, which may bias the job creation towards more modern or traditional activities.

At the very highest quantiles is located the modern segment of the informal sector. This segment is characterized by make use of some capital, have a fixed location in a office or plant outside of household, produce standardized goods, uses skilled labor, and undertake their activities in modern sectors (Ranis and Stewart, 1999; Moreno-Monroy *et al.*, 2012). Further, informal workers in this segment could be paid more for their remunerated characteristics than their counterpart in the formal sector and therefore earn competitive wages which can be comparable those offered in the formal sector (Marcouiller *et al.*, 1997; Bargain and Kwenda, 2010; Arabsheibani and Staneva, 2012). There are also non-wages benefits or advantage of being part of the informal sector, given the specific characteristics of individuals. Hence, in this modern segment there are incentives to voluntarily choose informality as a form of employment.

The lower wage gap and higher returns to skill in the informal sector than formal sector in less developed cities can be determined by higher size of modernity of the informal sector in Barranquilla and Cartagena. As mentioned, in these cities there is a higher size of modernity of the informal sector due to high specialization in industries with high productive linkages. Therefore, an informal sector highly modern can be a tough competitor of the formal small and medium segment and the formal large segment can prefer to have intermediate linkages with modern informal segment not only to save costs but also by the productive and technological capacity that can offer it. The existence of these production linkages between the modern informal segment and the formal sector can imply expansion of the first segment and its productivity with which its wages can be competitive with those paid in the formal sector (Ranis and Stewart, 1999; Marjit, 2003).

Besides the possible existence of wages benefits of being part of the informal sector in less developed cities, there may also be other incentives to choose informality. For example, 8% of difference in wages between sectors at the top end of the distribution can be easily compensated with the cost saving associated with to be unregistered.

Finally, in more developed cities the positive wage gap at the top of the distribution can imply that although the informal workers earn less than their counterpart formal workers, they find informal activities more profitable than formal activities. Informality can be seen as a deliberate choice of entrepreneurs to avoid start up cost. Also a greater independence and work schedule freedom or inefficiencies combined with high administrative costs of the social security system may discourage some workers from getting a job in the formal sector (Maloney 1999; Cunningham, 2001; Jütting *et al.*, 2008). Hence, in this higher-paid segment the specific characteristics of workers can imply a comparative advantage in the informal sector. This comparative advantage can be translated into higher non-wage benefits compared to potential wages in the formal sector, which might be incentives to choose informality.

5. Conclusions

In this paper we investigate the heterogeneity of the informal sector at the regional level in Colombia by analyzing decomposition of the wage gap between the formal and informal sector. We use the quantile regression decomposition method and correct by selectivity using semi-parametric methods. This econometric model allows us to analyze individuals across the entire distribution of wages and determine if the informal sector has its own internal duality.

Our results show that there is a marked heterogeneity in the informal sector in Colombia. We find that in general there are two distinct segments of workers in the informal sector who have different motivation to work in this manner. On the one hand, there is a lower-paid informal segment in which informality is seen as the only alternative form of employment. On the other hand, there is a higher-paid informal segment which is composed of individuals who, given their specific characteristics, are voluntarily informal. These results suggest that just as formal and informal activities co-exist, voluntary and involuntary informal employment co-exists. Informality may be a choice as well as being the result of labor market segmentation. Certainly, these are two concurrent scenarios of the same phenomenon.

We also find that there are striking differences in labor market characteristics between groups of cities, in particular with the kind of informal employment that exists. The results show that the largest share of informal employment is in the most traditional activities, that is, those where the majority of workers perform their activity in very small firms and without a fixed location. In less developed cities this segment represents about 70% of total informal employment and 60% of informal industrial employment, while in more developed cities it represents around 40% and 12%, respectively. With regards to the modern informal segment, these activities have a very low participation and there are not marked differences between groups of cities. For the industrial sector, in more developed cities the share of informal industrial employment in the modern informal segment is 12% and in less developed cities is around 10%. This result has been associated with the fact that in the latter group of cities Cartagena and Barranquilla have high specialization levels in linkage-intensive industries such as petrochemical, chemical and plastic industries, whereby the complementarities between the formal and informal sector can be more intense and therefore lead to the expansion of the modern informal segment.

Turning to the wage differential between formal and informal sector and its decomposition, the results show that at very bottom of the distribution there is a great positive wage gap in favor of formal workers in both groups of cities and the differential in returns to characteristics explain most of such gap. In this segment levels of human capital and other remunerable characteristics are very low and given greater importance of the differential in rates of return to characteristics between sectors on wage gap, there is a marked segmentation effect. This result indicates that at these points of the distribution the informal sector represents the disadvantaged sector where workers end up as a last resort option to get a paid job.

At very top of the distribution the differences in the degree of modernity of the informal sector between groups of cities drive the different patterns. In less developed cities the wage gap between two sectors is much narrower than in more developed cities. Even we can think in the existence of an informal employment wage premium. This low wage gap can be consistent with greater freedom of choice between formal and informal sector working given the modern and specific type of employment generated in less developed cities. On the other hand, regardless of the groups of cities, choosing to be an informal worker in these points of the distribution can be in part due to the fact that high-paying occupations informal workers may to some extent accept lower wages in order to avoid having to contribute to social security system which can be perceived to be inefficient.

From a political perspective our findings suggest that to combat informal employment is necessary to understand better the different realities within the cities, as well as different groups within the informal sector. It is essential to distinguish between individuals who voluntary choose informality and therefore they are not necessarily worse-off compared to those working in the formal sector, and individuals who do not have any choice at all other than staying informal and are systematically excluded of the formal sector. This latter group of individuals is the segment that contributes significantly on overall wages inequality and poverty in Colombia and policies should be addressed to remedy this bottleneck.

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Appendix

Table A1. Informality rate by metropolitan area

Medellín	47.38
Bogotá	52.13
Manizales	52.50
Pereira	58.15
Cali	65.66
Bucaramanga	66.46
Ibagué	69.03
Barranquilla	70.76
Villavicencio	71.53
Cartagena	72.64
Pasto	72.75
Montería	75.55
Cúcuta	76.93

Note: we included government employees, employers and self-employees to calculate the informality rate.

Figure A1. Wage differentials between formal and informal sector over different quantiles of the wage distribution by metropolitan area

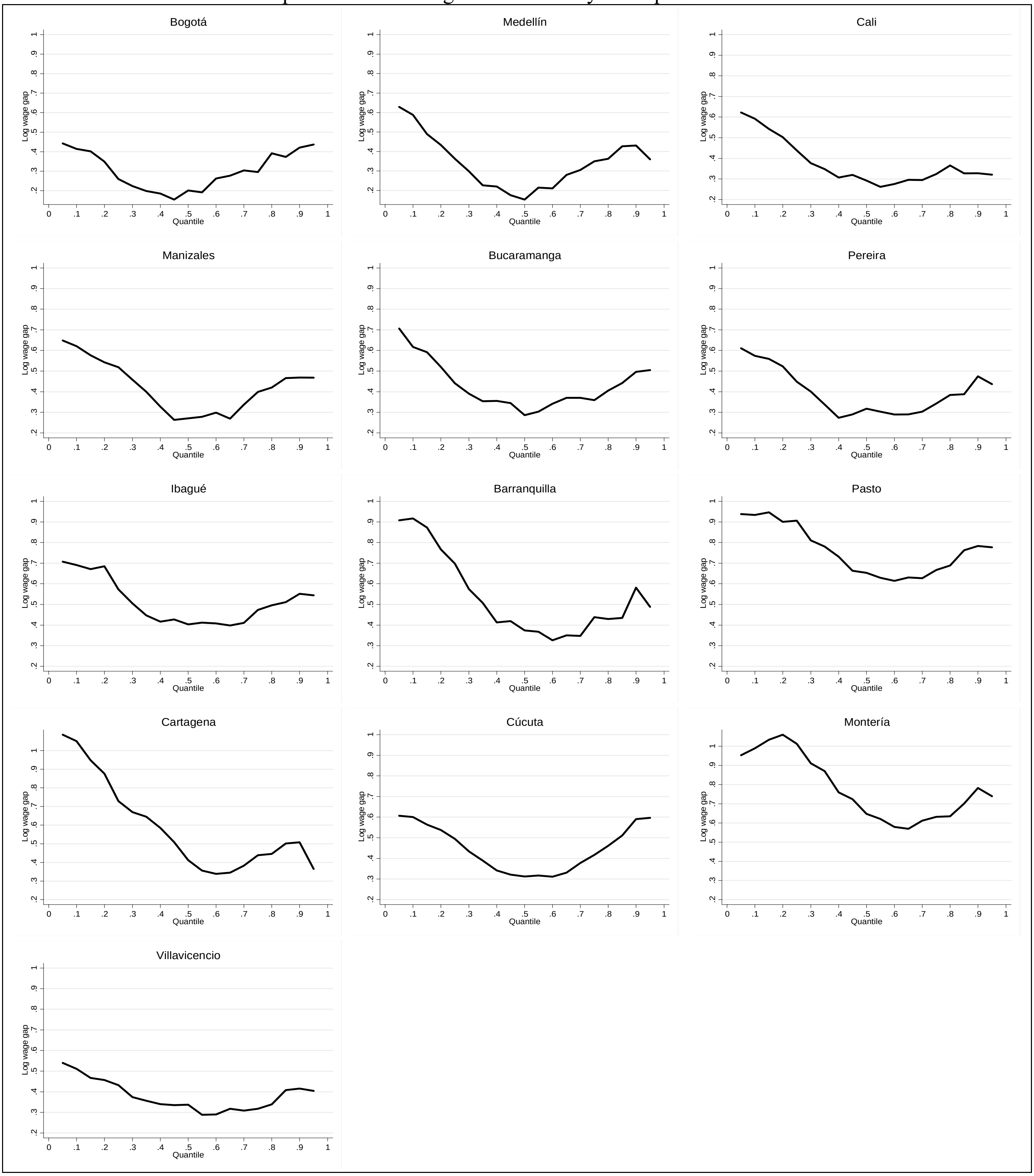
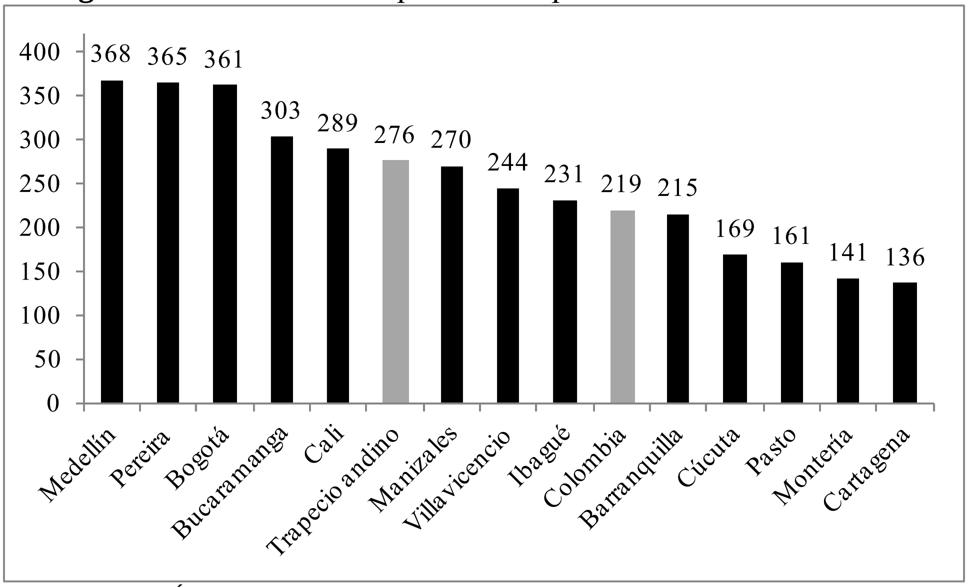


Figure A2. Number of telephone lines per 1000 inhabitants in 2007



Source: *Sistema Único de Servicios Públicos de Colombia* (www.siu.gov.co).

Figure A3. Index of modernity by industry

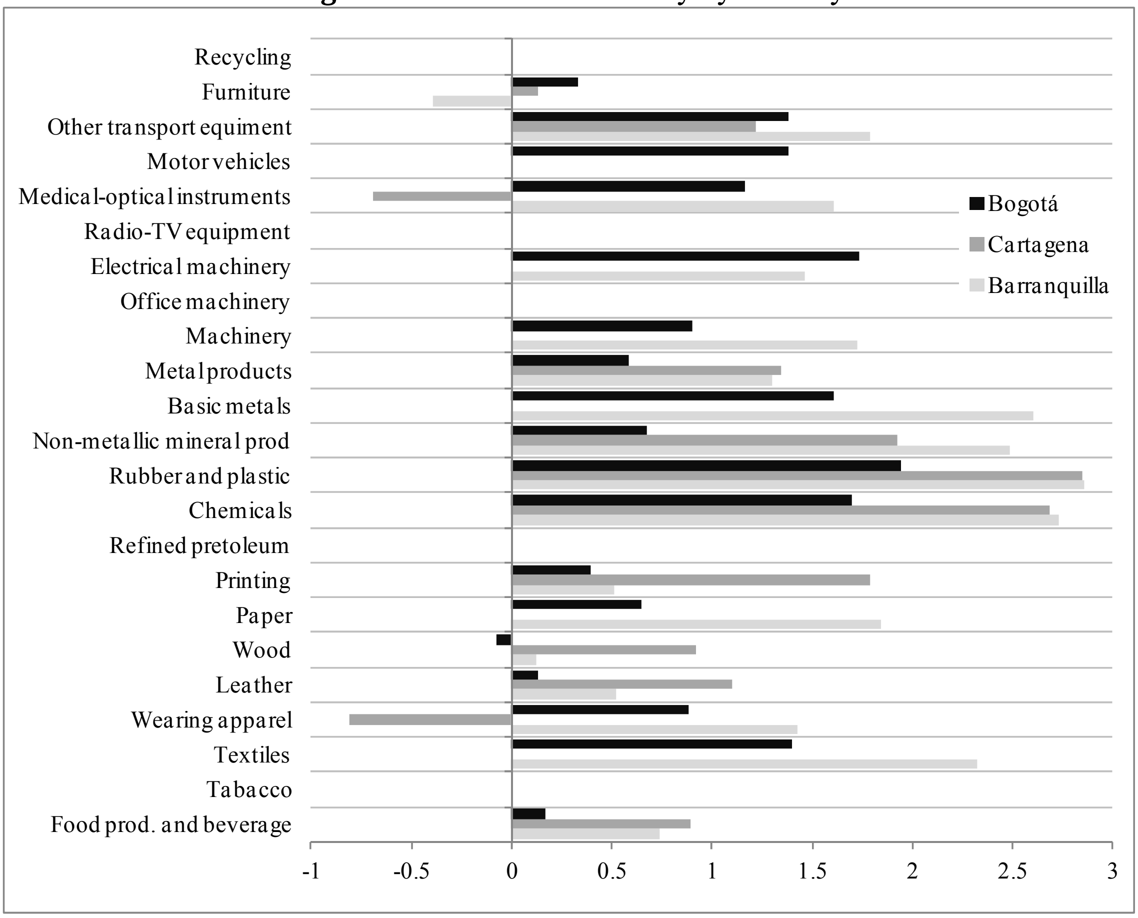
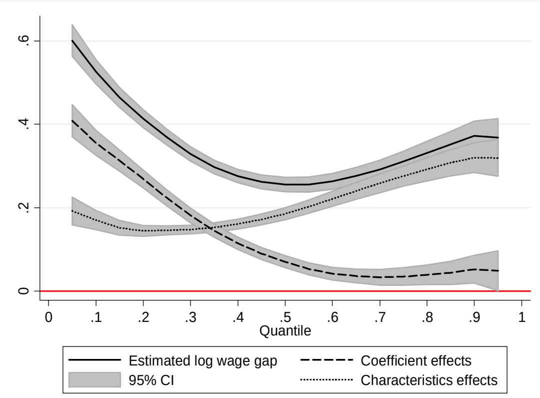


Figure A4. Decomposition results with other groups of cities

a) Bogotá, Medellín, Manizales and Cali



b) Cúcuta, Montería, Pasto and Cartagena

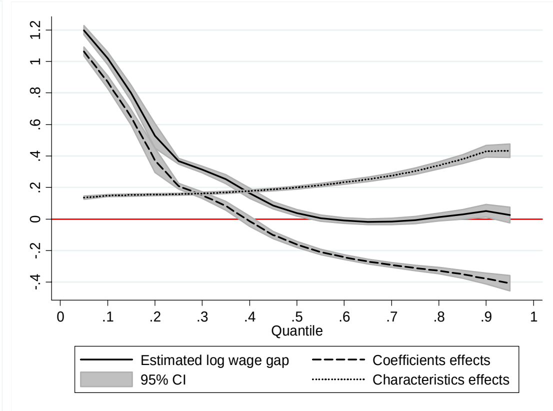


Table A2. Quantile regressions for total sample with corrections for selectivity
(y = Log real hourly wage)

	Formal workers							
	OLS	**5%**	**10%**	**25%**	**50%**	**75%**	**90%**	**95%**
Constant	7.540***	7.271***	7.453***	7.572***	7.556***	7.594***	7.689***	7.829***
	(410.75)	(182.36)	(282.55)	(515.1)	(385.98)	(301.87)	(190.59)	(153.84)
λ	0.065***	0.164***	0.177***	0.087***	0.024***	0.036***	0.026	0.040
	(6.17)	(7.46)	(11.91)	(10.18)	(2.16)	(2.47)	(1.07)	(1.25)
Education levels								
Lower secondary education	0.063***	0.073***	0.059***	0.052***	0.041***	0.066***	0.087***	0.085***
	(7.20)	(3.90)	(4.81)	(7.36)	(4.46)	(5.52)	(4.56)	(3.59)
Higher secondary education	0.172***	0.153***	0.141***	0.100***	0.116***	0.195***	0.274***	0.324***
	(19.74)	(7.81)	(11.19)	(14.20)	(12.51)	(16.50)	(14.62)	(14.03)
Bachelor/Master	0.493***	0.289***	0.320***	0.396***	0.497***	0.589***	0.647***	0.670***
	(42.22)	(10.87)	(18.20)	(41.14)	(39.85)	(36.93)	(25.25)	(21.04)
Experience	0.005***	0.003**	0.002***	0.002***	0.004***	0.005***	0.006***	0.005***
	(7.15)	(2.34)	(2.35)	(3.93)	(5.74)	(5.98)	(4.48)	(3.01)
Experience^2	-0.0001***	-0.0001***	-0.0001***	-0.0001***	-0.0001***	-0.0001***	-0.0001***	-0.0001
	(-6.10)	(-3.77)	(-3.63)	(-5.20)	(-5.29)	(-4.20)	(-2.45)	(-1.06)
Tenure	0.013***	0.015***	0.010***	0.008***	0.012***	0.013***	0.016***	0.016***
	(12.62)	(6.98)	(6.79)	(9.63)	(11.29)	(9.61)	(7.47)	(5.97)
Tenure^2	-0.0001***	-0.0004***	-0.0002***	-0.0001**	-0.0001**	0.00001	-0.0001	-0.0001
	(-2.95)	(-4.33)	(-2.77)	(-2.31)	(-2.11)	(-0.42)	(-1.25)	(-1.34)
Male	0.044***	-0.001	-0.001	0.011***	0.041***	0.077***	0.094***	0.094***
	(9.60)	(-0.14)	(-0.13)	(3.08)	(8.39)	(12.55)	(9.75)	(7.74)
Size of firm								
11 – 50 employees	0.055***	0.055***	0.012	0.033***	0.049***	0.059***	0.064***	0.058***
	(6.37)	(3.10)	(0.99)	(4.82)	(5.31)	(5.08)	(3.43)	(2.44)
More than 51 employees	0.103***	0.066***	0.020	0.049***	0.091***	0.127***	0.150***	0.137***
	(10.30)	(3.17)	(1.38)	(6.09)	(8.59)	(9.34)	(6.81)	(4.84)
Observations	25,392							

	Informal workers							
	OLS	**5%**	**10%**	**25%**	**50%**	**75%**	**90%**	**95%**
Constant	7.117***	6.316***	6.525***	6.834***	7.169***	7.429***	7.619***	7.782***
	(506.18)	(184.07)	(244.24)	(350.91)	(467.5)	(463.19)	(293.46)	(223.75)
λ	-0.046***	-0.014	-0.049***	-0.035**	-0.024*	-0.033***	-0.073***	-0.101***
	(-3.89)	(-0.51)	(-2.23)	(-2.15)	(-1.87)	(-2.51)	(-3.47)	(-3.67)
Education levels								
Lower secondary education	0.095***	0.098***	0.083***	0.086***	0.096***	0.106***	0.095***	0.114***
	(9.98)	(4.27)	(4.67)	(6.56)	(9.29)	(10.03)	(5.67)	(5.15)
Higher secondary education	0.228***	0.194***	0.215***	0.227***	0.210***	0.201***	0.239***	0.272***
	(22.18)	(7.44)	(10.71)	(15.73)	(18.75)	(17.56)	(13.07)	(11.28)
Bachelor/Master	0.582***	0.487***	0.508***	0.530***	0.551***	0.624***	0.630***	0.640***
	(24.49)	(8.49)	(11.10)	(15.96)	(21.29)	(23.57)	(14.72)	(11.39)
Experience	0.010***	0.013***	0.015***	0.013***	0.010***	0.009***	0.009***	0.008***
	(11.84)	(6.43)	(8.72)	(11.07)	(10.80)	(8.83)	(5.38)	(3.72)
Experience^2	-0.0001***	-0.0002***	-0.0002***	-0.0002***	-0.0001***	-0.0001***	-0.0001***	-0.0001
	(-8.00)	(-4.95)	(-6.61)	(-8.53)	(-7.68)	(-5.83)	(-3.03)	(-1.62)
Tenure	0.023***	0.035***	0.031***	0.028***	0.020***	0.017***	0.020***	0.015***
	(12.05)	(7.82)	(9.09)	(10.62)	(9.64)	(8.29)	(5.96)	(3.38)
Tenure^2	-0.001***	-0.001***	-0.001***	-0.001***	-0.001***	-0.0004***	-0.001***	-0.0003
	(-8.24)	(-6.69)	(-7.41)	(-7.49)	(-5.99)	(-5.00)	(-3.65)	(-1.55)
Male	0.103***	0.091***	0.091***	0.092***	0.094***	0.103***	0.130***	0.120***
	(12.51)	(4.47)	(5.80)	(8.25)	(10.49)	(11.07)	(8.87)	(6.30)
Size of firm								
11 – 50 employees	0.207***	0.293***	0.272***	0.210***	0.162***	0.142***	0.175***	0.217***
	(18.43)	(11.05)	(12.84)	(13.49)	(13.18)	(11.15)	(8.7)	(8.30)
More than 51 employees	0.312***	0.386***	0.392***	0.295***	0.248***	0.243***	0.342***	0.433***
	(17.58)	(8.92)	(11.50)	(11.88)	(12.83)	(12.36)	(11.06)	(10.66)
Observations	18,203							

Note: ***, **, *, denotes significance at 1%, 5% and 10%, respectively. ( ) t statistics. Experience is calculated as (age-year of education-6). All models include industry dummies and occupation dummies. Up to primary school and 1-10 employees are the excluded categories in education and size of firm variables, respectively.

Table A3. Quantile regressions for more developed cities (Group 1) with corrections for selectivity
(y = Log real hourly wage)

	Formal workers								Informal workers							
	OLS	**5%**	**10%**	**25%**	**50%**	**75%**	**90%**	**95%**	**OLS**	**5%**	**10%**	**25%**	**50%**	**75%**	**90%**	**95%**
Constant	7.497***	7.239***	7.429***	7.575***	7.534***	7.529***	7.628***	7.812***	7.255***	6.532***	6.696***	6.984***	7.287***	7.512***	7.723***	7.886***
	(431.42)	(207.56)	(313.61)	(600.03)	(519.89)	(311.57)	(180.33)	(141.75)	(431.26)	(121.72)	(205.26)	(350.75)	(472.1)	(452.85)	(253.31)	(184.71)
λ	0.035***	0.146***	0.165***	0.083***	0.009	0.0002	-0.031	0.017	-0.006	0.028	0.022	0.021	-0.011	-0.024	-0.029	-0.037
	(3.10)	(6.53)	(10.93)	(10.14)	(0.95)	(0.01)	(-1.09)	(0.45)	(-0.54)	(0.81)	(1.07)	(1.55)	(-1.04)	(-1.13)	(-1.36)	(-1.26)
Education levels																
Lower secondary education	0.068***	0.065***	0.059***	0.039***	0.037***	0.073***	0.093***	0.096***	0.076***	0.004***	0.07***	0.083***	0.090***	0.084***	0.093***	0.086***
	(7.87)	(3.96)	(5.20)	(6.27)	(5.15)	(6.12)	(4.46)	(3.63)	(6.77)	(0.11)	(3.35)	(6.30)	(8.74)	(7.79)	(4.64)	(3.06)
Higher secondary education	0.184***	0.147***	0.132***	0.087***	0.117***	0.213***	0.303***	0.355***	0.198***	0.116***	0.174***	0.195***	0.200***	0.197***	0.220***	0.254***
	(21.30)	(8.55)	(11.40)	(13.82)	(16.27)	(17.85)	(14.63)	(13.61)	(16.36)	(3.03)	(7.56)	(13.47)	(17.97)	(16.89)	(10.23)	(8.55)
Bachelor/Master	0.534***	0.323***	0.356***	0.435***	0.533***	0.632***	0.676***	0.685***	0.512***	0.349***	0.389***	0.413***	0.550***	0.565***	0.768***	0.810***
	(44.90)	(13.42)	(21.12)	(49.19)	(53.78)	(38.12)	(23.17)	(18.30)	(17.84)	(4.07)	(7.30)	(12.45)	(20.91)	(20.15)	(14.52)	(11.27)
Experience	0.004***	0.004***	0.002**	0.002***	0.004***	0.005***	0.006***	0.005***	0.009***	0.012***	0.012***	0.012***	0.010***	0.007***	0.005***	0.004*
	(6.69)	(3.05)	(2.18)	(4.18)	(8.10)	(5.90)	(3.65)	(2.23)	(8.85)	(3.89)	(6.30)	(10.22)	(10.42)	(7.47)	(2.93)	(1.68)
$Experience^2$	-0.0001***	-0.0001***	-0.0001***	-0.0001***	-0.0001***	-0.0001***	-0.0001**	-0.00002	-0.0002***	-0.0002***	-0.0002***	-0.0002***	-0.0002***	-0.0001***	-0.0001	-0.00003
	(-5.39)	(-4.42)	(-3.39)	(-5.65)	(-7.38)	(-3.73)	(-1.89)	(-0.46)	(-7.23)	(-4.11)	(-6.25)	(-9.17)	(-8.24)	(-5.49)	(-1.55)	(-0.58)
Tenure	0.014***	0.014***	0.010***	0.008***	0.011***	0.016***	0.019***	0.017***	0.025***	0.049***	0.045***	0.029***	0.019***	0.021***	0.025***	0.017***
	(13.69)	(6.74)	(7.36)	(10.34)	(13.15)	(11.08)	(7.92)	(5.34)	(10.15)	(6.78)	(10.31)	(10.38)	(8.33)	(9.16)	(5.63)	(2.64)
$Tenure^2$	-0.0001***	-0.0002***	-0.0002***	-0.0001*	0.0001	-0.0001	-0.0002**	-0.0002	-0.001***	-0.002***	-0.002***	-0.001***	-0.0005***	-0.001***	-0.001***	-0.0004
	(-3.38)	(-2.85)	(-3.32)	(-1.77)	(0.33)	(-1.51)	(-2.08)	(-1.52)	(-7.03)	(-7.31)	(-10.62)	(-8.20)	(-4.96)	(-5.65)	(-3.76)	(-1.15)
Male	0.057***	0.010	0.004	0.014***	0.052***	0.097***	0.114***	0.098***	0.098***	0.098***	0.083***	0.101***	0.096***	0.102***	0.104***	0.100***
	(12.01)	(1.15)	(0.62)	(4.21)	(13.17)	(15.04)	(10.34)	(6.89)	(10.19)	(3.29)	(4.71)	(9.16)	(10.87)	(10.97)	(6.22)	(4.26)
Size of firm																
11 – 50 employees	0.068***	0.057***	0.026***	0.041***	0.055***	0.080***	0.085***	0.059***	0.165***	0.205***	0.197***	0.143***	0.134***	0.125***	0.145***	0.178***
	(7.99)	(3.38)	(2.21)	(6.54)	(7.67)	(6.76)	(4.18)	(2.19)	(12.54)	(5.45)	(8.48)	(9.53)	(11.05)	(9.66)	(6.09)	(5.40)
More than 51 employees	0.124***	0.089***	0.048***	0.060***	0.101***	0.156***	0.169***	0.132***	0.169***	0.121***	0.163***	0.112***	0.138***	0.192***	0.259***	0.324***
	(13.05)	(4.74)	(3.75)	(8.68)	(12.72)	(11.98)	(7.46)	(4.41)	(8.66)	(2.08)	(4.71)	(5.01)	(7.74)	(10.32)	(7.50)	(6.66)
Observations	25,368								13,723							

Note: ***, **, *, denotes significance at 1%, 5% and 10%, respectively. ( ) t statistics. Experience is calculated as (age-year of education-6). All models include industry dummies and occupation dummies. Up to primary school and 1-10 employees are the excluded categories in education and size of firm variables, respectively.

Table A4. Quantile regressions for less developed cities (Group 2) with corrections for selectivity
(y = Log real hourly wage)

	Formal workers								**Informal workers**							
	OLS	**5%**	**10%**	**25%**	**50%**	**75%**	**90%**	**95%**	**OLS**	**5%**	**10%**	**25%**	**50%**	**75%**	**90%**	**95%**
Constant	7.559***	7.448***	7.494	7.576***	7.605***	7.609***	7.640***	7.807***	6.965***	6.201***	6.389***	6.715***	7.002***	7.251***	7.463***	7.586***
	(229.79)	(119.27)	(144.6)	(313.4)	(220.34)	(153.92)	(101.09)	(85.02)	(422.32)	(172.48)	(221.78)	(310.56)	(364.92)	(360.79)	(234.51)	(175.6)
λ	0.085***	0.247***	0.197***	0.105***	0.062***	0.050**	0.025**	0.032***	-0.086***	-0.032	-0.043	-0.033**	-0.063***	-0.061***	-0.185***	-0.190***
	(5.07)	(7.86)	(7.44)	(8.46)	(3.55)	(2.00)	(2.19)	(2.65)	(-4.54)	(-0.80)	(-1.29)	(-2.06)	(-2.86)	(-2.69)	(-5.30)	(-4.03)
Education levels																
Lower secondary education	0.081***	0.072**	0.086***	0.079***	0.054***	0.073***	0.108***	0.080**	0.099***	0.128***	0.103***	0.083***	0.090***	0.098***	0.109***	0.100***
	(5.49)	(2.52)	(3.69)	(7.21)	(3.45)	(3.26)	(3.23)	(2.04)	(8.82)	(5.40)	(5.40)	(5.70)	(6.92)	(7.25)	(5.29)	(3.66)
Higher secondary education	0.173***	0.113***	0.155***	0.124***	0.118***	0.192***	0.278***	0.264***	0.248***	0.224***	0.219***	0.213***	0.231***	0.238***	0.281***	0.298***
	(11.61)	(3.87)	(6.59)	(11.18)	(7.52)	(8.48)	(8.37)	(6.64)	(19.93)	(8.19)	(9.90)	(12.81)	(15.95)	(16.17)	(12.34)	(9.90)
Bachelor/Master	0.471***	0.242***	0.296***	0.363***	0.476***	0.581***	0.648***	0.649***	0.666***	0.580***	0.629***	0.598***	0.645***	0.687***	0.764***	0.643***
	(24.39)	(6.26)	(9.30)	(24.82)	(23.53)	(19.99)	(14.98)	(12.65)	(23.63)	(9.88)	(13.18)	(16.14)	(19.71)	(20.82)	(14.94)	(9.32)
Experience	0.005***	0.0001	0.001	0.001**	0.004***	0.006***	0.008***	0.010***	0.012***	0.013***	0.015***	0.014***	0.012***	0.011***	0.012***	0.013***
	(4.98)	(-0.18)	(0.36)	(1.95)	(3.64)	(4.14)	(3.57)	(3.83)	(11.83)	(6.05)	(8.02)	(10.30)	(10.24)	(8.75)	(6.33)	(4.96)
Experience^2	-0.0001***	-0.00004	-0.00003	-0.00003*	-0.0001***	-0.0001***	-0.0001**	-0.0001***	-0.0002***	-0.0002***	-0.0002***	-0.0002***	-0.0002***	-0.0002***	-0.0002***	-0.0002***
	(-3.95)	(-1.00)	(-0.90)	(-1.83)	(-3.08)	(-3.06)	(-2.03)	(-2.29)	(-8.71)	(-4.62)	(-6.16)	(-8.43)	(-7.79)	(-6.43)	(-4.20)	(-3.23)
Tenure	0.009***	0.010***	0.007***	0.005***	0.009***	0.011***	0.010***	0.012***	0.023***	0.028***	0.027***	0.028***	0.021***	0.020***	0.018***	0.019***
	(6.07)	(3.35)	(2.93)	(4.62)	(5.39)	(4.97)	(2.74)	(2.72)	(11.10)	(6.82)	(7.77)	(10.26)	(8.44)	(8.33)	(5.07)	(3.83)
Tenure^2	-0.00005	-0.0003**	-0.0001	-0.00003	-0.00001	-0.00001	0.0001	-0.00004	-0.001***	-0.001***	-0.001***	-0.001***	-0.0005***	-0.001***	-0.0004***	-0.0005**
	(-0.82)	(-2.37)	(-0.84)	(-0.67)	(-0.14)	(-0.12)	(0.46)	(-0.22)	(-6.69)	(-4.56)	(-5.06)	(-6.75)	(-4.44)	(-5.19)	(-2.88)	(-2.26)
Male	0.020***	-0.018	-0.031***	-0.003	0.018***	0.038***	0.067***	0.077***	0.130***	0.120***	0.108***	0.113***	0.128***	0.142***	0.143***	0.144***
	(2.92)	(-1.36)	(-2.85)	(-0.62)	(2.47)	(3.68)	(4.35)	(4.30)	(13.23)	(5.68)	(6.31)	(8.86)	(11.15)	(11.73)	(7.60)	(5.53)
Size of firm																
11 – 50 employees	0.048***	0.027	0.023	0.039***	0.029*	0.045**	0.063*	0.031	0.228***	0.303***	0.294***	0.218***	0.191***	0.171***	0.217***	0.242***
	(3.34)	(1.02)	(1.04)	(3.65)	(1.91)	(2.09)	(1.92)	(0.8)	(16.55)	(10.42)	(12.20)	(11.97)	(11.90)	(10.4)	(8.71)	(7.25)
More than 51 employees	0.074***	-0.014	-0.011	0.029**	0.044***	0.094***	0.142***	0.114***	0.427***	0.472***	0.454***	0.378***	0.365***	0.350***	0.503***	0.579***
	(4.02)	(-0.41)	(-0.39)	(2.12)	(2.27)	(3.43)	(3.31)	(2.24)	(16.90)	(8.18)	(9.70)	(11.10)	(12.44)	(11.82)	(11.20)	(9.62)
Observations					10,925								12,262			

Note: ***, **, *, denotes significance at 1%, 5% and 10%, respectively. ( ) t statistics. Experience is calculated as (age-year of education-6). All models include industry dummies and occupation dummies. Up to primary school and 1-10 employees are the excluded categories in education and size of firm variables, respectively.

Table A5. Quantile regressions for more developed cities (Group 1) without corrections for selectivity
(y = Log real hourly wage)

	Formal workers								Informal workers							
	OLS	**5%**	**10%**	**25%**	**50%**	**75%**	**90%**	**95%**	**OLS**	**5%**	**10%**	**25%**	**50%**	**75%**	**90%**	**95%**
Constant	7.457***	7.075***	7.245***	7.479***	7.525***	7.528***	7.662***	7.791***	7.255***	6.547***	6.702***	6.981***	7.287***	7.507***	7.719***	7.883***
	(645.22)	(317.65)	(412.1)	(799.3)	(709.99)	(461.05)	(262.73)	(220.65)	(432.07)	(115.50)	(203.86)	(332.00)	(475.94)	(460.77)	(250.72)	(179.44)
Education levels																
Lower secondary education	0.071***	0.077***	0.067***	0.052***	0.038***	0.073***	0.091***	0.097***	0.076***	0.003	0.071***	0.087***	0.089***	0.084***	0.091***	0.085***
	(8.25)	(4.77)	(5.30)	(7.51)	(4.84)	(6.17)	(4.20)	(3.66)	(6.75)	(0.09)	(3.38)	(6.24)	(8.75)	(7.94)	(4.50)	(2.98)
Higher secondary education	0.191***	0.177***	0.164***	0.109***	0.119***	0.213***	0.296***	0.359***	0.196***	0.118***	0.179***	0.200***	0.196***	0.193***	0.216***	0.245***
	(23.18)	(10.93)	(13.21)	(16.39)	(15.72)	(18.57)	(14.20)	(14.32)	(16.77)	(2.97)	(7.82)	(13.46)	(18.35)	(17.40)	(10.27)	(8.21)
Bachelor/Master	0.545***	0.378***	0.406***	0.466***	0.536***	0.632***	0.666***	0.690***	0.509***	0.368***	0.388***	0.416***	0.547***	0.548***	0.765***	0.794***
	(47.94)	(16.49)	(22.41)	(49.54)	(51.48)	(39.83)	(22.74)	(19.14)	(18.19)	(4.15)	(7.38)	(12.11)	(21.49)	(20.51)	(15.11)	(11.19)
Experience	0.005***	0.004***	0.002***	0.002***	0.004***	0.005***	0.006***	0.005**	0.009***	0.012***	0.012***	0.013***	0.010***	0.007***	0.005**	0.003
	(6.94)	(3.48)	(2.37)	(4.31)	(7.42)	(5.94)	(3.58)	(2.26)	(8.87)	(3.73)	(6.64)	(10.04)	(10.42)	(7.42)	(2.55)	(1.28)
Experience^2	-0.0001***	-0.0001***	-0.0001**	-0.0001***	-0.0001***	-0.0001***	-0.0001**	-0.0001	-0.0002***	-0.0003***	-0.0002***	-0.0002***	-0.0002***	-0.0001***	-0.00005	-0.00001
	(-5.32)	(-4.31)	(-2.50)	(-4.89)	(-6.66)	(-3.76)	(-1.96)	(-0.40)	(-7.22)	(-3.98)	(-6.46)	(-8.85)	(-8.25)	(-5.50)	(-1.29)	(-0.16)
Tenure	0.014***	0.014***	0.011***	0.008***	0.011***	0.016***	0.019***	0.017***	0.025***	0.050***	0.045***	0.029***	0.019***	0.022***	0.026***	0.016**
	(13.75)	(7.45)	(7.04)	(9.56)	(11.92)	(11.10)	(7.64)	(5.41)	(10.15)	(6.52)	(10.25)	(10.07)	(8.55)	(9.42)	(5.86)	(2.47)
Tenure^2	-0.0001***	-0.0003***	-0.0002***	-0.0001*	0.00001	-0.0001	-0.0002**	-0.0002	-0.001***	-0.002***	-0.002***	-0.001***	-0.001***	-0.001***	-0.001***	-0.0003
	(-3.48)	(-3.64)	(-3.36)	(-1.82)	(0.29)	(-1.51)	(-1.98)	(-1.58)	(-7.03)	(-7.02)	(-10.61)	(-8.03)	(-5.15)	(-5.65)	(-4.02)	(-1.05)
Male	0.059***	0.021**	0.016***	0.019***	0.052***	0.097***	0.112***	0.100***	0.097***	0.094***	0.083***	0.103***	0.094***	0.099***	0.105***	0.097***
	(12.61)	(2.45)	(2.24)	(5.17)	(12.16)	(15.28)	(9.96)	(7.10)	(10.18)	(3.01)	(4.72)	(8.85)	(10.79)	(10.91)	(6.21)	(4.01)
Size of firm																
11 – 50 employees	0.085***	0.127***	0.100***	0.078***	0.059***	0.080***	0.072***	0.068***	0.162***	0.216***	0.205***	0.153***	0.130***	0.115***	0.134***	0.155***
	(12.63)	(10.30)	(10.14)	(14.51)	(9.52)	(8.52)	(4.31)	(3.25)	(13.76)	(5.87)	(9.70)	(10.64)	(12.07)	(10.26)	(6.31)	(5.21)
More than 51 employees	0.147***	0.189***	0.151***	0.113***	0.106***	0.156***	0.151***	0.145***	0.162***	0.157***	0.189***	0.131***	0.125***	0.170***	0.221***	0.277***
	(25.03)	(17.39)	(17.45)	(24.11)	(19.75)	(19.33)	(10.46)	(8.10)	(11.14)	(3.39)	(7.17)	(7.38)	(9.47)	(12.53)	(8.69)	(7.73)
Observations				25,368								13,723				

Note: ***, **, *, denotes significance at 1%, 5% and 10%, respectively. ( ) t statistics. Experience is calculated as (age-year of education-6). All models include industry dummies and occupation dummies. Up to primary school and 1-10 employees are the excluded categories in education and size of firm variables, respectively.

Table A6. Decomposition results

	Total sample				Group 1				Group 2			
Q	Raw log wage gap	Estimated log wage gap	Characteristics	Coefficient	Raw log wage gap	Estimated log wage gap	Characteristics	Coefficient	Raw log wage gap	Estimated log wage gap	Characteristics	Coefficient
0.05	0.813	1.103	0.136	0.967	0.604	0.603	0.197	0.406	0.886	1.191	0.097	1.095
		(0.022)	(0.006)	(0.022)		(0.019)	(0.016)	(0.018)		(0.014)	(0.006)	(0.014)
0.10	0.752	0.886	0.142	0.744	0.570	0.539	0.175	0.364	0.903	1.035	0.107	0.928
		(0.017)	(0.004)	(0.017)		(0.014)	(0.012)	(0.016)		(0.019)	(0.004)	(0.019)
0.15	0.710	0.714	0.146	0.568	0.528	0.481	0.155	0.327	0.851	0.846	0.112	0.735
		(0.022)	(0.004)	(0.022)		(0.012)	(0.009)	(0.013)		(0.021)	(0.004)	(0.021)
0.20	0.658	0.565	0.149	0.417	0.487	0.433	0.146	0.287	0.804	0.669	0.111	0.558
		(0.017)	(0.003)	(0.017)		(0.011)	(0.007)	(0.011)		(0.025)	(0.004)	(0.024)
0.25	0.554	0.447	0.151	0.296	0.409	0.389	0.146	0.243	0.723	0.434	0.111	0.323
		(0.017)	(0.003)	(0.017)		(0.010)	(0.005)	(0.010)		(0.027)	(0.003)	(0.027)
0.30	0.477	0.335	0.153	0.182	0.343	0.350	0.148	0.203	0.622	0.34	0.115	0.224
		(0.013)	(0.004)	(0.013)		(0.009)	(0.005)	(0.009)		(0.012)	(0.004)	(0.011)
0.35	0.402	0.274	0.158	0.116	0.269	0.321	0.154	0.167	0.531	0.273	0.122	0.151
		(0.011)	(0.004)	(0.011)		(0.009)	(0.005)	(0.009)		(0.012)	(0.004)	(0.012)
0.40	0.368	0.216	0.167	0.049	0.258	0.299	0.162	0.137	0.502	0.194	0.131	0.063
		(0.012)	(0.004)	(0.012)		(0.009)	(0.006)	(0.008)		(0.016)	(0.004)	(0.016)
0.45	0.344	0.156	0.178	-0.022	0.265	0.286	0.174	0.112	0.47	0.093	0.144	-0.051
		(0.012)	(0.005)	(0.011)		(0.009)	(0.006)	(0.008)		(0.016)	(0.005)	(0.016)
0.50	0.358	0.120	0.192	-0.072	0.244	0.278	0.188	0.091	0.464	0.046	0.158	-0.112
		(0.010)	(0.005)	(0.008)		(0.009)	(0.007)	(0.008)		(0.011)	(0.006)	(0.01)
0.55	0.332	0.106	0.209	-0.103	0.228	0.278	0.205	0.073	0.412	0.017	0.176	-0.159
		(0.008)	(0.006)	(0.007)		(0.010)	(0.008)	(0.008)		(0.01)	(0.006)	(0.009)
0.60	0.312	0.106	0.230	-0.124	0.253	0.283	0.223	0.060	0.416	0.004	0.194	-0.190
		(0.008)	(0.007)	(0.007)		(0.010)	(0.009)	(0.008)		(0.009)	(0.008)	(0.008)
0.65	0.333	0.111	0.250	-0.140	0.296	0.294	0.241	0.053	0.419	0.003	0.214	-0.211
		(0.008)	(0.007)	(0.007)		(0.011)	(0.010)	(0.009)		(0.009)	(0.008)	(0.007)
0.70	0.366	0.117	0.270	-0.153	0.325	0.308	0.26	0.048	0.405	0.012	0.238	-0.226
		(0.009)	(0.008)	(0.008)		(0.011)	(0.011)	(0.009)		(0.010)	(0.009)	(0.008)
0.75	0.423	0.129	0.287	-0.158	0.357	0.326	0.277	0.048	0.473	0.025	0.267	-0.241
		(0.010)	(0.010)	(0.008)		(0.012)	(0.012)	(0.01)		(0.012)	(0.011)	(0.009)
0.80	0.42	0.145	0.306	-0.161	0.356	0.346	0.295	0.051	0.484	0.044	0.296	-0.252
		(0.011)	(0.011)	(0.009)		(0.014)	(0.013)	(0.012)		(0.013)	(0.012)	(0.010)
0.85	0.471	0.167	0.326	-0.159	0.407	0.370	0.314	0.057	0.514	0.064	0.326	-0.262
		(0.013)	(0.013)	(0.011)		(0.015)	(0.016)	(0.014)		(0.014)	(0.014)	(0.012)
0.90	0.478	0.204	0.360	-0.156	0.425	0.392	0.329	0.063	0.603	0.091	0.357	-0.266
		(0.017)	(0.017)	(0.014)		(0.018)	(0.018)	(0.017)		(0.017)	(0.017)	(0.016)
0.95	0.494	0.235	0.380	-0.144	0.418	0.393	0.332	0.061	0.575	0.089	0.381	-0.292
		(0.021)	(0.022)	(0.021)		(0.023)	(0.023)	(0.024)		(0.022)	(0.019)	(0.021)

Note: ( ) Bootstrap standard errors based on 1000 repetitions.