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Gustavo Canavire-Bacarreza
Universidad EAFIT and IZA

Luis C. Carvajal-Osorio
Universidad EAFIT

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IZA – Institute of Labor Economics

Schaumburg-Lippe-Straße 5–9
53113 Bonn, Germany

Phone: +49-228-3894-0
Email: publications@iza.org

www.iza.org

ABSTRACT

Two Stories of Wage Dynamics in Latin America: Different Policies, Different Outcomes*

This article explores the variation in the wage distributions of two Latin American countries, Bolivia and Colombia, which have had different political and economic strategies in recent years. Using data from household surveys, a decomposition of the wage distribution in each country using functional principal component analysis is conducted. The results suggest that Bolivia, which has implemented left-wing economic policies, has experienced a general increase in wages, especially benefiting the least skilled workers and the informal sector. On the other hand, the wage distribution in Colombia, whose economic policy has focused on free-market principles, has become more concentrated around the median wage, mainly due to changes in formal sector wages.

JEL Classification: J31, J38, C14

Keywords: wage dynamics, functional principal component analysis, wage distributions, Latin America, Bolivia, Colombia

Corresponding author:
Gustavo Javier Canavire-Bacarreza
Inter-American Development Bank
1300 New York Ave NW
Washington, DC 20577
USA
E-mail: gcanavire@gmail.com

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Wages are an indicator of the state of the economy and the well-being of the workforce. As economies develop, the structure of the labor market changes, thereby affecting the wage distribution. This paper aims to explore the differences in the evolution of the wage distribution in different political contexts by comparing two developing Latin American countries, Bolivia and Colombia, that have taken different political paths. Since 2006, when Evo Morales became president of Bolivia, the country has shifted toward left-wing policies, such as the expansion of the public sector and increased levels of social assistance (Canavire-Bacarreza and Rios-Avila, 2015). During the same time frame, Colombia has implemented policies to foster economic growth through free-market principles and improved national security (Aristizábal-Ramírez et al., 2015).

In spite of the differences in economic policies, Bolivia and Colombia have many similarities. Both countries experienced a period of fast economic growth in the late 2000s and early 2010s, mainly driven by the commodities boom of that period. However, both economies are still among the most unequal in the world (World Bank, 2017), and although there have been reductions in the poverty rates of both countries, more than 25% of the population lives in poverty in both Bolivia and Colombia (ECLAC, 2016). In addition, the average educational attainment of the population aged 25 or older in both cases is below the mean for advanced economies (11 years) (Barro and Lee, 2013). Furthermore, about half of the labor force works in the informal sector (INE, 2017; DANE, 2017). Behrman (1999) notes that low education levels of the workforce and a high prevalence of informality are characteristic of labor markets in developing countries. These similarities imply that the effects of policies on the evolution of wages will be more evident, since other possible causes of wage variation, such as economic growth or labor market composition, do not differ by much.

To analyze the evolution of the wage distribution in both countries, we employ a decomposition technique called functional principal component analysis (FPCA). This method, first developed by Kneip and Utikal (2001) and extended by Huynh et al. (2011), allows the decomposition a family of probability density functions into its mean and a time-specific deviation from the mean. From the FPCA decomposition, we obtain a profile of changes in the wage distribution over time in each country. This allows us to compare the dynamics of the wage distributions and to identify the key differences between them.

In previous applications of FPCA decomposition, Huynh and Jacho-Chávez (2010) found that the dynamics of firm size distributions in the United Kingdom are affected by the non-random exit of young firms. Huynh et al. (2011, 2015) analyzed the evolution of firm size, labor productivity and leverage distributions for firms in Canada, finding that firms tend to become larger and less dependent on financial leverage. In their analysis of the distribution of sales and employment in Ukrainian firms, Huynh et al. (2016) discover important heterogeneity in the evolution of these distributions across regions, industries and turnover status. Chu et al. (2016) adapt the FPCA decomposition to account for stratified random sampling and apply this method to the distribution of consumer prices in the United Kingdom. They find strong correlations between the dynamics of the retail prices and other economic indicators like the unemployment and the inflation rate.

This decomposition has a series of interesting characteristics. Since it is a non-parametric method, there is no *a priori* restriction on the shape of the probability density function. Moreover, it describes the whole wage distribution, instead of focusing only on the mean wage or certain quantiles. The extension of FPCA proposed by Huynh et al. (2011) allows us to include discrete covariates to capture the differences in the evolution over time across subsets of the sample, thus providing more information about the changes observed in the unconditional probability densities.

The contribution of this article to the literature on wage dynamics is twofold. To the best of our knowledge, this is the first paper to use FPCA decomposition to study the dynamics of wage distributions, thus presenting a novel methodology with which to study changes in wage distributions over time.[1] Furthermore, we analyze the labor markets of two Latin American economies. By doing so, this article adds to the existing literature on wage distributions and wage dynamics in the region and in developing countries in general (e.g., Atal et al., 2009; Carrillo et al., 2014; Fernández and Messina, 2017).

By applying this technique to data obtained from household surveys in both countries, we found that Bolivia achieved a rather uniform increase in wages during Evo Morales' presidency, especially benefiting workers with less education and those in the informal sector. On the other hand, between 2008 and 2015, the wage distribution in Colombia became more concentrated around the median wage. This change was mostly attributed to changes in the formal sector of the economy. In relation to Bolivia, wage variation in Colombia was distributed more evenly between males and females and between the least and the most educated workers.

This paper is organized as follows: Section II presents some of the existing literature on wage dynamics and wage determination. Section III provides some background on labor markets in Bolivia and Colombia. The data are presented along with descriptive statistics for both countries in Section IV. Section V describes the functional principal component analysis method and its application to wage distributions. The results are presented and discussed in Section VI, and Section VII concludes.

II. Review of wage dynamics literature

The literature on wage determinants and wage inequality is very large, and the topic has been approached in many different ways. Many authors have ap-

[1] The application section of Kneip and Utikal (2001) deals with the distribution of household income in the United Kingdom. Their approach is different from ours since they consider aggregate household income, regardless of its source (e.g., capital gains, unemployment subsidies, transfers...) while we focus on labor remuneration alone at the individual level.

proached wage inequality from a supply-demand standpoint (see Katz and Autor, 1999, and Acemoglu and Autor, 2011, for a review), where observed changes in wages are explained by shifts in the supply and demand for labor. Other authors (Blau and Kahn, 1996; Fortin and Lemieux, 1997; Fitoussi, 1994; Even and Macpherson, 2003; Betcherman, 2014, among others) have explored the effects of certain institutions like unions, minimum wages or labor regulations on wages. Moreover, several studies (e.g., Arulampalam et al., 2007; Fang and Sakellariou, 2015; Panizza and Qiang, 2005) have focused on labor market discrimination, finding important differences in labor remuneration for different groups of the workforce.

Market-based explanations of wage inequality assert that differences in wages are caused by the differences in the relative supply and demand of certain types of workers. In particular, the literature has found that the technological changes in recent years have led to an increase in demand for skilled workers in relation to their unskilled counterparts. Indeed, this change is sometimes called skill-based technological change (SBTC). Juhn et al. (1993) find an increase in wage differentials between skilled and unskilled workers in the United States between 1963 and 1989, and they attribute such phenomenon to an increase in the market return to skills. Autor et al. (2006) show a trend towards polarization in the United States' labor market in the 1980s and 1990s, where the most skilled workers benefit more from SBTC while it makes the least skilled workers more prone to replacement by computers and automation, further reducing the relative demand for unskilled labor.

While supply and demand shifts constitute an important part of the explanation behind wage inequality, institutional factors should not be overlooked. For instance, Blau and Kahn (1996) observe that male wage inequality in the United States is higher than in other developed countries like Austria, Germany or Sweden, especially at the bottom of the wage distribution. They find that individual characteristics do not fully explain this difference: the low degree of unionization in the United States also contributes, as collective wage bargaining, which positively affects wages for the least paid workers, is less common than it is in developed European nations. Fortin and Lemieux (1997) find that the decline of unionization in the United States in the 1980s had an important effect on wage inequality for males, while the wage gap for females was more affected by decline in real value of the minimum wage. It is important to notice, however, that institutional factors and changes in labor supply and demand are not mutually exclusive causes of wage inequality; they should be understood as complementary explanations. Weiss and Garloff (2011) present a model in which both factors are intertwined and jointly explain why, when faced to similar technological changes, the wage distribution in the United States widened more than in Europe, where it manifested mainly through adjustments in the levels of employment.

Another key component of wage inequality is discrimination based on characteristics that have no effect on labor performance like gender or race. There is a vast literature suggesting that women earn lower wages than men performing similar jobs (Blau and Kahn, 2016, and Weichselbaumer and Winter-Ebmer, 2005, provide a survey of previous studies on gender wage gaps). There are two analogous phenomena in female wage distributions: the "glass ceiling," which is found at the top of the distribution and consists of highly skilled women earning less than comparable men, and the "sticky floor" at the bottom of the distribution, consisting in lower wages for the least skilled women in comparison to the least skilled men. Fang and Sakellariou (2015) study wage distributions in the developing world and find that sticky floors are predominant in Asia and Africa, while glass ceilings are more common in the transition economies of Europe (just as discovered by Arulampalam et al., 2007). There is evidence of sticky floors in Latin American countries with low income per capita, such Bolivia and Peru, and glass ceilings in middle income countries, such as Uruguay and Brazil (Carrillo et al., 2014).

Since understanding wage determinants and dynamics entails many different aspects, the methodological approaches have been just as diverse. Previous studies have used several techniques that consider the wage distribution as a whole in order to examine its evolution over time such as quantile regression (Buchinsky, 1998), counterfactual wage distribution estimation (DiNardo et al., 1996) and combinations of these two methods (Melly, 2005).

The literature on wage inequality and wage dynamics in the labor markets of developed countries is more extensive than that of developing economies, and many of the theoretical results and methods are built from stylized facts from such economies. However, labor markets in developing countries have some unique characteristics. For instance, Freeman and Oostendorp (2000) study the wages for 161 occupations in over 150 countries between 1983 and 1998, finding that skill differentials are higher in developing economies because of institutional factors and because of the lower degree of educational attainment in such countries. Minimum wage and employment protection laws reduce wage inequality in developing economies, although such policies do not yield significant gains in terms of efficiency (Betcherman, 2014). Another important feature in developing economies is job informality. Yamada (1996) notes that in these economies, the informal sector provides a competitive alternative to the formal economy for many workers; workers will transition from the informal sector to other sectors only if they can find better opportunities elsewhere.

Despite the aforementioned differences, labor markets in developing countries have been affected by similar shocks to those experienced in developed economies, such as SBTC or institutional change. In India, for example, the returns to higher education increased in the 1990s, particularly benefiting workers who earned the highest wages (Azam, 2012). The author notes that heterogeneity in the returns to education led to an increase in wage inequality in India. An example of the role of institutions in developing labor markets is the study by Bakis and Polat (2015) on the wage changes in Turkey in the 2000s. In that country, wage inequality declined mainly due to a 2004 reform that increased real minimum wages.

Wage dynamics in Latin America are similar to those in other developing areas. During the 1980s and 1990s, wage inequality in the region increased not only because of the technological changes of the time, which had similar effects in developed economies, but also because of policies implemented during that time, such as capital market liberalization, tax reforms or domestic financial sector reforms (Behrman et al., 2000). In recent years, however, the trend has reversed, and some countries have experienced reductions in wage inequality (Fernández and Messina, 2017). These authors found that wage inequality in Argentina, Brazil and Chile declined in the late 1990s and 2000s. They attribute these decreases to changes in the composition of labor markets and to reductions in education and experience premiums. Nevertheless, discrimination is still an important phenomenon in Latin America. Atal et al. (2009) analyze gender and ethnic wage gaps in 18 countries in the region and find that, on average, men are paid 10% more than women and ethnic minorities earn approximately 13% less than non-minorities. The authors also note that there exists great heterogeneity across countries in both gender and ethnic gaps.

III. Background: Labor Markets in Bolivia and Colombia

Bolivia and Colombia are two developing Latin American countries that share many characteristics in spite of their differences in population (Colombia is almost five times more populated than Bolivia) and economy size (Colombia has both higher output and higher GDP per capita than Bolivia). In table 1 we present some economic indicators for both countries in 2015. From table 1 we observe that both economies are heavily reliant on commodities and benefited greatly from the commodity boom of the late 2000s and early 2010s, growing faster than the Latin American average growth rate for the period of study (3%) (World Bank, 2017). Furthermore, although Colombia has a higher human development index than Bolivia, both countries still face important obstacles to development. More than one in four citizens in both countries live in poverty and income inequality in both countries are among the highest in the world. In addition, both countries have high rates of job informality and both fall behind in terms of average education of the adult population in relation to developed economies.

The differences in economic policies in the last decade between Bolivia and Colombia are much more evident. Under President Evo Morales, Bolivia's economic policy has focused on the improvement of the well-being of the population through redistribution and equality, whereas Colombia has implemented policies aiming towards economic growth and prosperity (Aristizábal-Ramírez et al., 2015).

Table 1—: Economic indicators for Bolivia (left) and Colombia (right). All indicators are for 2015, unless otherwise stated. Sources: World Bank (2017), Barro and Lee (2013), Center for International Development (2017), UNDP (2017), UDAPE (2017), DANE (2017)

		Bolivia	**Colombia**
Population (millions)		10.72	48.23
Gross Domestic Product (Billion 2011 USD, PPP)		70.05	626.27
GDP per capita (2011 USD, PPP)		6,531.52	12,985.38
Average GDP growth 2006-2015		5.04	4.57
Average GDP per capita growth 2006-2015		3.36	3.45
GDP sectoral share	Agriculture	13%	7%
	Mining/Construction	19%	20%
	Manufacturing	13%	13%
	Services	55%	60%
Main Exports		Natural Gas (48%)	Crude Oil (39%)
		Zinc (10%)	Coal (14%)
		Soybean (6%)	Coffee (6%)
		Lead (4%)	Gold (4%)
		Precious Metals (3%)	Bananas (3%)
Average Labor Participation Rate 2006-2015		72.38	66.93
Average Unemployment Rate 2006-2015		3.77	10.72
Average Labor Informality Rate 2006-2015		56.77	50.44
Average Years of Education[a]		7.77	8.45
Human Development Index		0.674	0.727
Poverty headcount ration at national poverty lines		38.6	27.8
GINI Index (2014)		48.4	53.5

[a]Average for population 25 years old or older. Data for 2010

A. *Bolivia*

Evo Morales was elected in 2005 and became the first indigenous and socialist president of Bolivia in 2006. During his presidency, Bolivia has distanced itself from the influence of Western institutions, and he has passed several economic reforms such as the nationalization of important industrial sectors (e.g., hydrocarbons, mining), the creation of social welfare programs and the implementation of anti-discrimination law to protect indigenous populations. Furthermore, President Morales increased royalty taxes for hydrocarbons, providing additional revenue with which to increase public spending (Hicks et al., 2015; Canavire-Bacarreza and Rios-Avila, 2015).

During Morales' presidency, the minimum wage in Bolivia has grown significantly. In 2005, the monthly minimum wage was 440 bolivianos (US$ 55). By 2015, it had increased fourfold to 1,656 bolivianos (US$ 238) (Canavire-Bacarreza and Rios-Avila, 2015). In addition, the unemployment rate has been lower than the Latin American average for the studied period (INE, 2017; ILO, 2017) (see Figure 1).[2] However, the job informality rate is over 50% (UDAPE, 2017) and is

[2]The Latin American average unemployment rate for the period 2006-2015 was 7.5% (ILO, 2017).

among the highest in the region (ILO, 2017).[3]

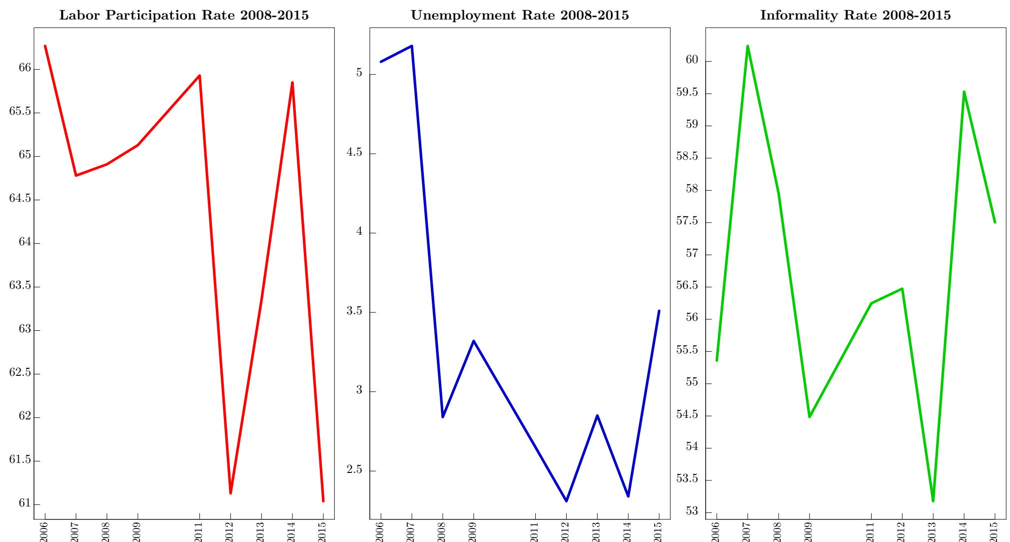

Figure 1. : Labor Market Statistics for Bolivia. Sources: INE (2017); UDAPE (2017)

B. Colombia

The 2000s and 2010s have been a period of steady economic growth and improvement of life conditions in Colombia. Presidents Álvaro Uribe (2002-2010) and Juan Manuel Santos (since 2010) have managed to significantly reduce the intensity of the Colombian armed conflict, thus providing a sense of confidence in the country's economy. Their economic policies have been targeted at promoting private investment and free markets (Aristizábal-Ramírez et al., 2015). Indeed, the 2010-2014 National Development Plan states that the main goal of the government is achieving economic prosperity through improvements in national security, employment and poverty alleviation (DNP, 2011). Some of the policies that have been implemented in recent years include free trade agreements with Colombia's main trading partners,[4] privatization of public companies and several reforms to reduce the cost of labor for employers.

Between 2006 and 2015, the Colombian labor market showed several signs of improvement in line with the economic situation of this period. Labor participation has increased slightly, while unemployment and job informality have decreased steadily, although both rates are still above the Latin American average (see Figure 2). Real wages in Colombia, however, have not increased much during this

[3] In 2015, the average rate of informality in Latin America was 46.8% (ILO, 2016).

[4] Colombia has free trade agreements with the United States, Mexico, the European Union, South Korea, Chile and the Andean Community of Nations (Bolivia, Ecuador and Peru), among others.

time frame. This slow growth in wages has been commonplace in Colombian history, as Urrutia and Ruiz (2010) found after analyzing the behavior of real wages for 170 years. Additionally, Arango Thomas et al. (2011) discovered that real wages in Colombia are, to some extent, flexible to changes in labor supply and demand, depending on economic activity. However, the observed rigidities in some sectors and regions may be caused by simultaneous supply and demand shocks. More recently, Morales and Medina (2016) studied the effects on the labor market of a 2012 tax reform that reduced payroll taxes by 13.5 points. They found that this measure was effective in reducing unemployment, but it had little effect on wages.

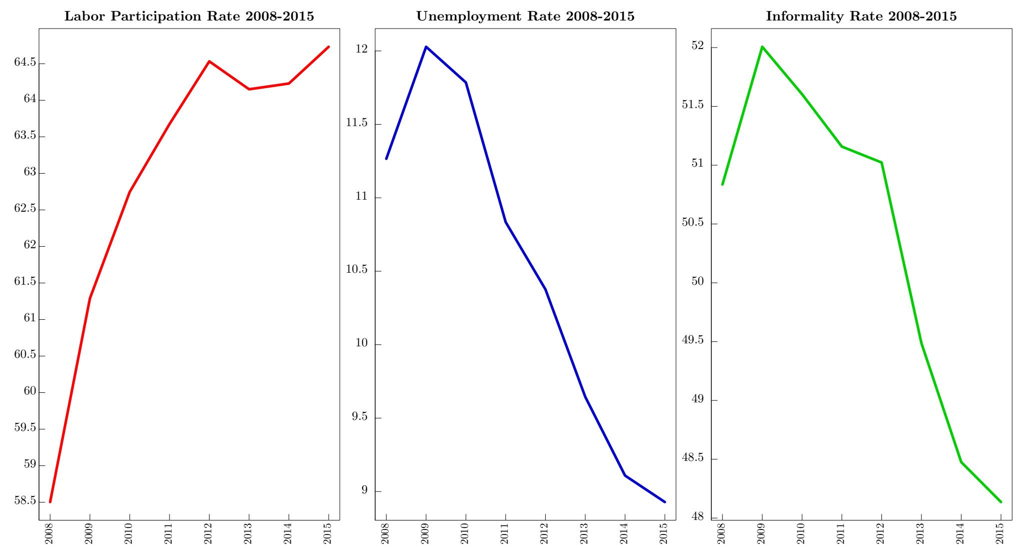

Figure 2. : Labor Market Statistics for Colombia. Source: DANE (2017)

IV. Data

The data used in this paper come from household surveys conducted by the national office of statistics in each country (Bolivia's Instituto Nacional de Estadística - INE and Colombia's Departamento Administrativo Nacional de Estadística - DANE). In the case of Bolivia, the data span nine years from 2006, when President Evo Morales took office, to 2015.[5] On the other hand, data from Colombia are available from 2008 to 2015.[6] Household surveys in both countries

[5]Data for 2010 are missing because the INE did not conduct this household survey during that year.

[6]Although there are household surveys from Colombia for years prior to 2008, we do not use them because of methodological changes between the previous survey, the Encuesta Continua de Hogares (ECH), and the Gran Encuesta Integrada de Hogares (GEIH), which is the current format since 2008.

gather information about sociodemographic characteristics, such as gender, age, marital status and education, and provide information regarding the occupation status and labor conditions of each member of the household.

For this article, we include workers in urban areas in both countries whose ages are between 15 and 65 years old. Following Canavire-Bacarreza and Rios-Avila (2015), we exclude rural workers due to the volatility of rural labor markets. In total, the dataset contains more than 54,000 observations for Bolivia and over 1.1 million observations for Colombia. On average, there are approximately 6,000 observations per year for Bolivia and approximately 140,000 observations per year for Colombia.

In both Bolivia and Colombia, household surveys inquire about monthly labor income. To make the measures comparable, we define labor income in the following way: For employed workers, the monthly labor income consists of the net salary after legal deductions. On the other hand, labor income for self-employed workers is the available income for household consumption after discounting the costs related to their occupation.

To account for the differences in income related to differences in hours worked and to full- or part-time labor, we divide the reported monthly income by the monthly hours worked, thus obtaining hourly wages. Then, we adjust the computed hourly income for inflation using the average annual Consumer Price Index for each country. After obtaining real hourly wages for each country, they are converted to 2010 United States dollars (USD) using the exchange rate for each country adjusted for purchasing power parity (PPP). Thus, the final wage variable is the logarithm of the real hourly wage in 2010 USD (PPP).

Furthermore, we classify the labor force based on three criteria in order to provide further insights about the subsets of the population that have been the most affected (positively or negatively) by the changes in the wage distribution: gender, educational attainment and sector of the economy in which the person works. The categories in both datasets are defined in the same way to avoid differences in the results caused by discrepancies in the classification of the workforce.

Education in this analysis is divided into three levels: the first, labeled "Primary Education," includes all workers who have no formal education or whose highest education degree is elementary school or lower. "Secondary Education" includes those workers who have an education level comparable to high school in the United States ("Secundaria" in Bolivia and "Bachillerato" in Colombia). Finally, workers who have post-secondary education, either a university degree or technical education, are included in the "Tertiary Education" level. Including education allows us to split the workforce by skill, since more education implies a higher level of human capital.

To consider the economic sector, we divide the sample into public and private sector workers. A worker belongs to the public sector if he/she works at a public entity at any level (national, regional or local) or if the company where he/she works is owned by the state. Then, we split the private sector into formal and informal sectors using the International Labor Organization definitions.[7] A worker is in the informal sector if he/she is self-employed, a domestic employee, an unpaid employee at a family organization, or works at a firm with five or less employees. If a worker does not fit into any of these criteria, he/she is considered to be working in the formal sector. The sector distinction is particularly relevant for developing countries because of their high rates of job informality (see Figures 1 and 2) and because of the differences in rules and institutions in the formal and informal sectors.

Table 2 shows the composition of the labor market in Bolivia and Colombia. In relation to Colombia, Bolivia has higher workforce participation among males and similar levels of education. The rates of informality in both countries are still very high: Approximately one-half of the workforce works in the informal sector in both Bolivia and Colombia.

Table 2—: Discrete variable categories and relative frequencies. Values in parentheses are corrected for sample weights

Variable		**Frequency**	
Name	**Categories**	**Bolivia**	**Colombia**
Gender	Male	58.8% (59.1%)	52.4% (53.4%)
	Female	41.2% (40.9%)	47.6% (46.6%)
Education	Primary Education	29.5% (31.2%)	36.7% (34.9%)
	Secondary Education	39.1% (38.7%)	31.6% (30.4%)
	Tertiary Education	31.4% (30.1%)	31.7% (34.8%)
Economic Sector	Public	16.5% (15.1%)	5.1% (4.4%)
	Formal	28.5% (30.0%)	37.0% (42.2%)
	Informal	55.0% (54.9%)	57.9% (53.4%)
Number of Observations		54,631	1,120,837

The main descriptive statistics for real hourly wages in each country are in Table 3. Figures 3 and 4 show the wage probability density function by year for Bolivia and Colombia, respectively. These figures suggest that real wages in Bolivia have exhibited a steady upward trend during the analyzed period, whereas real wages in Colombia did not increase as much. Instead, the wage distribution in Colombia has compressed around the median, suggesting higher levels of wage concentration. This phenomenon is especially notable in the last two years of the studied period. In addition, we observe that during the period of study, the mean hourly wage in Bolivia was higher than that in Colombia. Interestingly, this is true only after accounting for PPP, as wages in Colombia are higher than in Bolivia after converting to United States dollars using the official exchange rate for each country.

It is worth noting that both countries have a national minimum wage. However, there are two reasons why it does not constitute a lower bound for the wage distribution. First, self-employed workers constitute approximately 40% of the

[7] See Hussmanns (2004) for a discussion of the definitions of informal job and informal sector.

Table 3—: Descriptive Statistics, Real Hourly Wage in 2010 USD PPP. Numbers in parentheses are corrected for sample weights

(a) Bolivia.

N	54,631
Mean	4.573 (4.438)
Median	3.237 (3.056)
Standard Deviation	6.198 (6.928)
Minimum	0.012
Maximum	660.451

(b) Colombia.

N	1,120,837
Mean	3.561 (4.085)
Median	2.365 (2.479)
Standard Deviation	6.408 (7.556)
Minimum	0.000
Maximum	2,625.314

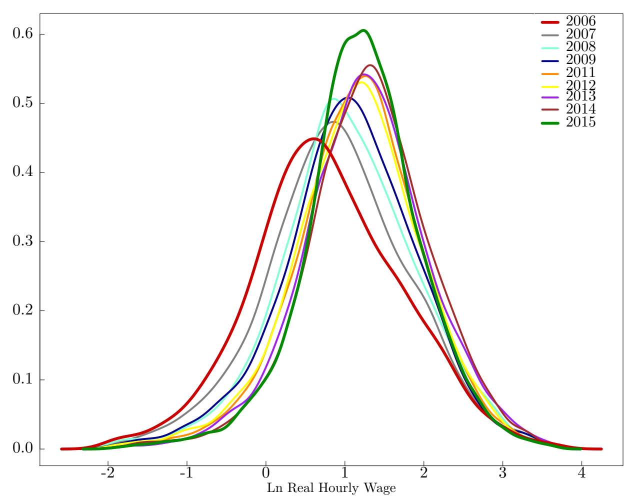

Figure 3. : Wage densities by year for Bolivia. Densities were calculated using a second-order Gaussian kernel. The bandwidths were chosen using Silverman's (1986) rule-of-thumb approximation

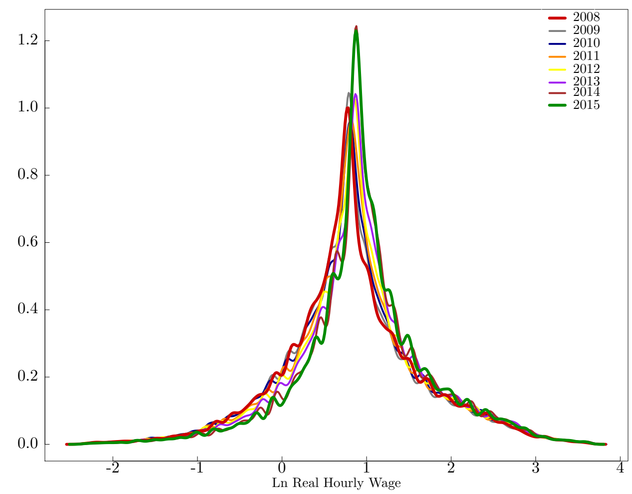

Figure 4. : Wage densities by year for Colombia. Densities were calculated using a second-order Gaussian kernel. The bandwidths were chosen using Silverman's (1986) rule-of-thumb approximation

labor force in both countries (INE, 2017; DANE, 2017). Since these workers do not have employment contracts that guarantee the enforcement of minimum wage laws, it is possible for this type of worker to earn less than the minimum wage. Second, the wage distributions used in this article are measured in hours, whereas the minimum wage in both countries is expressed in monthly terms for full-time jobs. Legislation in both countries stipulates that no worker can work more than 48 hours a week. Thus, it would be possible to obtain a minimum hourly wage. Nevertheless, data from both countries suggest that this measure is not always enforced. More than 25% of formal sector workers in the samples for Bolivia and Colombia work over 48 hours (INE, 2017; DANE, 2017). Therefore, even in companies that comply with minimum wage laws, workers may earn an hourly wage below the equivalent minimum hourly wage. Since a lower bound discontinuity is not present in the data, FPCA can be applied to each family of distributions.

In addition to the previously presented descriptive statistics, we calculate the 90/10, 90/50 and 50/10 wage gaps over time to examine how has wage inequality changed over time (see Figures 5 and 6). These gaps are calculated by dividing the earnings of the highest percentile by the earnings of the lowest percentile. Measuring these three ratios allows us to assess changes in overall inequality, at the top and at the bottom of the distribution, respectively. In both countries, wage inequality has decreased significantly. In Bolivia, the main changes in wage inequality are seen at the top of the wage distribution, whereas the reduction in wage inequality in Colombia is more evident for the lowest wages.

Tables 4 and 5 compare the wage of some subsets of the population in Bo-

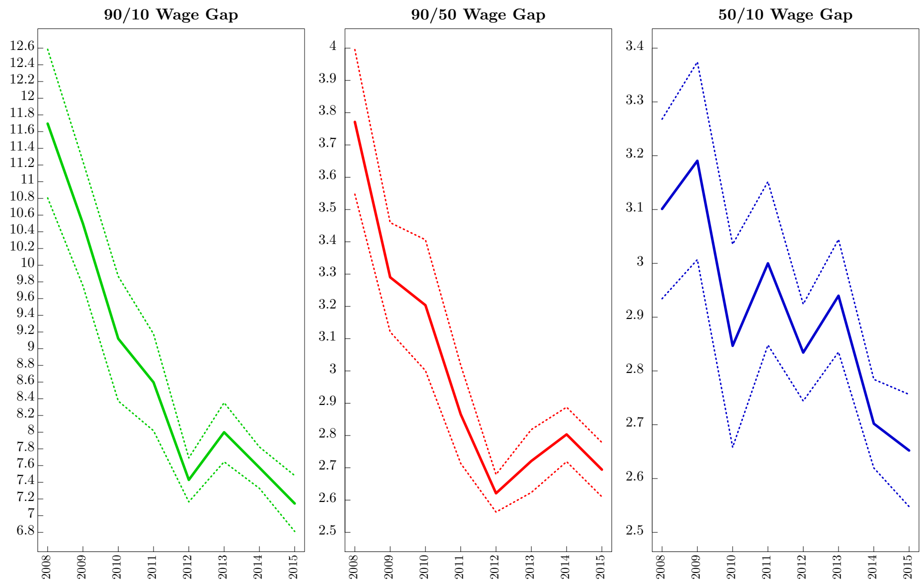

Figure 5. : Wage gaps by year - Bolivia. Dotted lines represent the 95% confidence interval

Figure 6. : Wage gaps by year - Colombia. Dotted lines represent the 95% confidence interval

livia and Colombia, respectively. In both countries, males earn more, and as expected, skilled workers earn a wage premium over their unskilled counterparts. Additionally, workers in the public sector in both countries have higher wages.

Table 4—: Mean Real Hourly Wage (in 2010 USD PPP) by some characteristics - Bolivia

Variable	**Mean**		**Difference**	**P-Value**
Gender	Male 4.749	Female 4.321	0.428	0.000
Education	Tertiary Education 6.500	Secondary Education or less 3.691	2.809	0.000
Sector	Public 7.245	Formal Private 4.601	2.644	0.000
	Formal Private 4.601	Informal Private 3.757	0.844	0.000

Table 5—: Mean Real Hourly Wage (in 2010 USD PPP) by some characteristics - Colombia

Variable	**Mean**		**Difference**	**P-Value**
Gender	Male 3.733	Female 3.373	0.360	0.000
Education	Tertiary Education 6.191	Secondary Education or less 2.340	3.851	0.000
Sector	Public 8.855	Formal Private 3.961	4.894	0.000
	Formal Private 3.961	Informal Private 2.839	1.121	0.000

V. Functional Principal Component Analysis

A. *Overview*

Functional principal component analysis (hereafter, FPCA) is the adaptation of multivariate principal component analysis (PCA) to functional data. Like PCA, FPCA is a technique of dimensionality reduction that decomposes data into the most important modes of variation (components). However, as the data are functional (each observation is a function defined on a common bounded interval), the components are not random variables defined in $\mathbb{R}^n$, where n is the number of observations, but random functions defined in the $\mathcal{L}^2$ space of square-integrable functions.

Kneip and Utikal (2001) propose the use of FPCA to characterize the evolution of a family of probability density functions $\{f_t\}_{t=1}^T$ over time. Based on the Karhunen-Loève decomposition, they represent each density of $\{f_t\}_{t=1}^T$ as follows:

$$(1) \qquad f_t = f_\mu + \sum_{j=1}^{L} \theta_{tj} g_j.$$

Equation (1) states that the FPCA decomposition consists in expressing each density f_t as the sum of the mean of the family of distributions $f_\mu = T^{-1} \sum_{t=1}^{T} f_t$ and a time-specific deviation from the mean $\sum_{j=1}^{L} \theta_{tj} g_j$. These deviations will be referred to as deformations, as in Kneip and Utikal (2001). If the deformation of the probability density function is positive (negative) at wage level w in year t, it implies that the proportion of the population earning a wage of w in year t is greater than (less than) the average proportion of the population that earned that wage during the period of study. Moreover, the magnitude of the deformation tells us how large are the shifts in proportion at wage level w. Since deformations are defined for all the points in the support of the wage distribution functions, we can characterize the shifts in proportion across the whole wage distribution.

Each deformation has two terms: A time-invariant common component (g_j), which corresponds to the j-th eigenfunction from the FPCA (Kneip and Utikal, 2001), describing the cross-sectional differences in the distribution for a given year and common mean distribution and a time-varying strength coefficient θ_{tj}, which captures the evolution of densities over time, allowing the identification of the differences and similarities of the distributions (Huynh et al., 2016). The number of components needed to fully characterize the family of probability density functions is given by L, the number of nonzero eigenvalues of the empirical covariance operator.

B. Estimation Strategy

As previously described, FPCA decomposition requires the estimation of an empirical covariance operator. As an alternative, Kneip and Utikal (2001) propose the following procedure to find g_j and θ_{tj}. They estimate the $T \times T$ matrix M, whose elements are defined by

$$(2) \qquad M_{ts} = \langle f_t - f_\mu \rangle \langle f_s - f_\mu \rangle \ \forall t, s,$$

where the scalar product $\langle \xi_1, \xi_2 \rangle$ is defined by $\langle \xi_1, \xi_2 \rangle = \int \xi_1(x) \xi_2(x) dx$.

The eigenvectors $\mathbf{p}_r = (p_{r1}, \ldots, p_{rT})$ and corresponding nonzero eigenvalues $\lambda_1 \geq \lambda_2 \cdots \geq \lambda_L$ of the matrix M are related to g_j and θ_{tj} in equation (1) as follows:

$$(3) \qquad \theta_{tr} = \lambda_r^{1/2} p_{tr},$$

(4) $$g_r = \lambda_r^{-1/2} \sum_{t=1}^{T} p_{tr} f_t = \frac{\sum_{t=1}^{T} \theta_{tr} f_t}{\sum_{t=1}^{T} \theta_{tr}^2}.$$

The estimation methodology presented in Kneip and Utikal (2001) applies to the estimation of continuous univariate distributions. Huynh et al. (2011) extend that method to allow the incorporation of categorical variables by using Li and Racine's (2003) technique to calculate kernel estimation of mixed continuous and discrete variables. We use this extension of the methodology to perform the estimations in order to account for the heterogeneity of the labor force and to assess the differences in wage dynamics across groups.

Let X denote the continuous variable, and let $X^d = \{x_1^d, x_2^d, x_3^d\}$ be the set of categorical variables x_k^d. The procedure presented by Huynh et al. (2011) to estimate θ_{tj} and g_j in (1) consists of three steps. First, each probability density function at time t is estimated as follows:

(5) $$\widehat{f}_{t,h} = \frac{1}{n_t} \sum_{i=1}^{n_t} \frac{1}{h} W\left(\frac{x - X_{it}}{h}\right) L_{\upsilon,x^d,X_i^d t}.$$

In equation (5), $W(\cdot)$ is a univariate kernel estimator for the continuous variable, and $L_{\upsilon,x^d,X_{it}^d} = \prod_{s=1}^{r} l(x^{d_s}, X_{it}^{d_s}, \upsilon)$ is the product kernel estimator of the discrete variables. The bandwidth used in the kernel estimation of the continuous variable is h, whereas υ is the bandwidth vector used for the kernel estimation of the discrete variables. For our estimations, we employ a second-order Gaussian kernel estimator.

Using these estimations, the elements of $\widehat{M}$, the estimator of M, are computed using equation (2).

The eigenvectors $\mathbf{p}_r = (p_{r1}, \ldots, p_{rT})$ and corresponding nonzero eigenvalues $\lambda_1 \geq \lambda_2 \cdots \geq \lambda_T$ of the matrix $\widehat{M}$ are then calculated. $\widehat{\theta}_{tr}$ and $\widehat{g}_r$ are estimated analogously to (3) and (4) using a different set of kernel estimators with bandwidth b:

(6) $$\widehat{\theta}_{tr} = \widehat{\lambda}_r^{1/2} \widehat{p}_{tr},$$

(7) $$\widehat{g}_r = \widehat{\lambda}_r^{-1/2} \sum_{t=1}^{T} \widehat{p}_{tr} \widehat{f}_{t,b} = \frac{\sum_{t=1}^{T} \widehat{\theta}_{tr} \widehat{f}_t}{\sum_{t=1}^{T} \widehat{\theta}_{tr}^2}.$$

Huynh et al. (2011) prove that their method keeps the consistency of θ_{tr} and the asymptotic normality of g_r.

The bandwidth choice strategy is the one adopted by Huynh et al. (2016). First, we use Silverman's (1986) rule-of-thumb approximation to calculate the bandwidth for the wage distributions $\tilde{b}$ and indicator functions to compute bandwidths for the discrete variables. These bandwidths are then rate corrected by setting $\widehat{h} = \tilde{b}^{5/4}$ and $\widehat{b} = \tilde{b} \times T^{-1/5}$, as suggested by Kneip and Utikal (2001) and Huynh et al. (2011).[8]

VI. Results

We present the results from the FPCA decomposition in four parts. First, the dynamic scree plots are shown to determine how many components are needed to explain a good proportion of the total density temporal variability. Second, we use the dynamic strength components $\widehat{\theta}_{tr}$ to analyze the evolution of the wage distribution over time. Third, the common components $\widehat{g}_r$ are presented to identify the points in the distribution where changes have occurred. Finally, we present total deformations to show the overall movement of the wage distribution and to explore how different groups of the labor force have contributed to total variation.

A. *Dynamic Scree Plot*

The dynamic scree plots (Figure 7) gather the proportion of total change in the distribution attributable to each component j by plotting the ratio of each estimated eigenvalue $\widehat{\lambda}_j$ and the total sum of estimated eigenvalues $\sum_{i=1}^{T} \widehat{\lambda}_i$. In the analysis for Bolivia, the first and second components explain an important proportion of total variation (47.2% and 34.5%, respectively). For Colombia, the first and second components contribute 59.5% and 16.1%, respectively, of total variation. To explain as much of the variation as possible, the first two components will be used for each country.

B. *Dynamic Score Components*

The dynamic score components $\widehat{\theta}_{tr}$ capture the evolution over time of the family of wage distributions. The first two dynamic score components for Bolivia and Colombia are plotted in Figure 8.

The dynamic score components for Bolivia change over time in opposite directions except in two periods: both components decrease in 2011 and increase in 2012. The second dynamic score component, while decreasing after 2012, has values closer to zero than first dynamic score component during the same time

[8] The bandwidths used for estimations are presented in the Appendix

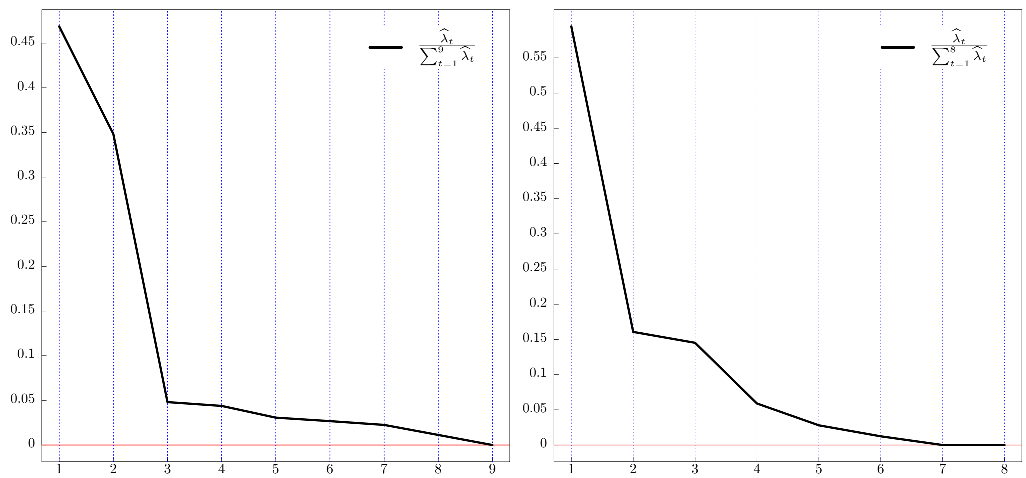

Figure 7. : Dynamic scree plot for Bolivia (left) and Colombia (right)

frame. Then, the net effect is positive, and the wage distribution moves toward higher values.

In the case of Colombia, $\widehat{\theta}_{t,1}$ shows an increasing trend across most of the period, only starting to decrease after 2014, suggesting slow but constant growth in wages. On the other hand, $\widehat{\theta}_{t,2}$ exhibits a downward trend until 2011, when it begins to recover. The joint movement of both components suggests a sluggish evolution of wages between 2008 and 2013, with moderate growth in 2014 and 2015.

As the dynamic score components change over time for the wage distribution, we contrast them with some macroeconomic series to see if the movement of the wage distribution is similar to other variables. The correlation coefficients of the first two dynamic score components with select macroeconomic variables are presented in Table 6. We calculate these correlations as a way to discover comovements between the series.

In Bolivia, the first dynamic score component is negatively correlated with the unemployment and informality rates. Furthermore, the correlation of the first dynamic strength component with GDP per capita growth is positive, in line with the findings of several authors (e.g., King and Rebelo, 1999; Xu et al., 2015). The correlation between the investment/GDP ratio and the first component is also positive. This suggests that wages have behaved similarly to output. The second dynamic strength component has is negatively correlated with occupation rates and GDP per capita growth, while it is positively correlated with unemployment and informality. In this case, we observe that wages and labor aggregates have moved in opposite directions. From the behavior of both components, we can see that wages in Bolivia are moderately related to both economic activity and labor

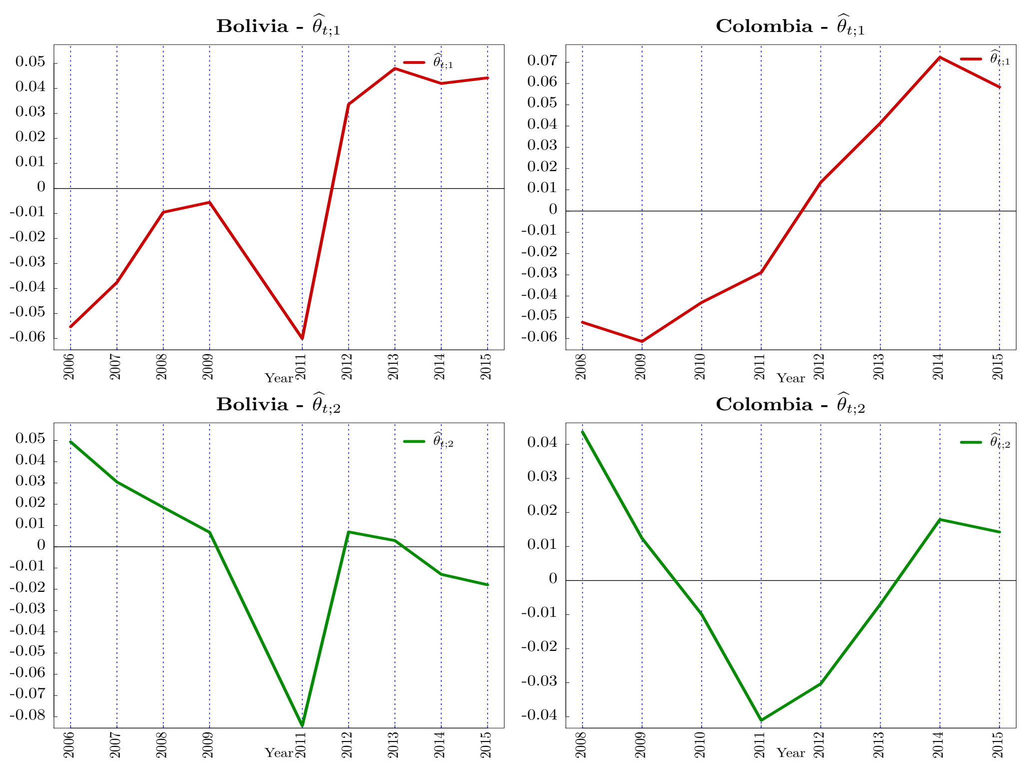

Figure 8. : First two dynamic score components $\widehat{\theta}_{tr}$: $\widehat{\theta}_{t1}$ (top) and $\widehat{\theta}_{t2}$ (bottom) for Bolivia (left) and Colombia (right)

market dynamics.

In Colombia, there is a strong positive correlation between the first dynamic score component and occupation rates, coupled with a strong negative correlation between wages and unemployment. These correlations suggest that wages are very related to the levels of employment. Moreover, we find a high positive correlation between this component and the investment/GDP ratio. The correlation between the first common component and GDP growth, albeit positive, is not as strong. Robin (2011) finds that wages in the middle of the distribution are less procyclical than those at the extremes. Since the wage distribution in Colombia is very concentrated around the median, the total correlation should be smaller than it would be if the distribution had a higher standard deviation. This might also explain why the correlation between wages and GDP growth is stronger in Bolivia. The correlations of the second dynamic strength component with the unemployment and informality rates are negative, as for the first component, thus reinforcing the correlation between wages and levels of employment. Nevertheless, the correlation between this component and GDP growth is negative. Therefore, wages in Colombia seem more related to changes in the labor market than to variations in output.

Table 6—: Correlation coefficients for $\widehat{\theta}_{t,1}$ and $\widehat{\theta}_{t,2}$ and some macroeconomic variables. Source of macroeconomic series: DANE (2017), World Bank (2017), INE (2017)

(a) Bolivia

Variable	**Correlation with $\widehat{\theta}_{t,1}$**	**Correlation with $\widehat{\theta}_{t,2}$**
Unemployment Rate	-0.555	0.585
Occupation Rate	-0.477	-0.214
Informality Rate	-0.419	0.250
GDP per capita growth	0.389	-0.131
Inflation Rate	-0.371	-0.158
Investment/GDP ratio	0.573	-0.758

(b) Colombia

Variable	**Correlation with $\widehat{\theta}_{t,1}$**	**Correlation with $\widehat{\theta}_{t,2}$**
Unemployment Rate	-0.972	-0.051
Occupation Rate	0.871	-0.451
Informality Rate	-0.917	-0.297
GDP per capita growth	0.261	-0.615
Inflation Rate	-0.319	0.657
Investment/GDP ratio	0.855	0.214

C. *Common Components*

The common components $\hat{g}_r$ gather the cross-sectional differences between a distribution for a given set of categories and the mean distribution. From Equation (7), it should be evident that there are as many $\widehat{g}_r$ as possible combinations of values for the categorical variables.[9] In this case, there are $2 \times 3 \times 3 = 18$ different combinations. To summarize the behavior of all $\widehat{g}_r$, they are summed and gathered as *total common components* (TCC) $\tilde{g_r}$:

$$\tilde{g_r} = \sum_{x_i^d \in X^d} \widehat{g}_r.$$

The first two TCC for Bolivia and Colombia are displayed in Figure 9. In the case of Bolivia, both common components show a change from low levels of wages to higher levels, as seen in the evolution of the wage distribution over time (Figure 3). On the other hand, the first common component for Colombia shows little deviation in the extreme values and considerable movement around the median of the distribution, which is consistent with the concentration of wages around the median. The second common component for Colombia shows volatility in the center of the distribution and few differences at the extremes of the distribution.

D. *Dynamic Deformations*

The dynamic deformation $\widehat{\theta}_{tr}\widehat{g}_r$ shows the overall movement of the wage probability density function over time. It combines the differences over time due to different dynamic score components $\widehat{\theta}_{tr}$ and cross-sectional differences captured by the common components $\widehat{g}_r$.

To present the results in a more intuitive way, we rearrange equation (1) as in Kneip and Utikal (2001). Notice that in year $t = 1$, equation (1) is

$$f_1 = f_\mu + \sum_{j=1}^{L} \theta_{1j} g_j.$$

Subtracting this expression from equation (1) and rearranging, we obtain

$$f_t = f_1 + \sum_{j=1}^{L} g_j(\theta_{tj} - \theta_{1j}). \tag{8}$$

Using equation (8), we can interpret the dynamic deformation in time t as the deviation of the wage distribution in time t from the wage distribution at the

[9] Since calculating $\widehat{g}_r$ entails the estimation of $\widehat{f}_{t,b}$, the bandwidths vector change as the values of the categorical values change, leading to different kernel estimations and different common components.

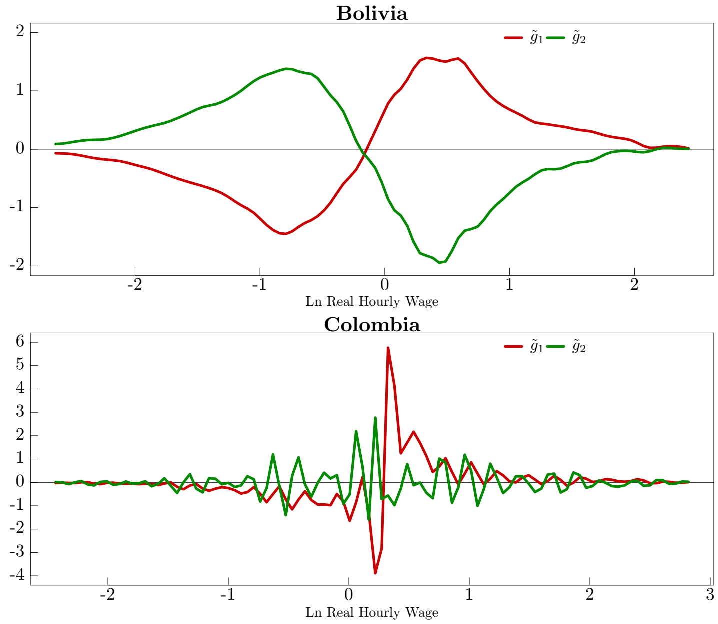

Figure 9. : First two total common components $\tilde{g}_r = \sum_{x_i^d \in X^d} \widehat{g}_r \;\; r = 1, 2$ for Bolivia (top) and Colombia (bottom)

beginning of our period of study. Then, we can interpret a positive (negative) deformation at wage level w in year t as an increase (decrease) of the proportion of the population earning a wage of w in relation to the first year we considered (2006 for Bolivia and 2008 for Colombia).

Furthermore, we employ the TCC ($\tilde{g}_r$) to provide a general view of the changes. The total deformation in period t for component r is equal to:

$$\tilde{g}_r(\widehat{\theta}_{tr} - \widehat{\theta}_{1r}) = \sum_{x_i^d \in X^d} \widehat{g}_r(\widehat{\theta}_{tr} - \widehat{\theta}_{1r}).$$

TCC can be decomposed to reflect the total component for a specific value k of any discrete variable x_j^d. By computing total components for specific values, it is possible to analyze the wage dynamics for specific subsets of the population. From the total components for a specific category, it is possible to obtain the total deformation for such a value:

$$\left[\tilde{g}_r(\cdot, x_j^d = k)\right](\widehat{\theta}_{tr} - \widehat{\theta}_{1r}) = \sum_{x_i^d,\, x_j^d = k} \left[\tilde{g}_r(\cdot, x_j^d = k)\right](\widehat{\theta}_{tr} - \widehat{\theta}_{1r}). \tag{9}$$

Note that the $\widehat{\theta}_{tr}$ used in computing the conditional total deformation in (9) are the same as those used in the unconditional total deformation. Hence, the relationship between the conditional and unconditional total deformations depends only on $\tilde{g}_r$. Using this result, Huynh et al. (2016) calculate the share of variation accounted for by each value of the discrete variable by regressing $\tilde{g}_r(\cdot, x_j^d = k)$ on $\tilde{g}_r$.

In the remainder of this section, only the first (and largest) component deformation will be analyzed for brevity. Moreover, even though it is possible to obtain deformations for all periods, this analysis will focus on the deformations for the last period (2015) in order to obtain the total movement of the wage distribution over the period of interest. The proportion of change according to each value of the discrete variables included in the estimation for the first components in each country are presented in Table 7.

Table 7—: Share of variation accounted for by each category of the discrete variables

Categories	**Share of variation**					
	Bolivia - $\widehat{\theta}_{,1}\widehat{g}_1$			**Colombia - $\widehat{\theta}_{,1}\widehat{g}_1$**		
	Male	**Female**	**Total**	**Male**	**Female**	**Total**
	67.5%	32.5%	100.0%	52.7%	47.3%	100.0%
Education						
Primary Education	9.0%	13.9%	22.9%	20.1%	13.8%	33.9%
Secondary Education	47.0%	11.2%	58.2%	21.5%	18.1%	39.6%
Tertiary Education	11.5%	7.4%	18.9%	11.1%	15.3%	26.5%
Sector						
Public	3.3%	1.9%	5.2%	0.0%	-0.1%	-0.1%
Formal	20.2%	9.5%	29.8%	33.0%	31.5%	64.4%
Informal	44.0%	21.0%	65.0%	19.7%	15.9%	35.7%

Figure 10 shows the total deformation for the first component $(\tilde{g}_1(\widehat{\theta}_{t;1} - \widehat{\theta}_{1;1}))$ for each country. In Bolivia, the magnitude of the changes in density is not very large, but it occurs at a large interval of values, which means that the increase in wages in Bolivia has been rather uniform. The behavior of the wage deformation is similar on both sides of the median, further supporting the idea of uniform growth in wages.

In Colombia, the total deformation for the first component suggests that both tails of the distribution have stayed stable over time. Changes to the left of the median have been less drastic but encompass a wider interval of values. The largest two peaks of variation are around the median, suggesting an important increase in wage concentration. The positive-valued peak of variation in larger in absolute value than the negative-valued one, suggesting that the increase of the share of the population earning wages around the median wage more than compensate the drastic drop in proportion of workers who earn slightly less than the median wage. Moving to the right tail of the distribution, variation is higher than that of the left tail but occurs over a smaller interval, thus fading away faster. To summarize, the movement of the whole wage distribution in Colombia between 2008 and 2015 is characterized by slight growth in wages paired with a considerable increase in wage concentration around the median wage.

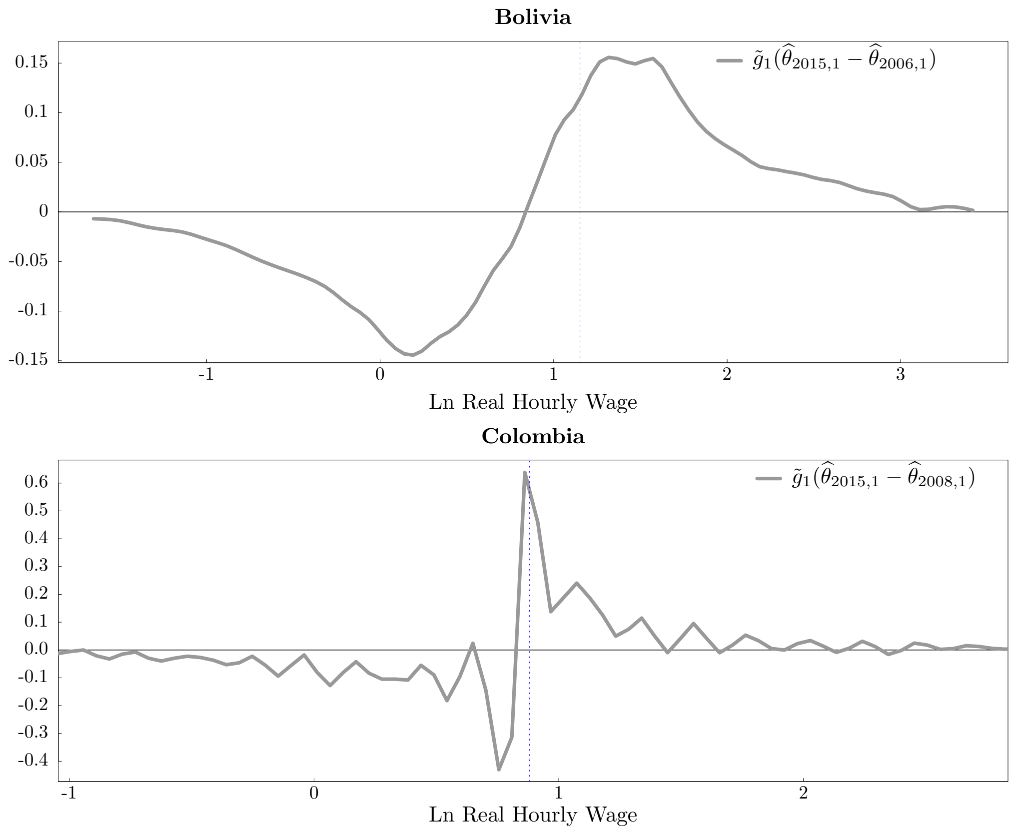

Figure 10. : Total deformation for the first component - Bolivia (top) and Colombia (bottom). The dotted line represents the median wage, corrected for sample weights

In the following subsections, we analyze how the total change is distributed between different groups of the workforce by comparing the total deformation for a specific category to the total deformation of the wage distribution. The graphs in these subsections represent total deformation as the shaded area and group-specific deformations as solid lines. The shares of variation shown in table 7 correspond to the percentage of the shaded area that is at or below the solid lines.

Differences by gender. — The differences in wage evolution by gender in Bolivia and Colombia are depicted in Figure 11. The changes in wages in Bolivia have mainly been due to changes in the wages of males, who have benefited from both a decrease in the proportion of workers who earn low wages and an increase in the proportion of workers earning higher wages. The wages of females have exhibited similar behaviors, but their magnitudes have been smaller. Women account for larger shares of variation at both extremes of the distribution.

On the other hand, the variation in wages in Colombia has been distributed more equally, although males accounted for a slightly larger share of total variation. Note, however, that females who earn low salaries exhibited less variation in wages than did low-paid males. As wages increase, so does the proportion of the change attributable to variation in the wages of females.

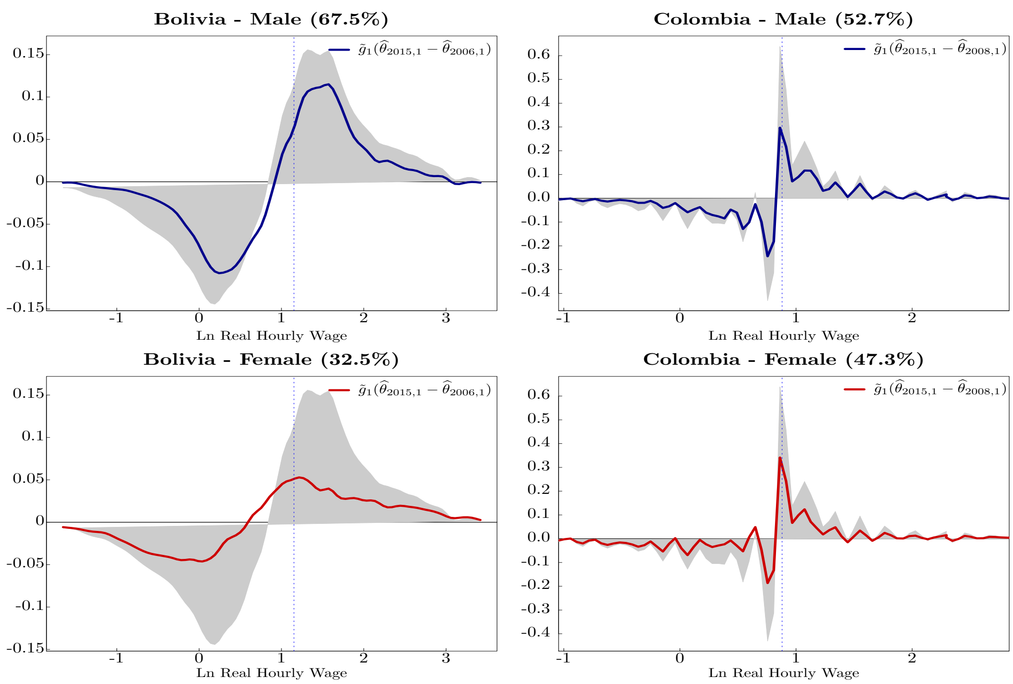

Figure 11. : Total deformation by gender: male (top) and female (bottom) in Bolivia (left) and Colombia (right). The percentages show the share of total variation attributed to each group. The shaded area represents the total deformation for the first component ($\tilde{g}_1(\widehat{\theta}_{t;1} - \widehat{\theta}_{1;1})$) in 2015. The dotted line represents the median wage, corrected for sample weights

In Colombia, the wages of females at the bottom of the distribution did not change as much those of males. Given that, on average, women earn less, this reduced share points to a sticky floor phenomenon. Such a phenomenon is less evident in Bolivia, where women who earned the lowest wages exhibited more variation than men. For higher values of wages in Colombia, the share of total variation attributed to females was similar to that attributed to men.

Differences by education. — The education levels of the Bolivian and Colombian workforces are not very dissimilar, but the shares of wage variation accounted for by each type of worker are noticeably different. In both countries, the most educated workers account for the smallest share of the change in wages. Colombian workers with tertiary education account for a larger proportion of the total change than their Bolivian counterparts, as can be seen in Figure 12. Indeed, over one-half of the total variation in wages in Bolivia is accounted for by workers with secondary education. Furthermore, workers with secondary education contribute more to total variation than more educated workers at all levels of remuneration, whereas in Colombia, despite their smaller contribution to total wage variation, the most skilled workers explain most of the variation at the highest levels of remuneration. This indicates that in Bolivia, more education does not translate into higher variation in wages.

Another difference in the wage dynamics of these countries is that Colombian females with higher education account for a larger proportion of total wage variation than similarly educated males, while in Bolivia, males account for a higher share of the total wage change. This means that the Colombian gender wage gap is reduced as the education level increases. In Bolivia, the opposite is true: female workers with primary education account for a higher share of total wage variation. For Bolivian women, increasing their education level does not imply a higher share of the total wage change.

Differences by sector. — In Figure 13, the total wage deformation for both countries is split by economic sector. In the case of Bolivia, two facts stand out: First, even though the Bolivian public sector employs more than 15% of the workforce, it does not make a large contribution to total wage variation. Second, more than one-half of the total wage change in Bolivia is attributable to the informal sector, implying that workers in the formal sector have not benefited as much from the general wage increase as informal workers have. This might hinder job formalization, since workers can reap larger increases in wages by remaining in the informal sector.

The Colombian case is the opposite of the Bolivian case, as the formal sector is the main contributor of wage variation. It is worth noting that like Bolivia, Colombia has high levels of job informality. Another remarkable result from Colombia is that real wages in the public sector have remained stable between 2008 and 2015.

VII. Conclusions

Throughout this article, we explore the differences in wage evolution in Bolivia and Colombia, two developing countries that have adopted different economic policies. To do so, we employ a decomposition method based on functional principal component analysis (FPCA), first developed by Kneip and Utikal (2001) and

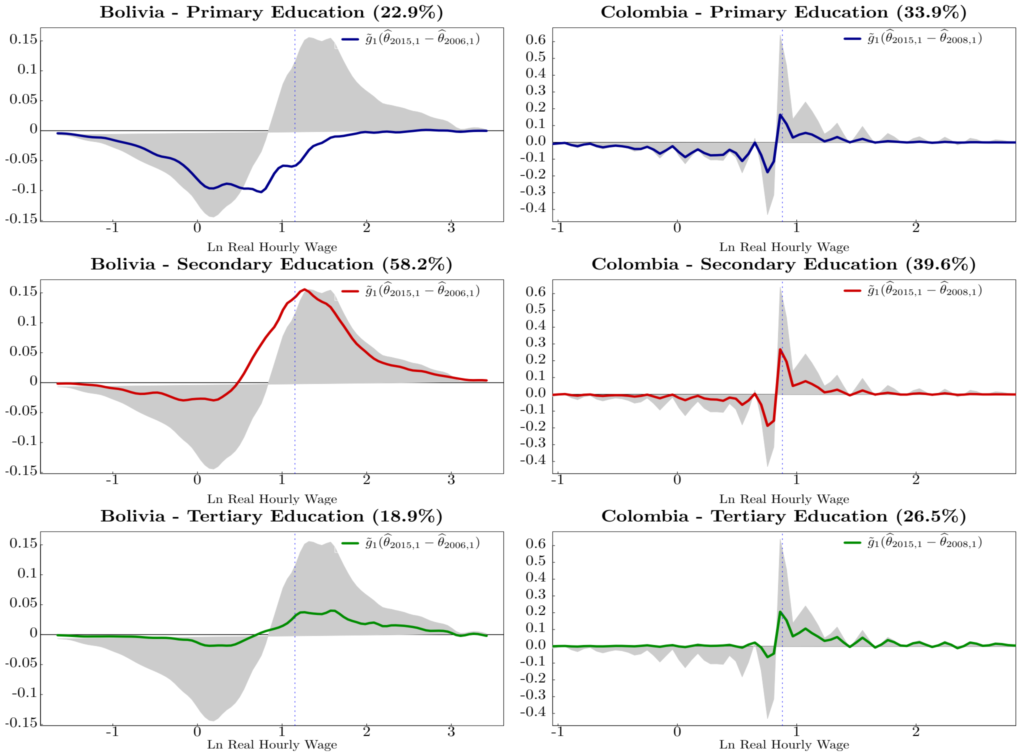

Figure 12. : Total deformation by education level: primary education (top), secondary education (middle) and tertiary education (bottom) in Bolivia (left) and Colombia (right). The shaded area represents the total deformation for the first component ($\tilde{g}_1(\widehat{\theta}_{t;1} - \widehat{\theta}_{1;1})$) in 2015. The dotted line represents the median wage corrected for sample weights

Huynh et al. (2011), to analyze the behavior of the whole wage distribution. This methodology has several features that makes it suitable for this kind of analysis, such as decomposition into components that contribute in different ways to the dynamics and the ability to characterize wage evolution for specific groups of the population. Another advantage of FPCA, highlighted by Huynh et al. (2016), is the ease of graphical representation of the changes in the distributions, thus facilitating the interpretation of the underlying dynamics.

To assess differences in wage dynamics, we use data from urban household surveys in both countries. The study period ranges from 2006, when Bolivia shifted toward socialist policies under President Evo Morales, to 2015. During the same period, Colombia was going through a process of national security improvement and free-market policy adoption. Due to data availability, the data from Colombia encompass the eight-year period from 2008 to 2015. This was a period of accelerated economic growth in both Bolivia and Colombia, but the wage dynamics in both countries exhibited important differences.

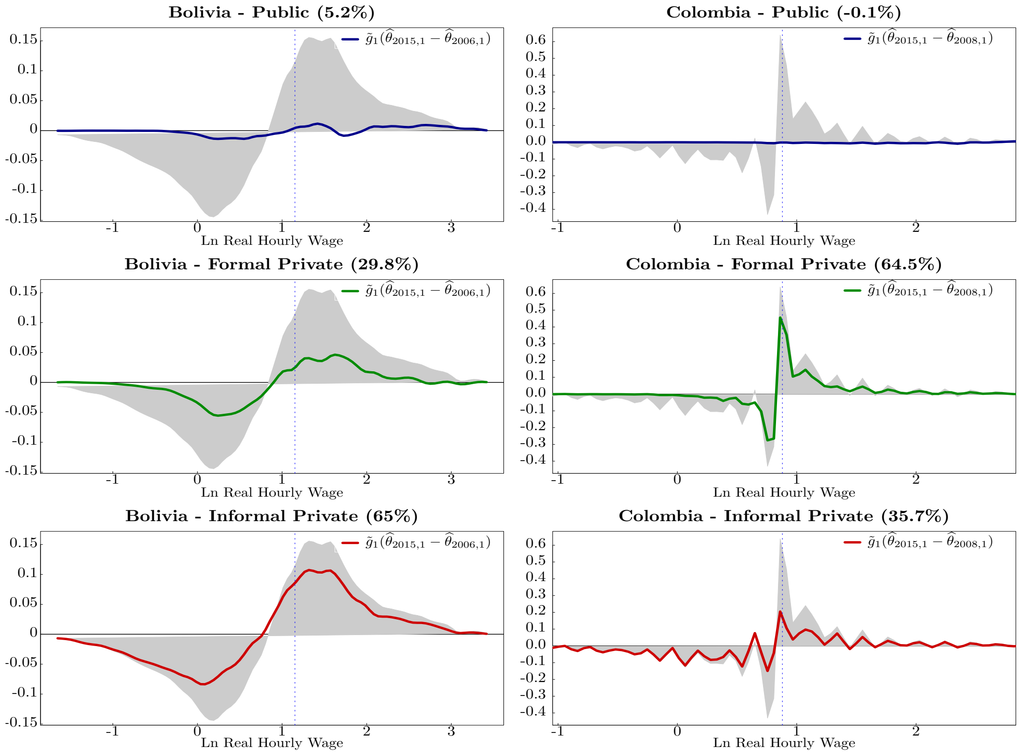

Figure 13. : Total deformation by sector of the economy: public sector (top), formal sector (middle) and informal sector (bottom) in Bolivia (left) and Colombia (right). The shaded area represents the total deformation for the first component ($\tilde{g}_1(\widehat{\theta}_{t;1} - \widehat{\theta}_{1;1})$) in 2015. The dotted line represents the median wage, corrected for sample weights

In Bolivia, there has been a steady growth in wages between 2006 and 2015, which has been roughly uniform across the whole wage distribution. Wage concentration has also slightly increased over the study period. On the other hand, while wages in Colombia have increased slowly, the main phenomenon observed in Colombia is an important increase in wage concentration around the median. These patterns are consistent with previous findings for both countries (Canavire-Bacarreza and Rios-Avila, 2015 for Bolivia; Morales and Medina, 2016 for Colombia; and Aristizábal-Ramírez et al., 2015 for both). In both countries, this behavior is linked to an increase in labor demand, which is more evident in the Colombian case.

However, the differences go beyond this general behavior. There are also disparities in terms of which groups have benefited the most from these changes in wages. For instance, wage variation in Colombia has been distributed more equally between genders, while the changes in wages for Bolivian males have been significantly larger than those for women. Interestingly, at both extremes of the wage distribution, in Bolivia, females accounted for more variation than men, whereas in Colombia, the differences in the share of variation were larger at the lowest levels of remuneration, suggesting a sticky floor phenomenon for women in Colombia, as found by Badel and Peña (2010).

Both Bolivia and Colombia still have large proportions of workers with low levels of education. Nevertheless, the returns to education in terms of wage variability are not homogeneous. Bolivian workers with secondary education have benefited more from the increase in wages than those with higher education, regardless of the wage level. Thus, the most skilled workers in Bolivia have not experienced a premium in wage variation compared to less educated workers. Colombian workers with higher education have also accounted for smaller shares of variation than less educated workers, but their returns differ from those of their Bolivian counterparts in three ways: First, they received a larger share of the change than did comparable Bolivian workers. Second, Colombian workers with higher education received most of the change in wages at the highest levels of remuneration, implying that they have an advantage in wage variability after a certain wage threshold. Finally, female workers with tertiary education accounted for a larger proportion of the changes in wages than did similarly educated males, suggesting that, unlike in Bolivia, the gender wage gap in Colombia is reduced for the most skilled female workers.

The analysis by economic sector yields other noteworthy results. The informal sector in Bolivia has benefited the most from the increase in wages over the last ten years. This implies that workers in the informal sector may not have an incentive to transition into the formal sector, as they can expect more changes in their remuneration by staying in the informal sector. Wage variation in Colombia, on the other hand, can be mostly attributed to changes in wages in the formal sector, which has benefited from laws reducing the cost of labor, such as the 2012 tax reform.

The differences in wage behavior in these countries are compatible with their economic policies. Bolivian policies focused on redistribution and equality have yielded higher wages for practically all workers, particularly benefiting the most unskilled workers, whereas the free-market principles that Colombia has followed have led to higher concentration of wages around the median wage, implying a process of convergence toward equilibrium wages.

Both countries face important barriers to further improving labor remuneration. Increased wages in Bolivia do not provide incentives for obtaining higher levels of education or creating more formal jobs. This hinders the accumulation of human capital and the growth of productivity. On the other hand, while the concentration of wages in Colombia suggests a decrease in wage inequality, it may also imply that worker remuneration is stagnant in real terms. In such cases, increases in productivity or in human capital are not rewarded. In addition, both countries have common challenges, such as improving the educational attainment of the workforce and reducing rates of informality.

Although Bolivia and Colombia have common characteristics, such as similar labor market composition and rapidly growing economies, wages in these countries have changed in distinct ways. This comparison of wage dynamics under different economic setups highlights the influence of economic policies on labor remuneration. No labor policy guarantees improvements in working conditions in any scenario; the particularities of each country should be taken into consideration in order to decide the best course of action. Further research can shed more light on the experiences of other countries and provide evidence that is useful to policymakers in developing countries.

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Appendix: Bandwidth selection

Table A1—: Bandwidths used in the estimations for Bolivia. ln(w): logarithm of real hourly wage, in 2010 USD; Educ: Educational attainment; Sec: Economic Sector

Year	**Bandwidth**			
	Rule-of-thumb approximation			
	ln(w)	**Gender**	**Educ**	**Sec**
2006	0.1884	0.0000	0.0000	0.0000
2007	0.1774	0.0000	0.0000	0.0000
2008	0.1786	0.0000	0.0000	0.0000
2009	0.1694	0.0000	0.0000	0.0000
2011	0.1304	0.0000	0.0000	0.0000
2012	0.1352	0.0000	0.0000	0.0000
2013	0.1276	0.0000	0.0000	0.0000
2014	0.1343	0.0000	0.0000	0.0000
2015	0.1107	0.0000	0.0000	0.0000

Table A2—: Bandwidths used in the estimations for Colombia. ln(w): logarithm of real hourly wage, in 2010 USD; Educ: Educational attainment; Sec: Economic Sector

Year	**Bandwidth**			
	Rule-of-thumb approximation			
	ln(w)	**Gender**	**Educ**	**Sec**
2008	0.0611	0.0000	0.0000	0.0000
2009	0.0607	0.0000	0.0000	0.0000
2010	0.0624	0.0000	0.0000	0.0000
2011	0.0586	0.0000	0.0000	0.0000
2012	0.0570	0.0000	0.0000	0.0000
2013	0.0596	0.0000	0.0000	0.0000
2014	0.0510	0.0000	0.0000	0.0000
2015	0.0504	0.0000	0.0000	0.0000