Unravelling Declining Income Inequality in Bolivia: Do Government Transfers Matter?

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Abstract

This paper documents and explains the remarkable decline in income inequality observed during the last decade in one of the most unequal countries in the world, Bolivia. Regarding the changes in the income distribution, we find significant differences in annual growth rates by quantile during the 1999-2011 period, much more related to the growth performance of the last half of the decade, i.e. the 2005-2011 period. While the first half was a period of relatively no growth for almost all quantiles; the second half was a period of high growth (6% on average), pro-poor growth (with average growth rates close to 8% for the bottom 3 deciles and rates around 6% for the middle quantiles); but not shared by everybody: the top 10% experienced growth rates below 1% and some Pen's "giants" even negative annual growth rates, as low as -6%. These uneven growth patterns have caused a remarkable decline in income inequality during the last half of the decade. During the 2005-2011 period, the bottom 20% has increased its income share in more than 40% while the top 10% has reduced as much as 40% of its income share, causing the Gini index to drop in 10 percentual points, from a level of .51 to .40.

To analyze the "proximate" determinants of Bolivia's income inequality decline, we perform a counterfactual á la Barros decomposition of inequality changes by income source. We find that almost all inequality changes are explained by distributional changes in labor earnings. Neither the changes in contributory transfers (pensions) nor the changes and the expansion of non-contributory social transfers (*renta dignidad*, *bono Juancito Pinto*, or *bono Juana Azurduy*, among others), nor the growth of remittances and of property income account for the remarkable decline in income inequality. Furthermore, an extended counterfactual decomposition of labor earnings reveals that changes in the wage distribution are much more important than changes in the utilization of the labor force (i.e. changes in the patters of participation, employment and hours of work). To explore the "ultimate" determinants of the changes in the wage inequality we also perform a counterfactual á la Machado-Mata decomposition of the distributional changes in wage inequality. We find that reductions in skill premia have made labor market prices the dominant factor in explaining the inequality decline, accounting for over 50% of the changes in inequality.

Keywords: Wage inequality, counterfactual density, full distribution accounting.

1. Introduction

Inequality has been a pervasive characteristic of Latin-America in general, and Bolivia in particular. However, after rising through the 1990s, income inequality in Latin America has decline steadily in recent years ([15], [16], [11]). The primary objective of this paper is to unravel the **proximate** and, if posible, the **ultimate** determinants of the equalizing changes in urban income inequality, while identifying the role played by government transfers and by other sources of income, specially the labor market.

The literature on the declining income inequality in Latin America during the 2000s and its determinants is scarce but growing. [14] identify two **proximate factors** that account for the decline in inequality in Argentina, Brazil, Mexico, and Peru: a decrease in earnings gap between high-skilled and low-skilled workers; and an increase in government transfers to the poor. They atribute the decrease in the earnings gap to the expansion of basic education during the last couple of decades, which has reduced the share of people with only primary and less than primary in the labor force. On the other hand, they atribute the equalizing contribution of government transfers to the implementation or expansions of large-scale conditional cash transfer programs such as *Jefes y Jefas de Hogar* in Argentina; *Bolsa Escola*, *Bolsa Familia* and *BPC* in Brazil; *Progresa/Oportunidades* in Mexico, and *Juntos* in Peru.

[9] uses counterfactual analysis to analyze the **determinants** of the inequality decline in the 2000s for 14 Latin-American countries. They find that nearly half of the average decline in inequality was due to changes in labor income. Changes in transfers on average contribute about one-sixth to the decline in inequality for the region, although they were more important in Chile, Colombia, Costa Rica, and the Dominican Republic. Changes in pensions account for one tenth of the overall decline, largely driven by important contributions in the case of Argentina and Brazil.

We find that the labor market accounts for the largest share of the decline, and that government transfers played a minor role in this process. Our results indicate that neither intensity of labor nor labor market participation decisions nor shifts in the labor market composition may be associated with the decline, but reductions in the skill premia via labor market prices were the dominant factor behind the evolution of income inequality in urban Bolivia during the 2000s.

Section 2 analyze the role of the changes in the wage distribution to explain the declining income inequality in Bolivia. Since we are interested not only in proximate determinants but also in ultimate determinants we analyze also the role of the relative supply, technology, international trade and labor market institutions to explain the observed changes in the skill premium. Section 3 analyze other labor market determinants of income inequality changes, i.e. changes in the distribution of hours of work and changes in the distribution of employment opportunities.Section 4 analyze the contribution of changes in the household income from government transfers in explaining changes in income inequality. Section 5 analyze the contribution of changes in the household income from inter-household transfers and the role of migration and remittances in explaining changes in income inequality. Section 6 summarize the results and concludes analyzing the policy implications of our evidence.

2. Data

We use the set of official household surveys for the 1999-2011 period harmonized by *Fundación ARU*. A full description of the harmonization process is beyond the scope of this paper, however it is important to note that the harmonization process address - to the extent that it is possible, three major comparability issues. First, we use *raw* data, i.e. the data *before* any cleaning and imputation procedures applied by the National Bureau of Statistics. Second, as usual in most of the harmonization process, we use a uniform definition of the income aggregates and other covariates. Third, and unlike other harmonization process, we adjust the difference in sampling schemes between surveys using post-stratification techniques to adjust the sampling weights.

To construct the income dataset, we first drop all households with missing per capita household income. Then we use the Blocked Adaptive Computationally-efficient Outlier Nomination (BACON) algorithm to nominate and drop outliers in the sample. This algorithm looks for unusually large observations in the data using a Mahalanobis distance and then performs a χ^2 test to determine whether an observation is an outlier. We used $\alpha = 0.0001$ for said hypothesis test.

When constructing the income variable, we are concerned with the identification of various income sources. With this in mind, we constructed household income allows the identification of several sources, and its components are listed on table 2.[2] Per capita household income, (just income from here on) is constructed as total household income divided among household members, with non-members dropped from the sample. Total household income is the sum of household labor earnings, household income from government transfers, household income from inter-household transfers, household rents from properties, household income from contributory social security and household income from other sources. Government transfers were imputed in all years according to the payment scheme observed for that year[3].

[2] More information regarding the construction of these variables is available on the web appendix.

[3] e.g. *Bonosol* a non-contributory social security cash tranfer was not paid in 2000, but was paid in 2001 (so there were two payments in that year), hence we imputed those payments in 2001.

Table 1: Income components

SOURCE	DESCRIPTION
Labor	Net income from primary activity
	Benefits from primary activity
	Total in kind income from primary activity
	Net income from secondary activity
	Total benefits from secondary activity
	Total in kind income from secondary activity
Interhousehold transfers	Family assistance
	Transfers from within the country
	Foreign transfers
Properties	Interests
	Real state properties and houses rental
	Agricultural Properties Rental
	Dividends
	Equipment rental
Social Security	Retirement
	Income for war veterans
	Disability
	Widowhood
	Other Rents
Other	Compensation for leaving a job
	Insurance Compensation
	Other Extraordinary Income

Source: Fundación ARU's harmonized series of household surveys

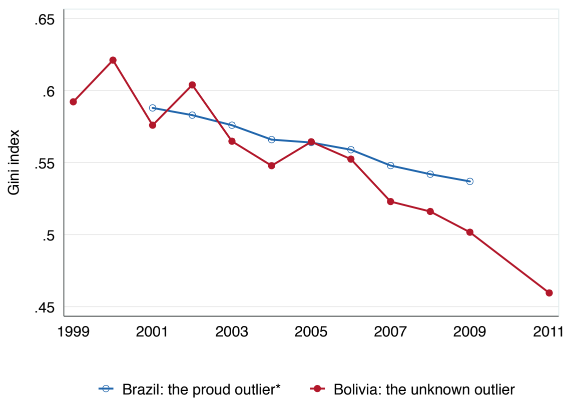
To construct the wage dataset, we keep workers with positive salary, whose age is between 18 and 65, and work full time -over 36 hours per week, only for the urban area. Hourly wage was constructed as total labor earnings divided by total hours worked, comprising both primary and secondary activities. In a very small percentage of the sample, earnings information was available while data on total hours worked was not. In these cases we imputed full time working hours.

3. An overview of income and wage inequality

3.1. Income inequality trends in Bolivia during the 2000s

A full description of the evolution of Bolivian inequality in the 2000s is beyond this paper and it may be found in [10]. However, we'll explain the most notorious features of this process. To grasp the magnitude of the fall of inequality in Bolivia, figure 1 compares the evolution of Brazilian and Bolivian income inequality:

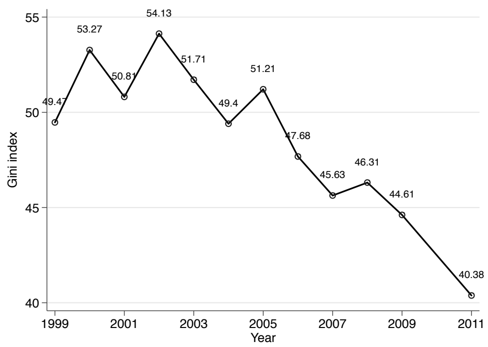
Figure 1: Evolution of Bolivian and Brazilian income inequality, 1999-2011



Source: Fundación ARU series of harmonized household surveys. Sample: 18-65 years old, full time (>36 hours) workers. Outliers were dropped from the sample. Outliers were nominated using the BACON algorithm ($\alpha = 0.0001$).
**Inequality in focus*, April 2012, The World Bank. Data comes from SEDLAC (CEDLAS and The World Bank)

Inequality in urban Bolivia also declined significantly, as shown in figure 2. The evolution of urban inequality behaved very differently before and after 2005, year of the start of the decline and of some notorious political changes in the country. During 1999-2005, inequality measured by the Gini index fluctuated erratically between 54 and 49.5. Nevertheless, in 2005-2011, the fall began at a fast pace: The Gini index fell 11 points during those 6 years, and to the best of our knowledge, this decline makes Bolivia the most succesful country in Latin America in reducing inequality in the 2000s ([10]).

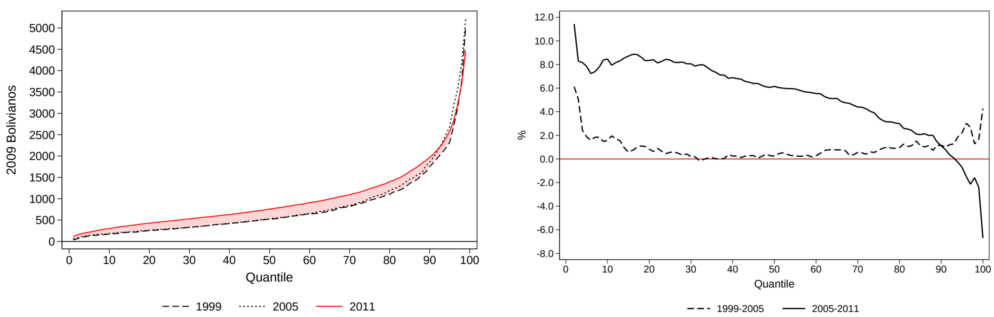
Figure 2: Evolution of Bolivian urban income inequality, 1999-2011



Source: Fundación ARU series of harmonized household surveys. Sample: 18-65 years old, full time (>36 hours) workers. Outliers were dropped from the sample. Outliers were nominated using the BACON algorithm ($\alpha = 0.0001$).

The distributional changes behind the decline show that 2005-2011 was a period of high growth for the bottom percentiles of the distribution. The left subfigure from figure 3 shows the Pen's parade for 1999, 2005 and 2011. The parade for 1999 and 2005 practically lie on the same line, while the 2011 parade is clearly shifted upwards for the first 94 percentiles. The income for the top percentiles was reduced, notice how the 2011 parade lies to the right of the 2005 parade at that part of the distribution. This changes in income are better understood with the right subfigure from figure 3, which shows the yearly growth rate of the average income by percentile. The dashed line on said subfigure shows growth rates during 1999-2005 very close to zero for percentiles 20 to 80, and positive growth only for the tails of the income distribution. Average income grew approximately 8% per year for the first 30 percentiles, and then the growth rate falls as one moves towards the top percentiles, and it falls as low as -7% for the *giants* on the top of the income distribution.

Figure 3: Urban sample: Pen's parades and average income by percentile growth rate



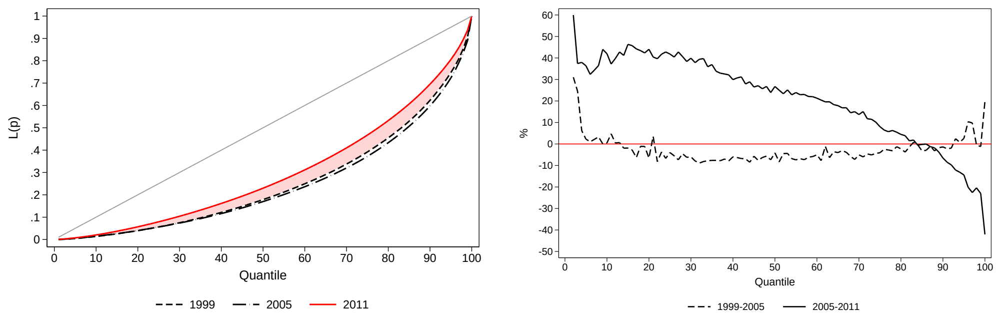
Pen's parades

Average income growth rate by quantile

Source: Fundación ARU series of harmonized household surveys. Note: Zeros and outliers were dropped from the sample. Outliers were nominated using the BACON algorithm ($\alpha = 0.0001$).

This differences in the growth of average income inevitably lead to gains and losses in income shares. Figure 4 shows the 1999, 2005 and 2011 per capita household income Lorenz curves. The 1999 and 2005 are very close to each other, while the 2011 curve dominates the other two. The right subfigure on figure 4 shows the gains in income share by percentile, which are negative for percentiles 10 to 80 until 2005, and positive for the remaining quantiles. However, after 2005 they fluctuate around 40% for the first 3 deciles, and the top percentiles had their income share reduced by as much as 40%. These changes lead to the nearly 20% reduction of the Gini index that motivates the remainder of the paper.

Figure 4: Urban sample: Lorenz curves and gains in income share by percentile



Lorenz curves

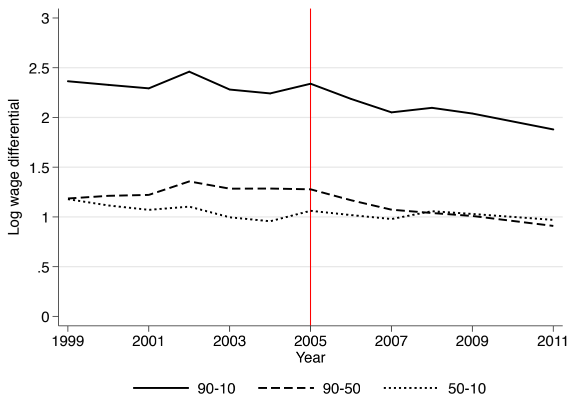
Gains in income share by quantile

Source: Fundación ARU series of harmonized household surveys. Note: Zeros and outliers were dropped from the sample. Outliers were nominated using the BACON algorithm ($\alpha = 0.0001$).

3.2. Wage inequality

Figure 5 depicts the evolution of wage inequality during the 2000s. The 90-10 log wage differential fluctuated around its 1999 level until 2005, initial year of the declining trend that went on until 2011. As shown on panel A of table 2, the 90-10 wage ratio fell 48% between 1999 and 2011, but almost all of the decline happened between 2005 and 2011, when the ratio fell 46%. Until 2005, the 90-10 only fell 2 log points.

Figure 5: Evolution of wage inequality, 1999-2011



Source: Fundación ARU series of harmonized household surveys. Sample: 18-65 years old, full time (>36 hours) workers. Outliers were dropped from the sample. Outliers were nominated using the BACON algorithm ($\alpha = 0.0001$).

Inequality did not vary the same way above or below the median. Between 1999 and 2005 upper and lower tail inequality displayed opposing trends, as inequality below the median fell 11.7 log points, while upper tail inequality rose by 9.22 log points. However, after 2005 the 90-50 and 50-10 ratios behaved similarly, but the decline was concentrated almost exclusively in the upper tail: a sharp decline in the 90-50 differential was observed, as it fell almost 37 points, while the 50-10 ratio showed a more modest fall, of a little over 9 log points. Falling upper tail inequality accounts for nearly 80% of the decline after 2005.

Figure 6 shows the evolution of wage inequality by gender, and the remaining panels on table 2 show its changes by subperiod, as well. For males, inequality behaved very similarly as full sample inequality: the 90-10 ratio did not rise or fall significantly between 1999 and 2005, and a clear falling trend is observed in the latter years of the period of analysis. The 90-10 ratio fell 37.5 log points between 1999 and 2011, nevertheless, it rose slightly, 2.9 points, until 2005, and fell over 40 points between 2005 and 2011. Offsetting trends in lower and upper tail inequality were present before and after 2005. Upper tail male inequality grew by 17.5 log points while the 50-10 ratio fell 14.5. After 2005, the decline in upper tail inequality is remarkable, as the 90-50 ratio fell 42.8 log points while the 50-10 ratio rose slightly 2.5 log points.

Wage inequality in the female sample shows a different behavior that the male and full sample inequality. Wage inequality among females fell almost twice as much as male wage

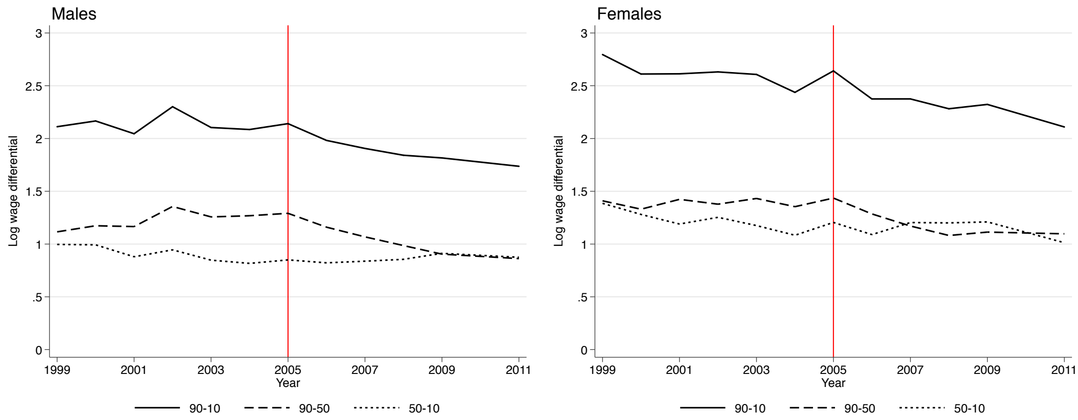
Table 2: Log wage differentials changes by subperiod (100 × log change)

Differential	Percent variation			Annualized percent change		
	1999-2011	1999-2005	2005-2011	1999-2011	1999-2005	2005-2011
A. Full sample						
90-10	-48.44	-2.5	-45.94	-4.04	-.42	-7.66
90-50	-27.58	9.22	-36.8	-2.3	1.54	-6.13
50-10	-20.86	-11.72	-9.14	-1.74	-1.95	-1.52
B. Males						
90-10	-37.49	2.9	-40.38	-3.12	.48	-6.73
90-50	-25.33	17.54	-42.87	-2.11	2.92	-7.15
50-10	-12.16	-14.64	2.49	-1.01	-2.44	.41
C. Females						
90-10	-68.58	-15.49	-53.09	-5.72	-2.58	-8.85
90-50	-31.29	2.6	-33.89	-2.61	.43	-5.65
50-10	-37.29	-18.09	-19.2	-3.11	-3.02	-3.2

Source: Fundación ARU series of harmonized household surveys. Sample: 18-65 years old, full time (>36 hours) workers. Outliers were dropped from the sample. Outliers were nominated using the BACON algorithm ($\alpha = 0.01$).

inequality, and the reduction in lower tail inequality was higher than the reduction of above the median inequality. There is a declining trend for the 90-10 ratio throught out the 2000s, but still, inequality fell more after 2005. The total inequality reduction was of 68.6 log points between 1999 and 2011, and 53 out of those 68 happened after 2005. Upper tail inequality behaves in similar fashion as upper tail male inequality, the rise before 2005 is not as pronounced, only 2.6 log points. After 2005, upper tail inequality falls 33.9 log points. The 50-10 ratio falls all throughout the 2000s in almost equal proportions before and after 2005, so the decline in inequality among females certainly accelerates after 2005, but cannot be atributed solely to declining upper tail inequality.

Figure 6: Evolution of wage inequality by sex, 1999-2011

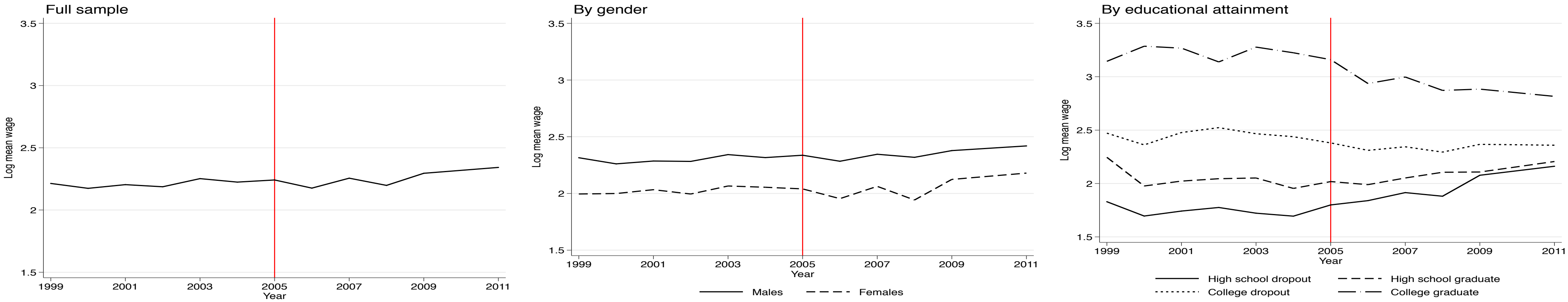


Source: Fundación ARU series of harmonized household surveys. Sample: 18-65 years old, full time (>36 hours) workers. Outliers were dropped from the sample. Outliers were nominated using the BACON algorithm ($\alpha = 0.0001$).

To start analyzing the distributional changes behind the decline in wage inequality, let us turn to figure 7. The leftmost subfigure on figure 7 shows the evolution of the log average wage for our full sample. Log average wage grew throughout the 2000s, but at a much faster rate after 2005. Between 1999 and 2005, it grew at a rate of 0.47% per year, but between 2005 and 2011, it did so at 1.68% per year, as seen on table . Splitting the sample by sex leads to the same conclusion: faster growth after 2005, however, growth was almost two times faster for females. Male average wage grew at a yeraly rate of 0.37% between 1999 and 2005, and at 1.37% per year after 2005. Average wage for females grew at 0.74% per year until 2005, but this rate is 2.32 from 2005 on. This translates into a total percent change in average wage for females of 18.4% from 1999 to 2011, with over three quarters of that change happening between 2005 and 2011. Similarly, nearly 80% of the total percent variation in male average wage occurred after 2005.

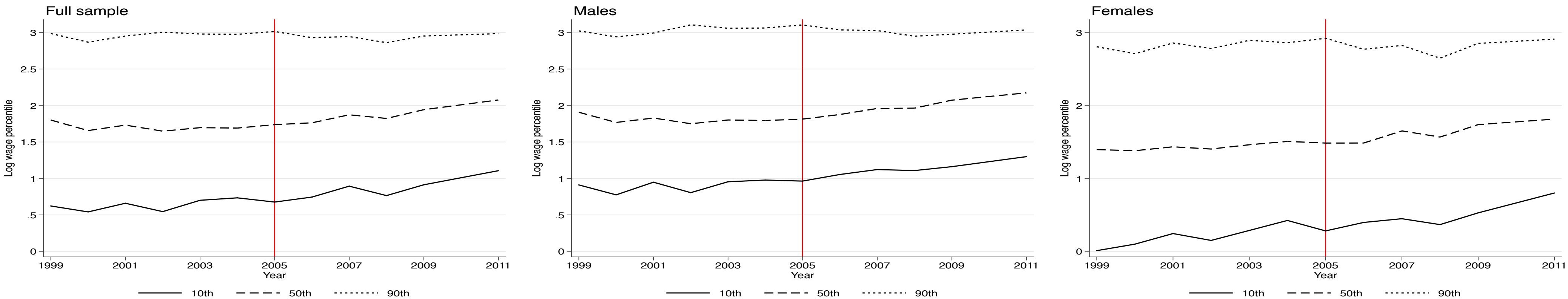
Splitting the sample by educational attainment in four categories: incomplete high school, complete high school, college dropouts and college graduates leads to insights necessary to understand the evolution of wage inequality. The rightmost subfigure on figure 7 shows the evolution of the log average wage by educational attainment. The average wage for high school dropouts grew and astounding 33.2% in the 13 years analyzed. It fell 3% in 1999-2005, but grew 36.2% in 2005-2011, at a yearly rate of 6% in such period. The average wage for high school graduates fell 22.7% until 2005, and then it grew 18.8%. Workers with college education saw their average income vary at negative rates. For college dropouts it fell 9.1% in 1999-2005, and an extra 2.1% after 2005. The average wage for college graduates fell almost 33% in 1999-2011. After a slight 1.6% growth between 1999 and 2005, it fell at a yearly rate of -5.73% in 2005-2011, leading to a -34.4% percent variation in said period.

Figure 7: Evolution of log average wages, 1999-2011



Source: Fundación ARU series of harmonized household surveys. Sample: 18-65 years old, full time (>36 hours) workers. Outliers were dropped from the sample. Outliers were nominated using the BACON algorithm ($\alpha = 0.0001$).

Figure 8: Evolution of the 10th, 50th and 90th percentiles of the log wage distribution by gender, 1999-2011



Source: Fundación ARU series of harmonized household surveys. Sample: 18-65 years old, full time (>36 hours) workers. Outliers were dropped from the sample. Outliers were nominated using the BACON algorithm ($\alpha = 0.0001$).

Table 3: Log average wage changes by subperiod (100 × log change)

Sample	Percent variation			Annualized percent change		
	1999-2011	1999-2005	2005-2011	1999-2011	1999-2005	2005-2011
Full	12.86	2.79	10.06	1.07	.47	1.68
Males	10.41	2.21	8.2	.87	.37	1.37
Females	18.41	4.47	13.94	1.53	.74	2.32
High school dropout	33.23	-2.99	36.22	2.77	-.5	6.04
High school graduate	-3.9	-22.71	18.81	-.33	-3.78	3.13
College dropout	-11.29	-9.13	-2.16	-.94	-1.52	-.36
College graduate	-32.82	1.58	-34.4	-2.73	.26	-5.73

Source: Fundación ARU series of harmonized household surveys. Sample: 18-65 years old, full time (>36 hours) workers. Outliers were dropped from the sample. Outliers were nominated using the BACON algorithm ($\alpha = 0.01$).

Analyzing the percentiles of the wage distribution shows that inequality declined mostly because of the steady growth of the 50th and 10th percentiles, while the 90th percentile fluctuated around its 1999 level throught the 2000s, as seen on figure 8 and table 4. The 90th percentile of the wage distribution grew 2.8% in 1999-2005 only to fall 2.9% in the subsequent subperiod. The total percent variation observed for the 50th wage percentile is 27.5%, as it fell 6.4% between 1999 and 2005 to rise 33.9%. The largest growth was observed for the 10th percentile, which grew constantly between 1999 and 2011, although its growth rate spiked after 2005. During 1999-2005, it grew at a yearly rate of 0.89%, but its yearly growth after 2005 was 7.2% per year, leading to a total percent variation of 43% between 2005 and 2011, and of 48.4% between the start and end years of our analysis. The growth of below the median and median income accounted for the vast majority in the total wage inequality decline in the 2000s.

These selected percentiles behave in a similar fashion in the male sample. Even though the 90th percentile has a small positive total percent variation between 1999 and 2011, it grew 8.2% until 2005, but afterwards it falls 6.9% during 2005-2011. The 50th percentile also fell and rose during the 2000s: fell 9.37% in 1999-2005, but grew 36% in 2005-2011. The 10th percentile grew throught the 2000s, but after 2005, it did so at a yearly rate over 6 times higher that its pre 2005 rate. This lead to a total percent variation of 38.8% between 1999 and 2011, and 33 out those 38, occurred due to changes during 2005-2011.

In the female sample, changes in inequality occurred to larger differences in growth rates among the selected percentiles. Whereas in the male sample the 90th percentile suffered very little changes during the entire period, in the female sample it grew 10.5% between 1999 and 2011. Before 2005, it had grown 11.6%, but in the latter period it fell slightly, 1.1%. In 1999-2011 The 50th and 10th percentiles grew 41.7% and 79% respectively, with nearly three quarters of said growth happening after 2005.

Table 4: Log wage percentile changes by subperiod (100 × log change)

Percentile	Percent variation 1999-2011	Percent variation 1999-2005	Percent variation 2005-2011	Annualized percent change 1999-2011	Annualized percent change 1999-2005	Annualized percent change 2005-2011
A. Full sample						
10	48.37	5.35	43.02	4.03	.89	7.17
50	27.51	-6.37	33.88	2.29	-1.06	5.65
90	-.08	2.85	-2.92	-.01	.47	-.49
B1. Males						
10	38.79	5.27	33.51	3.23	.88	5.59
50	26.63	-9.37	36	2.22	-1.56	6
90	1.3	8.17	-6.87	.11	1.36	-1.14
B2. Females						
10	79.04	27.07	51.97	6.59	4.51	8.66
50	41.74	8.98	32.77	3.48	1.5	5.46
90	10.46	11.58	-1.13	.87	1.93	-.19
C1. High school dropouts						
10	64.43	13.71	50.72	5.37	2.29	8.45
50	39.08	-2.66	41.74	3.26	-.44	6.96
90	23.88	-9.64	33.53	1.99	-1.61	5.59
C2. High school graduates						
10	27.06	-4.44	31.50	2.25	-0.74	5.25
50	21.77	-10.71	32.48	1.81	-1.78	5.41
90	-16.61	-29.24	12.63	-1.38	-4.87	2.10
C3. College dropouts						
10	-15.36	-43	27.63	-1.28	-7.17	4.61
50	-8.89	-17.74	8.85	-.74	-2.96	1.48
90	-4.75	12.11	-16.86	-.4	2.02	-2.81
C4. College graduates						
10	-17.18	-14.98	-2.2	-1.43	-2.5	-.37
50	-34.61	-4.76	-29.85	-2.88	-.79	-4.98
90	-33.65	9.87	-43.52	-2.8	1.64	-7.25

Source: Fundación ARU series of harmonized household surveys. Sample: 18-65 years old, full time (>36 hours) workers. Outliers were dropped from the sample. Outliers were nominated using the BACON algorithm ($\alpha = 0.01$).

Figure 9 shows the evolution of the selected percentiles by educational attainment, which show different trends among them. The trends for all selected percentiles in the incomplete high school category show growing tendencies during 1999-2011: high school dropouts' 90th wage percentile fell 9.6% until 2005, but grew 33.5% in 2005-2011. The 50th percentile also grew notoriously after 2005, 41.7%, after a small decline of 2.7% during 1999-2005. The 10th percentile achieved a percent variation four times higher after 2005 than its pre 2005 growth: 50.5% post 2005 against 13.7% in the previous subperiod. This was the percentile with the largest percent variation during 1999-2011, and during 2005-2011.

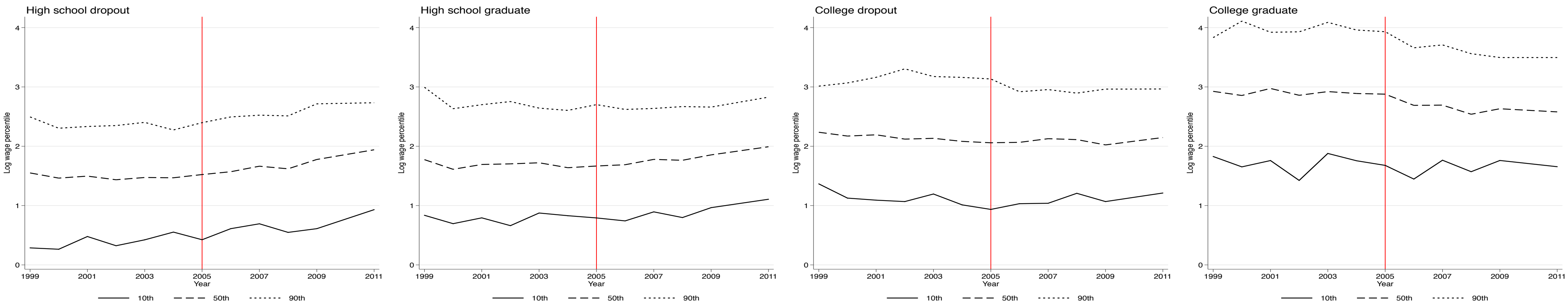
Among those workers with complete high school, all three selected percentiles show similar growth patters, a decline in 1999-2005 followed by a strong recovery after 2005, however, their full period results are different. The 10th and 50th percentiles had very similar growth percentages after 2005, both being very close to 31%, but the 50th percentile fell 6 percent points more than the 10th in 1999-2005, hence the difference in their net full period change. I the case of the 90th percentile, the 2005-2011 rise was not even half the nearly 30% fall pre 2005.

The 10th, 50th and 90th wage percentiles for workers with at least some college education varyied negatively in 1999-2011, altohugh their fluctuating patterns differ between those two categories. The 10th and 50th percentile in the college dropout category fell until 2005 but recovered afterwards. The 90th percentile rose in 1999-2005, but fell in 2005-2011. Regarding college graduates, these percentiles fell throughout the entire period, with the exception of the 90th, with grew 9.9% pre 2005, but registered the lowest growth rate of all, -43.5%, post 2005.

As it is evident from figure 10, which shows how the vast majority of workers in the top wage percentiles have a college degree, changes in the wage distribution that affect negatively workers with such educational attainment, will reduce inequality by moving top wages downwards, thus closing the wage gap between the more educated and the rest of the labor force. When turning to the evolution of the composition of the labor force in figure 11, there are no abrupt changes in the composition by sex nor the composition by educational attainment. Male participation in full time employment remained constant around 65%, but there were some changes in the composition by educational attainment.

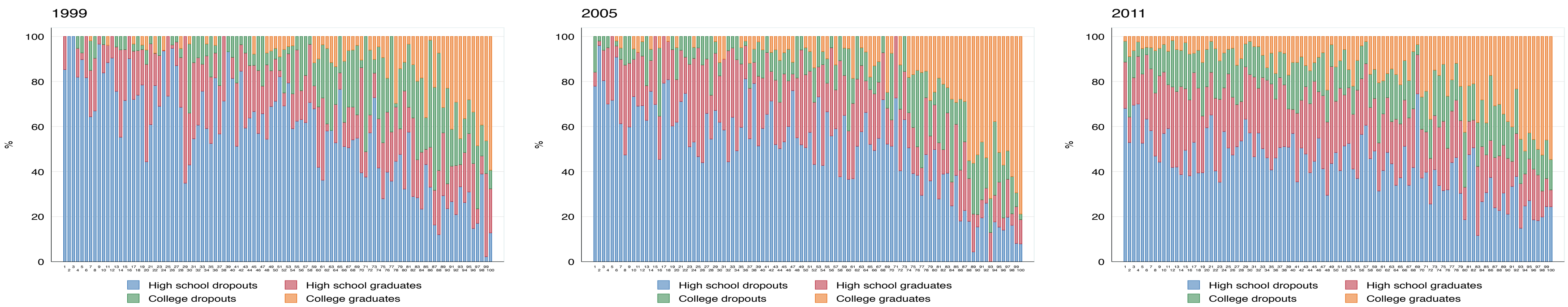
From 1999 to 2002, work force composition by educational attainment remained relatively unchanged, but then it started to become more educated. The share of full time workers with incomplete high school fell from 58% in 1999 to 43% in 2011, high school graduate share grew from 19% to 25%, the proportion of workers with some tertiaty education remained constant around 15%, but the employment of workers with a college degree rose substatially, from 9% to 16%.

Figure 9: Evolution of the 10th, 50th and 90th percentiles of the log wage distribution by educational attainment, 1999-2011



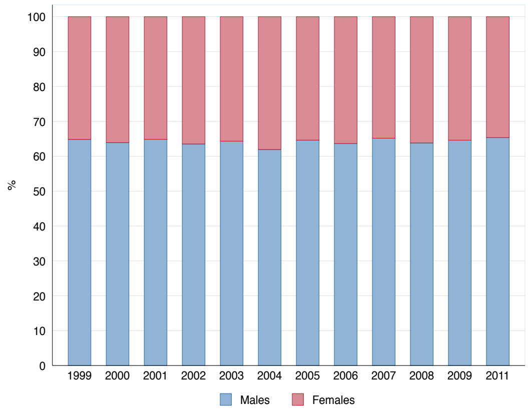
Source: Fundación ARU series of harmonized household surveys. Sample: 18-65 years old, full time (>36 hours) workers. Outliers were dropped from the sample. Outliers were nominated using the BACON algorithm ($\alpha = 0.0001$).

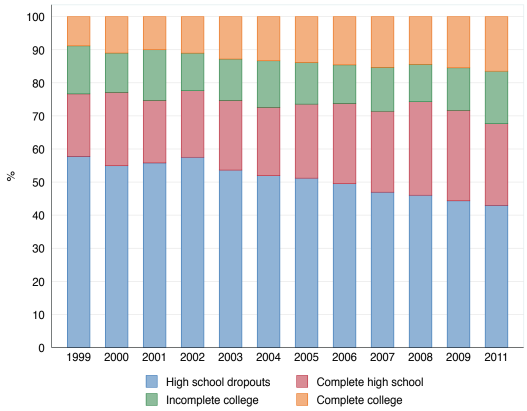
Figure 10: Labor force composition by educational attainment in the wage distribution, 1999, 2005 and 2011



Source: Fundación ARU series of harmonized household surveys. Sample: 18-65 years old, full time (>36 hours) workers. Outliers were dropped from the sample. Outliers were nominated using the BACON algorithm ($\alpha = 0.0001$).

Figure 11: Evolution of the labor force composition by gender and educational attainment, 1999-2011





Source: Fundación ARU series of harmonized household surveys. Sample: 18-65 years old, full time (>36 hours) workers. Outliers were dropped from the sample. Outliers were nominated using the BACON algorithm ($\alpha = 0.0001$).

4. Proximate determinants of income inequality

4.1. Methods

Let y be a random variable that may be written as the sum of n variables y^i, $i = 1, ..., n$. We seek to construct a counterfactual scenario $\tilde{y}^j$ that shows how the inequality of y would have evolved if some components of y, y^i, $i \neq j$ would have remained constant and other component y^j would have been allowed to vary in time, i.e.

$$y = \sum_i^n y^i$$

$$\tilde{y}^j = y^j + \sum_{i \neq j}^n \overline{y^i}$$

where $\overline{y^i}$ is some constant value for the i-th component y^i. We have a time series of t periods for y and each of its components. Paes de Barros, et. al (2006), propose the following decomposition to simulate changes in the inequality of y generated by the i-th component y^i:

1. Calculate the percentiles for the distribution of y for every period t.
2. Estimate the components' averages for each percentile c, $\overline{y_c}^i$, for every period t
3. Simulate a distribution for y, y_c in which $\overline{y_c}^i$ is imputed to every observation in percentile c, for every period t.

Based on the simulated distribution y_c, we construct the following counterfactual scenario:

1. We estimate each component's intertemporal average, $\overline{\overline{y_c}}^i$
2. We construct the counterfactual scenario given by:

$$\tilde{y_t}^j = \overline{y_c}^j + \sum_{i \neq j}^{n} \overline{\overline{y_c}}^i \tag{4.1}$$

one component is allowed to vary according to its percentile average $\overline{y_c}^j$, but all the others are left constant at their intertemporal average.

Our starting point for the analysis of the proximate determinants of the change in inequality is the analysis of the ability of each income component to track changes in per capita household income inequality. Let y_h denote the total household income for the h-th household in the sample, and let y_h be defined as the sum of household labor earnings y_h^{LM}, household government transfers y_h^G, inter-household transfers y_h^H, household rents from prperties y_h^P, household income from contributory social security y_h^{SS} and household income from other sources y_h^O. If there are N_h members in household h, it's per capita household income, y_h, is given by :

$$y_h = \frac{1}{N_h}\left[Y_h^{LM} + Y_h^{GT} + Y_h^{HT} + Y_h^P + Y_h^{SS} + Y_h^O\right] \tag{4.2}$$

Equation 4.2 makes explicit the contribution of our six proximate determinants of income inequality: 1) the labor market, where individuals offer hours of work to firms for exchange of a wage, or with other households to produce self-employment 2) The generosity and reach of redistributive policy, whether it's in cash or in kind, 3) off-market insurance mechanisms via inter-household transfers, usually through foreign remittances and 4) the coverage of contributory social security.

Thus, a simulated distribution would be given by

$$\tilde{y}_{ct} = \frac{1}{N_{ht}}\left[\overline{Y_{ct}^{LM}} + \overline{Y_{ct}^{GT}} + \overline{Y_{ct}^{HT}} + \overline{Y_{ct}^P} + \overline{Y_{ct}^{SS}} + \overline{Y_{ct}^O}\right] \tag{4.3}$$

where $\overline{Y_{ct}^{LM}}$ denotes the average per capita labor earnings for percentile c in year t. Hence, the counterfactual distribution for per capita household labor earnings would be:

$$\tilde{y}_{ct}^{LM} = \frac{1}{N_{ht}}\left[\overline{Y_{ct}^{LM}} + \overline{\overline{Y_c^{GT}}} + \overline{\overline{Y_c^{HT}}} + \overline{\overline{Y_c^P}} + \overline{\overline{Y_c^{SS}}} + \overline{\overline{Y_c^O}}\right] \tag{4.4}$$

where $\overline{\overline{Y_c^*}}$ represents the average of component Y_c^* during 1999-2011 for percentile c. We repeat this procedure for every income component we are able to identify.

Labor earnings is probably the most difficult component to model, as it is more complex in terms of its configuration, which depends on three factors:

1. Labor market participation decisions

2. Decisions on the amount of hours to work
3. Hourly wage

To analyze these component, notice that per capita labor earnings may be written as

$$y_h^{LM} = \frac{1}{n}\sum e_i w_i h_i \tag{4.5}$$

where n is the number of household members, e_i is a dummy variable that is 1 for employed household members, w_i is the hourly wage and h_i is the amount of total hours worked by the i-th individual in the household. The term $\frac{e_i}{n}$ may be further decomposed into

$$\frac{e_i}{n} = \frac{n_p}{n}\frac{e_i}{n_p} \tag{4.6}$$

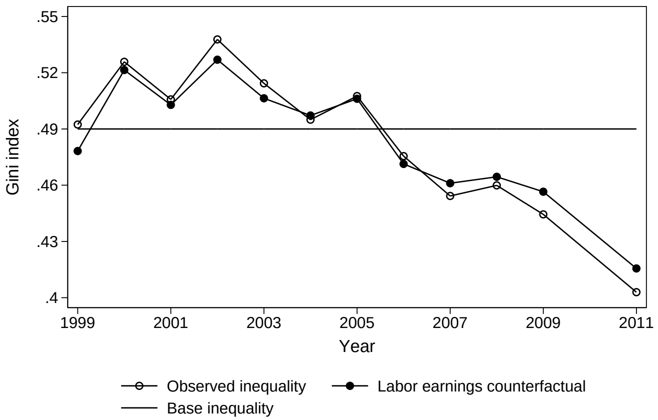
with $\frac{n_p}{n}$ is the labor market participation rate, and $\frac{e_i}{n_p}$ is the employment rate. We perform the Paes de Barros decomposition to equation 4.5 to identify which labor market factor within the household labor earnings component is better able to track observed inequality.

4.2. Results for the Paes de Barros decomposition

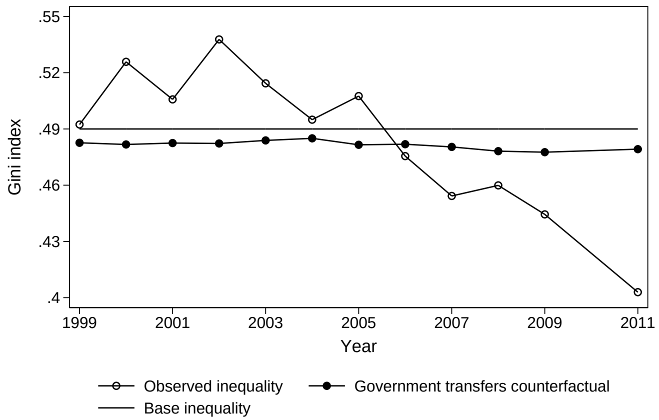
Figure 12 displays the results for the Paes de Barros decomposition by income source. The top leftmost subfigure from figure 12 shows the result for the labor earnings component, and the subfigure next to it, the results for the government transfers component. It is clear that the government transfers component is unable to reproduce the evolution of the Gini index, whereas the labor earnings component tracks inequality very closely: It moves almost perfectly throughout the pre 2005 fluctuations, and follows the post 2005 decline very closely. No other component is able to accompany the observed inequality path, and most resemble straight lines below to base inequality -the inequality one would observe if all components were left constant at their intertemporal average values.

After establishing that labor earnings is the main household income component, we need to determine whether it's relevance comes from changes in participation decisions, employment opportunities, labor intensity or due to wages. Figure 13 shows the result of the labor earnings component decomposition into these factors, and they are also conclusive as to which labor market factor is more important in explaining the evolution of observed inequality, which is hourly wage. Household members of various ages may decide to participate in the labor market and become employed, however, we only consider workers aged 18-65 in our analysis, as they account for over 87% of total household labor earnings, in over 86% of the households in the sample. Bearing this sample restriction in mind, which evidently prevents a better fit of our simulation, the wage component approximates better the decline from 2005 on -particularly from 2008 on, and the 1999-2003 fluctuations, than any other components. Thus, the relevance of the labor earnings component comes from labor market prices, and not from changes in participation decisions, employment opportunities or workers deciding to change their total hours of work.

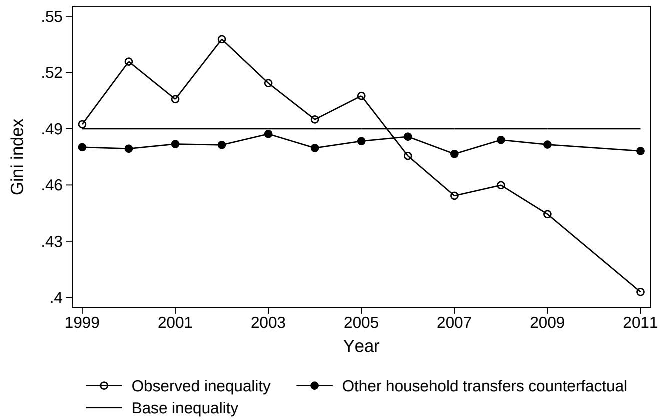
Figure 12: Urban sample: Counterfactual simulations by income source



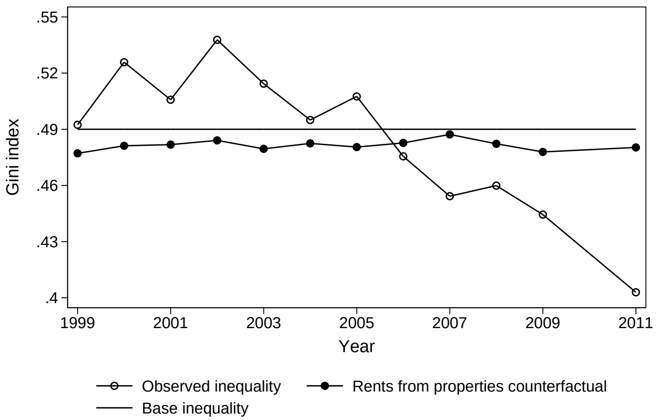
Labor earnings



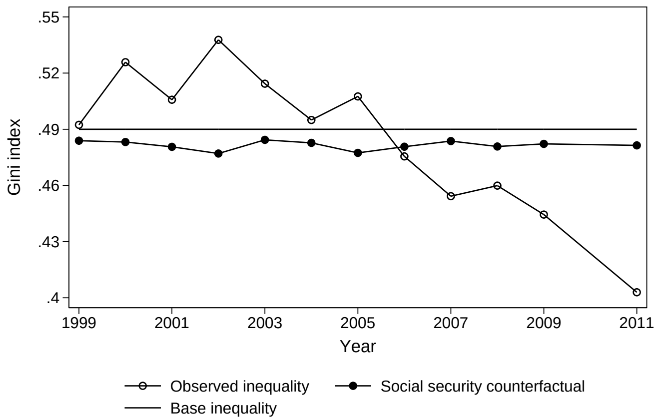
Government transfers



Inter-household transfers



Rents from properties

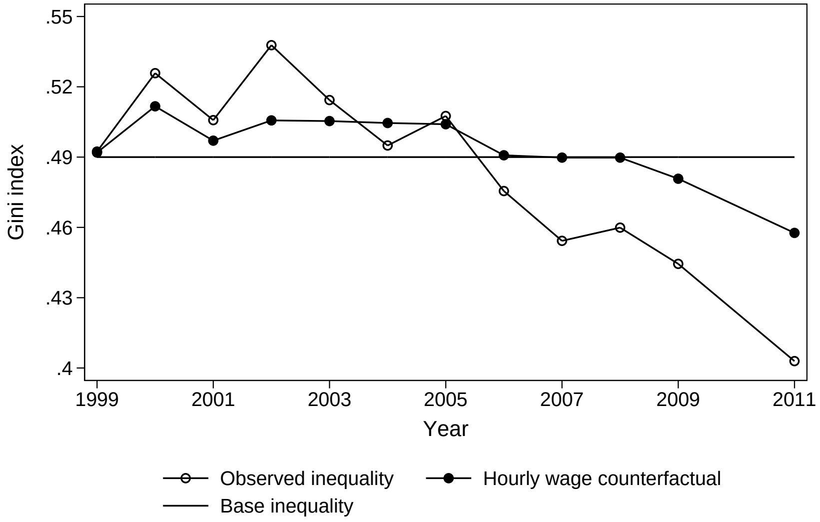


Social security

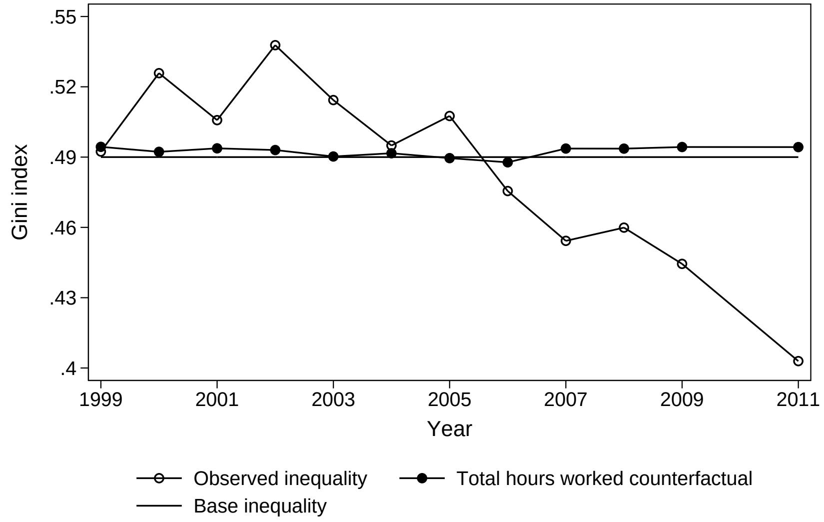
Source: Fundación ARU series of harmonized household surveys. Note: Zeros and outliers were dropped from the sample. Outliers were nominated using the BACON algorithm ($\alpha = 0.0001$).

4.3. Paes de Barros decomposition for labor earnings components

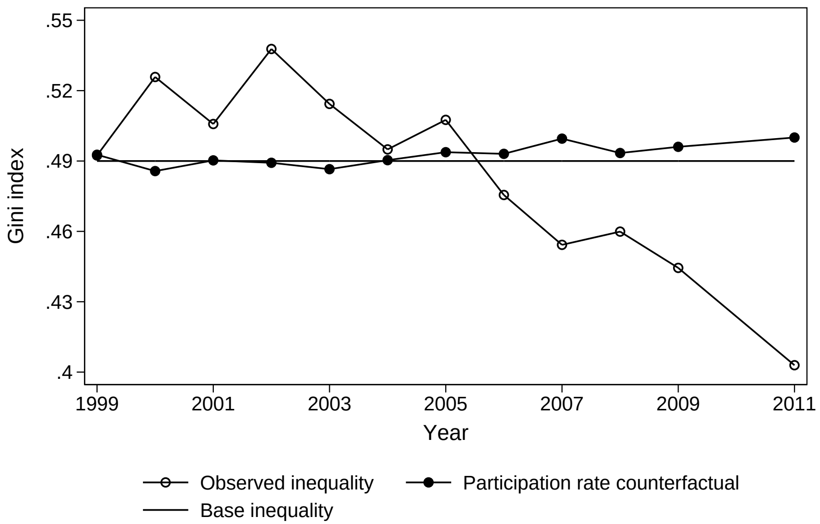
Figure 13: Urban sample: Counterfactual simulations by labor earnings source



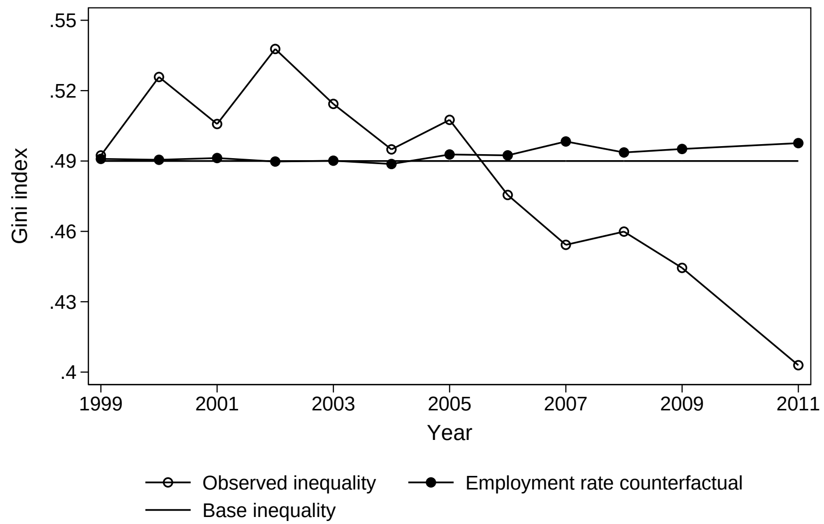
Hourly wage



Total hours worked



Participation rate



Employment rate

Source: Fundación ARU series of harmonized household surveys. Note: Zeros and outliers were dropped from the sample. Outliers were nominated using the BACON algorithm ($\alpha = 0.0001$).

5. Ultimate determinants of wage inequality

5.1. Methods

To analyze what we call *ultimate* determinants of wage inequality, we use two versions of a widely used decomposition method: The Juhn, Murphy and Pierce decomposition. First we use the original decomposition ([12]), and then we use a quantile version of [12], featured in [17] and [2].

5.1.1. The Juhn, Murphy and Pierce (JMP) decomposition

In [12], these authors developed a tool that allowed them to describe the components of wage density changes that could be attributed to observable prices, observable quantities and residuals: unobserved prices and quantities. Their method, the *full distribution accounting*, is described next. Let the wage equation for time t be

$$Y_{it} = X_{it}\beta_{it} + u_{it} \tag{5.1}$$

and let u_{it} be

$$u_{it} = F^{-1}(\theta_{it}|X_{it}) \tag{5.2}$$

where $F^{-1}(\cdot|X_{it})$ is the inverse cumulative distribution of wage residuals conditional on X_{it}, and θ_{it} is i's percentile rank in the residual distribution. In this framework, changes in inequality over time come from

1. Changes in the distribution of observable individual characteristics, X
2. Changes in the returns to such characteristics, β
3. Changes in the distribution of residuals, $(\theta|X)$

Define $\overline{\beta}$ to be the average price of observables over some lapse and $\overline{F}^{-1}(\cdot|X_{it})$ as the average cumulative distribution of residuals. Then, the difference in inequality between a given period and the period's average may be written as

$$Y_{it} = X_{it}\overline{\beta} + X_{it}(\beta_t - \overline{\beta}) + \overline{F}^{-1}(\theta_{it}|X_{it}) + [F^{-1}(\theta_{it}|X_{it}) - \overline{F}^{-1}(\theta_{it}|X_{it})] \tag{5.3}$$

and this difference allows the estimation of counterfactual distributions. To calculate the counterfactual distribution of wages holding constant observable prices and residuals at their average, and varying only the distribution of observable characteristics, we estimate

$$Y_{it}(1) = X_{it}\overline{\beta} + \overline{F}^{-1}(\theta_{it}|X_{it}) \tag{5.4}$$

To allow observable prices and quantities to vary over time, we calculate

$$Y_{it}(2) = X_{it}\beta_{it} + \overline{F}^{-1}(\theta_{it}|X_{it}) \tag{5.5}$$

Finally, to let all components vary simultaneously, we have

$$Y_{it}(3) = X_{it}\beta_{it} + F^{-1}(\theta_{it}|X_{it}) = Y_{it} \tag{5.6}$$

[12] propose the following decomposition:

1. $Y_{it}(1) - \overline{Y}$ is the component of the difference in inequality between t and the average period due to changing quantities
2. $Y_{it}(2) - (Y_{it}(1) - \overline{Y})$ is the marginal contribution of changing prices
3. $Y_{it}(3) - (Y_{it}(2)$ is the marginal contribution of changing residuals.

This is the original decomposition procedure. We use a slightly modidified version to make the results of this procedure comparable to the results of the other procedure: instead of relating changes to period average prices, quantities or unobservables, we use observed and unobserved prices and quantities from 1999. This alteration would cause equation 5.4 to be

$$Y_{it}(1) = X_{it}\beta_{1999} + F^{-1}_{1999}(\theta_{i,1999}|X_{i,1999}) \tag{5.7}$$

and similarly for equations 5.5 and 5.6. We refer to this procedure as the OLS version of the JMP decomposition.

5.1.2. Quantile implementation of the Juhn, Murphy and Pierce decomposition

Despite being a widely used tool, the original JMP decomposition is not conceptually appealing because it uses OLS regressions, a model for the conditional mean, to analyze changes throughout the entire distribution. This drawback has been overcome with the methodology proposed by Machado and Mata (MM) 2005, using quantile regressions. And later, Autor, Katz and Kearney (AKK) extended the original MM decomposition to allow for a richer decomposition of log wage differentials. We now detail this approach. Let $Q_\theta(w|X)$ denote the θ^{th} quantile of the distribution of log wages, conditional on the vector of covariates. These conditional quantiles can be modeled as

$$Q_\theta(w|X) = X'\beta(\theta) \tag{5.8}$$

If equation (5.8) is correctly specified, $Q_\theta(w|X)$ as a function of $\theta \in (0,1)$ provides a full characterization of the distribution of wages conditional on X. Realizations of w_i given X_i may be viewed as independent draws from the distribution $X_i'\beta(\theta)$, where the random variable θ is distributed uniformly on (0,1). After fitting the conditional quantile function, it is possible to use the estimated parameters $\hat{\beta}(\theta)$ to simulate the conditional distribution of w given X. By the Probability Integral Transformation, if θ_1, θ_2,...,θ_j are drawn from a uniform (0,1) distribution, the corresponding j estimates of the conditional quantiles of wages at X, $\hat{w} = \{X'\beta(\theta_i)\}_{i=1}^{j}$, constitute a random sample from the estimated conditional distribution of wages, given the set of covariates.

To generate a random sample from the marginal density of w, we can draw rows of data X_i from $g(X)$, and for each row, draw a random θ_j from the uniform (0,1) distribution. We then form $\hat{w}_i = X_i' \hat{\beta}(\theta_j)$ which is a draw from the wage density implied by the model. By repeating this procedure, we can draw an arbitrarily large sample from the desired distribution which is equivalent to numerically integrating the estimated conditional quantile function $\hat{Q}_\theta(w|X)$ over the distribution of X and θ to form

$$f(\hat{w}) = \int \int_{X,\theta} \hat{Q}_\theta(w|X) dX d\theta$$

By applying the labor force composition data $g_\tau(X)$ from time τ to the price matrix $\hat{\beta}_t(X)$ on time t, we can simulate the counterfactual distribution that would prevail if composition was that of period τ and prices were those of time t. Because the $\hat{\beta}_\tau(X)$ matrix describes the conditional distribution of wages for given values of X, this simulation captures the effects of composition on both between and within group inequality.

5.2. Extension to residual inequality

Melly 2005 and AKK 2004 extend the original MM approach to residual inequality in the following way. Defini the vector $\hat{\beta}(50)$ as a measure of between-group inequality, and denote it by $\hat{\beta}^b = \hat{\beta}(50)$. Now define a measure of within group inequality as the difference between the estimated coefficient vector $\hat{\beta}(\theta)$ and the median coefficient vector $\hat{\beta}^b$

$$\hat{\beta}^w(\theta) = [\hat{\beta}(\theta) - \hat{\beta}^b], \quad \theta \in (0,1) \tag{5.9}$$

By applying the coefficient matrix $\hat{\beta}^w(\theta)$ to the distribution of covariates, one can calculate the estimated dispersion of w that is exclusively attributable to residual inequality.
The conditional quantile model provides a complete characterization of the distribution of wages as a function of three components: the distribution of covariates, $g(X)$, and the vectors of between-group prices and the matrix of within (residual) prices:

$$f_t(\hat{w}_t) = f\left(g_t(X), \hat{\beta}_t^b, \hat{\beta}_t^w\right)$$

Now we estimate quantile coefficient vectors for each time period. These QR coefficients $\hat{\beta}$ provide the prices for the simulation exercise. Then, we calculate the residual price vector $\hat{\beta}^w$ using equation (5.9), and then draw simulated data from the distribution $f_t(\hat{w}_t) = f\left(g_t(X), \hat{\beta}_t^b, \hat{\beta}_t^w\right)$ by applying the matrices $\hat{\beta}_t^b, \hat{\beta}_t^w$ to the rows of $g_t(X)$.
The observed change in inequality between any two periods , t and τ, can be decomposed into three components using the following sequential decomposition. Let $\Delta Q_\theta = Q_\theta(f_\tau(w)) - Q_\theta(f_t(w))$ equal the observed change in the θ^{th} wage quantile between periods t and τ. Define

$$\Delta Q_\theta^X = Q_\theta\left(f(g_t(X), \hat{\beta}_t^b, \hat{\beta}_t^w)\right) - Q_\theta\left(f(g_\tau(X), \hat{\beta}_t^b, \hat{\beta}_t^w)\right)$$

As the contribution of changing quantities to ΔQ_θ. Let

$$\Delta Q_\theta^b = Q_\theta\left(f(g_\tau(X), \hat{\beta}_t^b, \hat{\beta}_t^w)\right) - Q_\theta\left(f(g_\tau(X), \hat{\beta}_\tau^b, \hat{\beta}_t^w)\right)$$

be the marginal contribution of changing between-group prices to ΔQ_θ. And finally define

$$\Delta Q_\theta^w = Q_\theta\left(f(g_\tau(X), \hat{\beta}_\tau^b, \hat{\beta}_t^w)\right) - Q_\theta\left(f(g_\tau(X), \hat{\beta}_\tau^b, \hat{\beta}_\tau^w)\right)$$

to be the marginal contribution of changing within-group prices to ΔQ_θ. In our estimations, τ denotes the earlier year.

5.3. Results for the OLS version of the Juhn, Murphy and Pierce decomposition

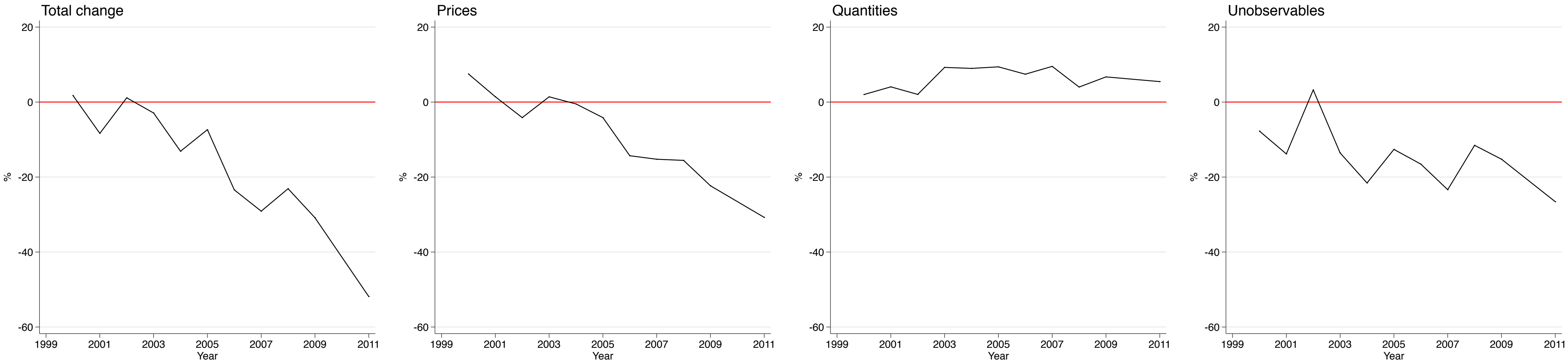
Figure 14 shows the results of the OLS JMP decomposition for the 90-10 ratio. The percent variation taking 1999 as the initial year is shown on the y axis, and the end year is on the x axis. The leftmost subfigure on figure 14 shows the evolution of the change in the 90-10 differential, for the full sample. Until 2005, the maximum total variation in the 90-10 ratio was -13.1% (year 2004), as seen on panel A of table 5. From 2005 on, the declining trend speeds up, to reach its minimum value in 2011, falling almost 52%. The contribution of observable quantities remained stable, never going over 10%, and positive, offsetting the trend in 1999-2011, hence observable prices and unobservable prices and quantities account for the decline. Unobservables never fluctuated below -26%, and do not have a clear falling tendency, as the one observable prices had, which after remaining close to 0 in 1999-2005, began to be the main driver for the decline, and from 2008 on, they become more important in magnitude than unobservables.

To determine if it was above or below the median inequality, let us turn to figure 15, which shows the results of this decomposition to the 90-50 and 50-10 differentials. It is clear from the leftmost subfigure on figure 15 that both ratios fell during 1999-2011, but it was the 90-50 ratio the one with the most clear and intense declining trend. Observable quantities did not play a significant role in the explanation of the change in below the median inequality, as it offset the effect of prices and unobservables, and it never went over 3%. Observable prices played a secondary role as the effect they had on the change in inequality follows the observed falling trend, but the magnitude of their contribution fails to reach half the magnitude of unobservables, which account for the vast majority of the decline in lower tail inequality.

The main driver behind the declining inequality trend is the effect of observable prices in above the median inequality. Observable quantities also have a positive, offsetting effect on the change of the 90-50 ratio that never surpassed the 10% mark. The effect of unobservables is negative and fluctuates around -10%, so it practically vanishes when considering the effect of quantities. So we left with the effect of prices, which was not meaningful until 2005, but from that year on, its declining trend accelerates to becoming the most meaningful factor when accounting for the declining trend: After 2005, its contribution fluctuates from half to two thirds of the total reduction.

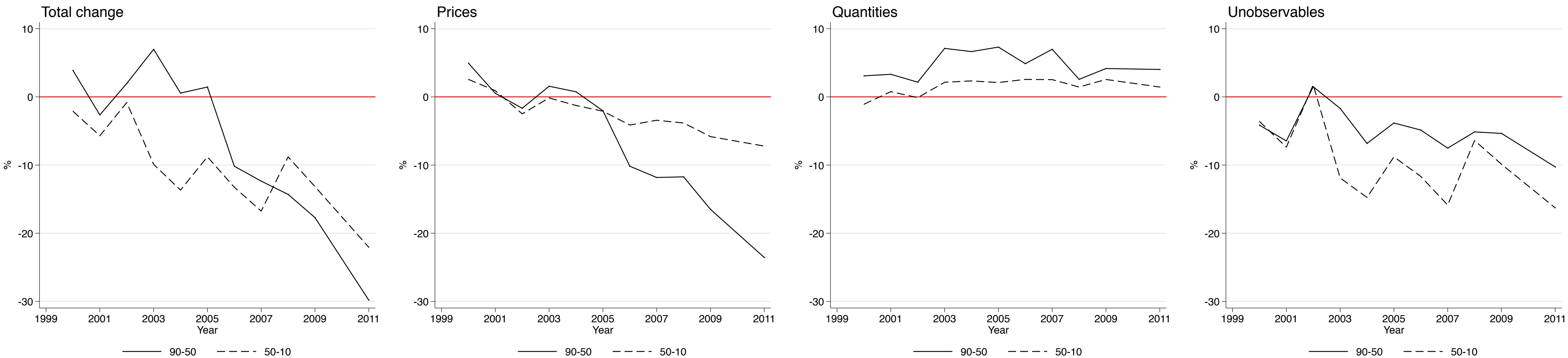
Splitting the sample by sex yields the same qualitative results. Results for the male sample, depicted in figure 16, make a conclusive statement regarding the role of workforce composition and prices in the inequality decline: When looking at the results for 2011, the year with lowest inequality, the contribution of prices is close to null, while observable prices account for half the inequality variation. When looking at lower and upper tail inequality in the male sample, the role of prices becomes even more important. From figure 17, it is evident than above the median inequality follows more closely the trend of the 90-10 differential, and the role of prices is even more important, as it explains the 1999-2005 slight inequality growth, and the even more important subsequent decline, as it contributes to three quarters of the total price effect. The results for the female sample, place greater importance on the role of prices. In the year with lowest inequality, 2011, out of the nearly 70 percent points reduction, 50 may be attributed to the effect of observable prices. The contribution of falling upper tail inequality is also higher in the female sample: Out of the 50 percent points due to the effect of prices, 40 come from falling above the median inequality in 2011.

Figure 14: Full sample: Contribution of observable and unobservable prices and quantities to the evolution of the change in inequality (90-10 percentile log wage differential, OLS JMP decomposition)



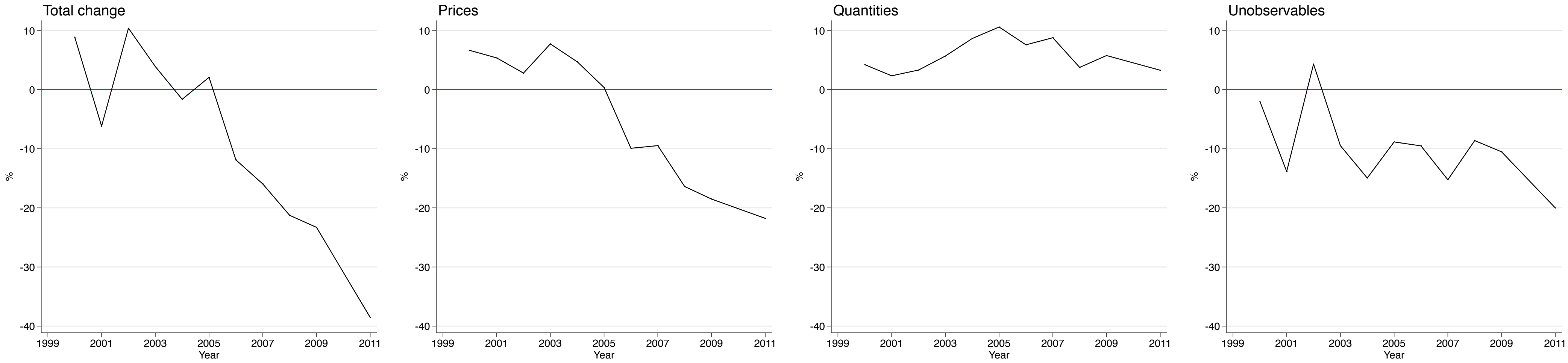
Source: Fundación ARU series of harmonized household surveys. Sample: 18-65 years old workers with positive salary. Outliers were dropped from the sample. Outliers were nominated using the BACON algorithm ($\alpha = 0.0001$). Note: The covariates include 4 education groups (incomplete high school, high school graduate, some college and college graduate), 10 experience groups and all the interactions among them.

Figure 15: Full sample: Contribution of observable and unobservable prices and quantities to the evolution of the change in inequality (90-50 and 50-10 percentile log wage differentials, OLS JMP decomposition)



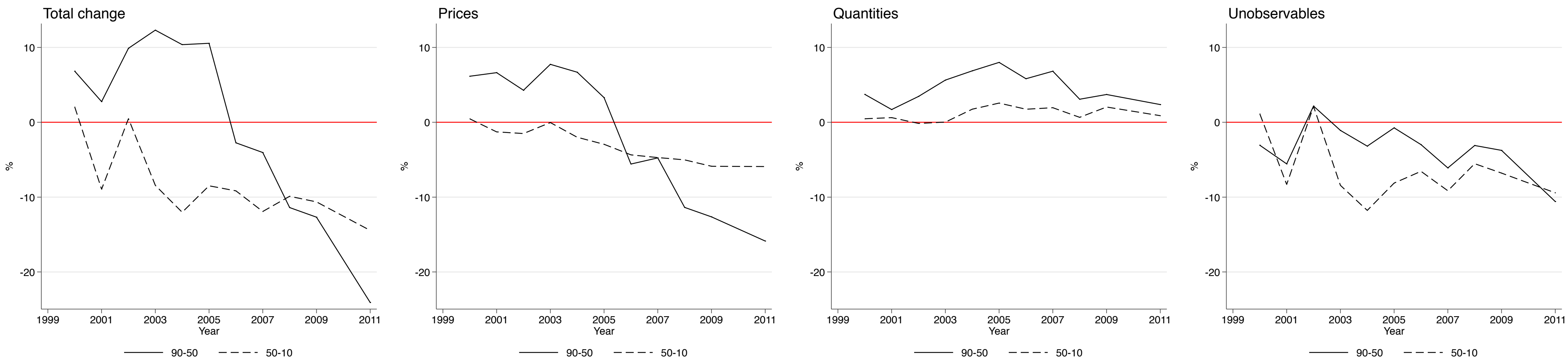
Source: Fundación ARU series of harmonized household surveys. Sample: 18-65 years old workers with positive salary. Outliers were dropped from the sample. Outliers were nominated using the BACON algorithm ($\alpha = 0.0001$). Note: The covariates include 4 education groups (incomplete high school, high school graduate, some college and college graduate), 10 experience groups and all the interactions among them.

Figure 16: Male workers: Contribution of observable and unobservable prices and quantities to the evolution of the change in inequality (90-10 percentile log wage differential, OLS JMP decomposition)



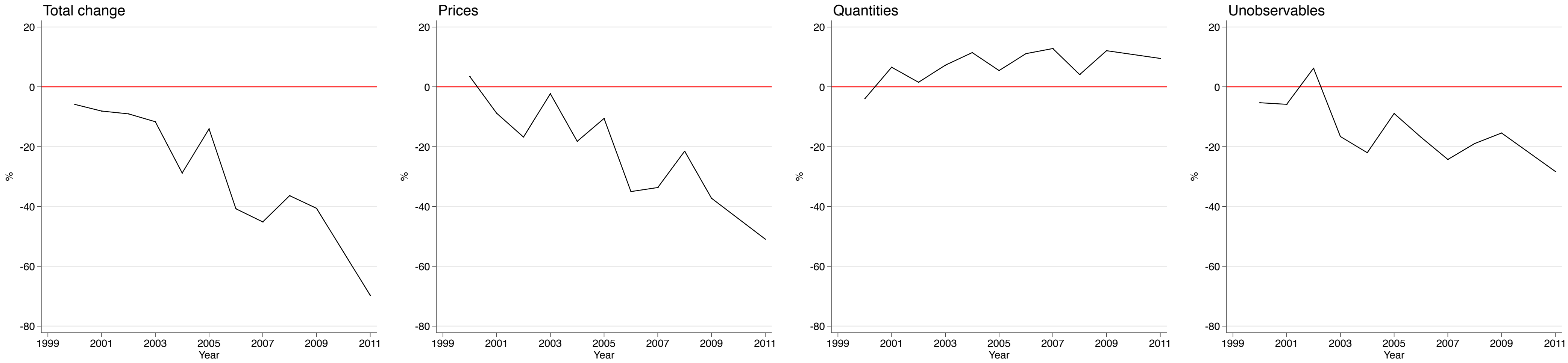
Source: Fundación ARU series of harmonized household surveys. Sample: 18-65 years old workers with positive salary. Outliers were dropped from the sample. Outliers were nominated using the BACON algorithm ($\alpha = 0.0001$). Note: The covariates include 4 education groups (incomplete high school, high school graduate, some college and college graduate), 10 experience groups and all the interactions among them.

Figure 17: Male workers: Contribution of observable and unobservable prices and quantities to the evolution of the change in inequality (90-50 and 50-10 percentile log wage differentials, OLS JMP decomposition)



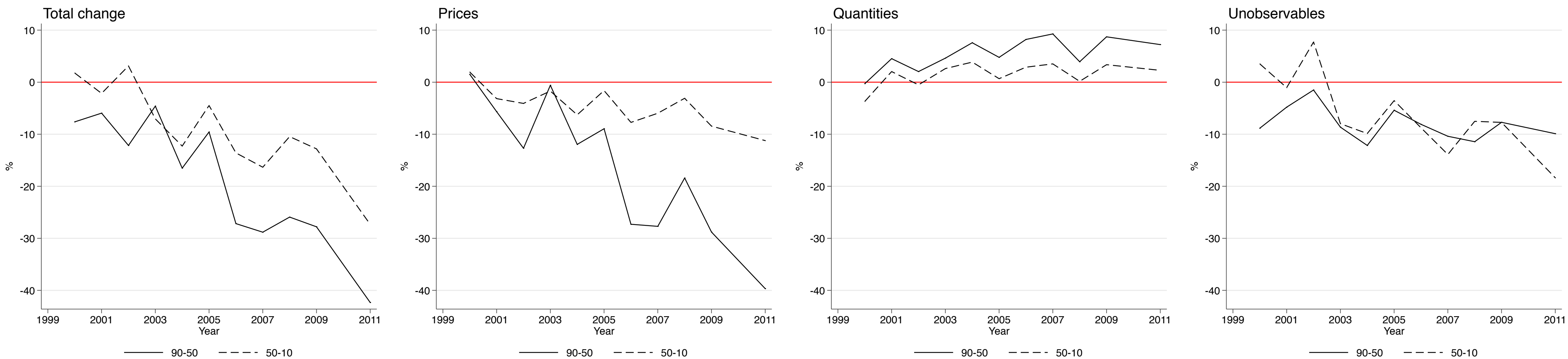
Source: Fundación ARU series of harmonized household surveys. Sample: 18-65 years old full time workers with positive salary. Outliers were dropped from the sample. Outliers were nominated using the BACON algorithm ($\alpha = 0.0001$). Note: The covariates include 4 education groups (incomplete high school, high school graduate, some college and college graduate), 10 experience groups and all the interactions among them.

Figure 18: Female workers: Contribution of observable and unobservable prices and quantities to the evolution of the change in inequality (90-10 percentile log wage differential, OLS JMP decomposition)



Source: Fundación ARU series of harmonized household surveys. Sample: 18-65 years old full time workers. Outliers were dropped from the sample. Outliers were nominated using the BACON algorithm ($\alpha = 0.0001$). Note: The covariates include 4 education groups (incomplete high school, high school graduate, some college and college graduate), 10 experience groups and all the interactions among them.

Figure 19: Female workers: Contribution of observable and unobservable prices and quantities to the evolution of the change in inequality (90-50 and 50-10 percentile log wage differentials, OLS JMP decomposition)



Source: Fundación ARU series of harmonized household surveys. Sample: 18-65 years old workers with positive salary. Outliers were dropped from the sample. Outliers were nominated using the BACON algorithm ($\alpha = 0.0001$). Note: The covariates include 4 education groups (incomplete high school, high school graduate, some college and college graduate), 10 experience groups and all the interactions among them.

Table 5: OLS JMP decomposition of changes in inequality 2000-2011

A. Full sample

Year	90-10 Total change	90-10 Character	90-10 Prices	90-10 Residua	90-50 Total change	90-50 Character	90-50 Prices	90-50 Residua	50-10 Total change	50-10 Character	50-10 Prices	50-10 Residuals
2000	1.77	2	7.5	-7.73	3.88	3.08	4.94	-4.14	-2.11	-1.08	2.56	-3.59
2001	-8.35	4.06	1.42	-13.83	-2.65	3.31	.51	-6.46	-5.7	.76	.91	-7.37
2002	1.14	2.04	-4.15	3.25	1.96	2.15	-1.67	1.48	-.83	-.11	-2.49	1.77
2003	-2.92	9.25	1.41	-13.57	6.98	7.11	1.56	-1.68	-9.9	2.14	-.15	-11.89
2004	-13.11	8.98	-.51	-21.58	.56	6.64	.75	-6.83	-13.67	2.34	-1.26	-14.75
2005	-7.36	9.4	-4.14	-12.62	1.44	7.3	-2.04	-3.83	-8.8	2.1	-2.1	-8.8
2006	-23.42	7.43	-14.31	-16.54	-10.17	4.87	-10.17	-4.87	-13.25	2.56	-4.13	-11.67
2007	-29.1	9.52	-15.25	-23.37	-12.36	6.98	-11.82	-7.52	-16.75	2.53	-3.43	-15.86
2008	-23.1	4	-15.56	-11.54	-14.3	2.57	-11.73	-5.14	-8.8	1.44	-3.83	-6.4
2009	-30.86	6.72	-22.33	-15.24	-17.7	4.16	-16.5	-5.36	-13.16	2.55	-5.83	-9.88
2011	-51.87	5.46	-30.76	-26.57	-29.81	4.02	-23.55	-10.28	-22.06	1.44	-7.22	-16.29

B. Males

Year	90-10 Total change	90-10 Character	90-10 Prices	90-10 Residua	90-50 Total change	90-50 Character	90-50 Prices	90-50 Residua	50-10 Total change	50-10 Character	50-10 Prices	50-10 Residuals
2000	8.86	4.2	6.62	-1.95	6.82	3.73	6.15	-3.07	2.04	.47	.46	1.12
2001	-6.19	2.32	5.35	-13.86	2.76	1.7	6.63	-5.56	-8.95	.62	-1.28	-8.3
2002	10.37	3.29	2.78	4.3	9.89	3.45	4.28	2.17	.48	-.15	-1.5	2.13
2003	3.88	5.66	7.71	-9.49	12.31	5.64	7.74	-1.08	-8.43	.02	-.04	-8.42
2004	-1.65	8.62	4.69	-14.96	10.37	6.87	6.69	-3.19	-12.02	1.75	-2	-11.77
2005	2.06	10.57	.35	-8.86	10.55	8	3.29	-.74	-8.49	2.57	-2.94	-8.12
2006	-11.9	7.56	-9.93	-9.53	-2.74	5.82	-5.58	-2.98	-9.16	1.74	-4.35	-6.55
2007	-15.96	8.76	-9.48	-15.25	-4.04	6.82	-4.76	-6.1	-11.92	1.95	-4.72	-9.15
2008	-21.27	3.74	-16.39	-8.63	-11.39	3.08	-11.37	-3.1	-9.89	.66	-5.02	-5.53
2009	-23.3	5.75	-18.52	-10.53	-12.68	3.71	-12.64	-3.75	-10.63	2.04	-5.88	-6.79
2011	-38.53	3.26	-21.78	-20.01	-24.08	2.37	-15.87	-10.59	-14.45	.88	-5.91	-9.42

C. Females

Year	90-10 Total change	90-10 Character	90-10 Prices	90-10 Residua	90-50 Total change	90-50 Character	90-50 Prices	90-50 Residua	50-10 Total change	50-10 Character	50-10 Prices	50-10 Residuals
2000	-5.86	-3.99	3.46	-5.32	-7.62	-.29	1.51	-8.84	1.76	-3.7	1.95	3.52
2001	-8.1	6.56	-8.82	-5.84	-5.95	4.52	-5.66	-4.8	-2.15	2.04	-3.16	-1.04
2002	-9.04	1.52	-16.78	6.22	-12.16	2.04	-12.7	-1.5	3.12	-.52	-4.08	7.72
2003	-11.67	7.25	-2.29	-16.62	-4.6	4.62	-.59	-8.64	-7.06	2.62	-1.7	-7.98
2004	-28.81	11.44	-18.22	-22.02	-16.52	7.58	-11.95	-12.16	-12.28	3.86	-6.27	-9.87
2005	-14.05	5.44	-10.57	-8.92	-9.57	4.77	-8.95	-5.39	-4.48	.67	-1.62	-3.54
2006	-40.77	11.09	-35.02	-16.84	-27.18	8.21	-27.3	-8.09	-13.59	2.88	-7.73	-8.75
2007	-45.16	12.8	-33.67	-24.28	-28.82	9.27	-27.7	-10.39	-16.34	3.52	-5.97	-13.89
2008	-36.38	4.09	-21.51	-18.96	-25.92	3.93	-18.41	-11.44	-10.46	.16	-3.09	-7.52
2009	-40.61	12.08	-37.25	-15.44	-27.79	8.72	-28.8	-7.71	-12.82	3.36	-8.45	-7.73
2011	-69.68	9.5	-50.91	-28.27	-42.34	7.22	-39.68	-9.89	-27.33	2.27	-11.23	-18.38

Source: Fundación ARU series of harmonized household surveys. Sample: 18-65 years old full time workers with positive salary. Outliers were dropped from the sample. Outliers were nominated using the BACON algorithm ($\alpha = 0.01$). Note: The covariates include 4 education groups (incomplete high school, high school graduate, some college and college graduate), 10 experience groups and all the interactions among them.

5.4. QR version of the Juhn, Murphy and Pierce decomposition

The use of quantile regressions to fit the observed distributions provide noticeable gains in precision, as the fit of the estimated distributions is better than the fit provided by the OLS model, as the difference between the observed change in inequality and the simulated change vary only in decimal places, as opposed to the difference between OLS simulated inequality and observed inequality, which can be as large as 4 percent points.

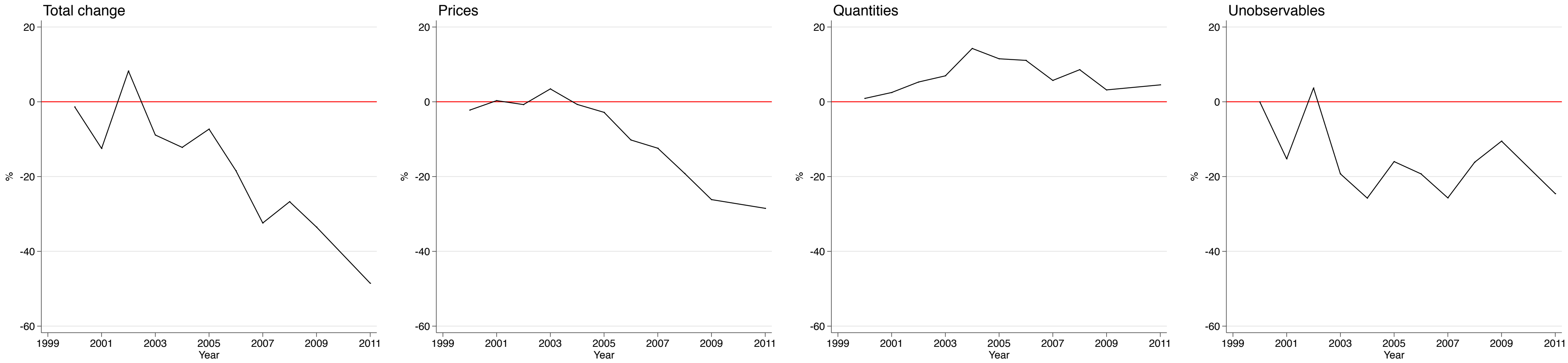
The results for these decompositions may be viewed in table 6, and in figures 20 through 25, and they confirm the findings of the OLS JMP decomposition: Offsetting trends for the quantities counterfactual, and observed prices as the main factor for the inequality decline, which was most intense above the median. Figure 20 shows the results of the QR JMP decomposition for the full sample 90-10 differential, where observed quantities and unobservables play a decisive role when explaining the changes in inequality until 2005, and the contribution of prices remains close to zero until such year. From 2005 on, changes in inequality are accounted for by prices and unobservables, and after 2008, the contribution of prices becomes crucial in determining the inequality trend. When distinguishing upper from lower tail inequality in figure 21, upper tail inequality is the clear trend setter. Both the 50-10 and 90-50 ratios declined during 1999-2011, but after 2005, the above the median observed prices component contributes the most to the inequality fall, and the fall in below the median inequality is almost exclusively driven by unobservable prices and quantities.

The results for the male sample shown in figure 22 are consistent with full sample results, with a smaller, offsetting contribution of observable quantities, with a maximum contribution of 10 percent points, a maximum contribution of residuals of 20 percent points, and prices being the leading effect for the decline. Upper tail inequality also accounts for the majority of the decline, with a commanding price effect. Below the median inequality is also mostly accounted for by the effect of residuals, but prices played a clear role in the fall of this ratio.

In the female sample, whose results are show on figures 24 and 25, the role of prices and residuals also account for the majority of the decline, as it happened all throughout 1999-2011, below and above the median with similar intensity. Observable prices played a major factor in the upper tail inequality decline, while residuals did so in lower tail inequality. The role of composition never exceeded 10 percent points throughout 1999-2011.

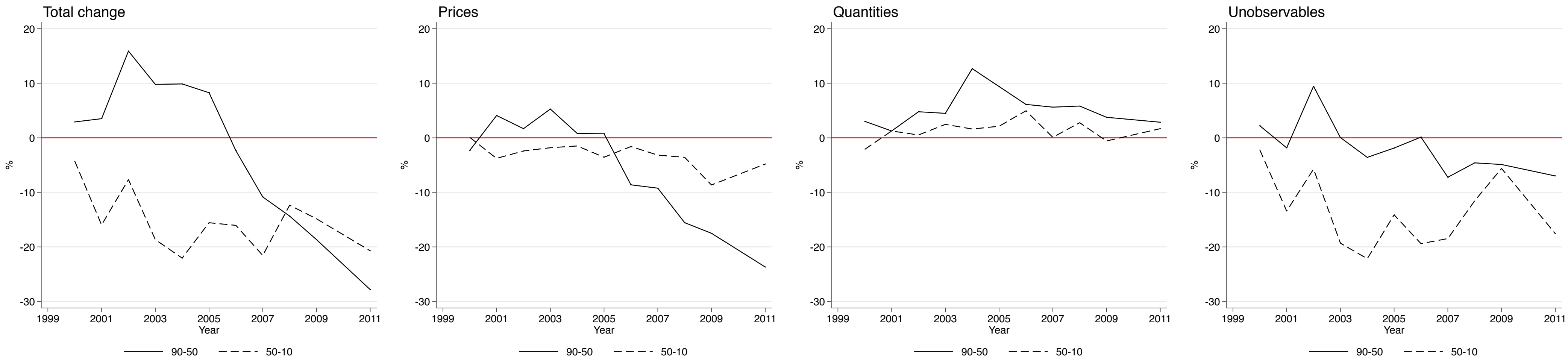
To conclude, labor force composition played a minor role in the decline, and in all cases, its effect was increasing on inequality: the effect of composition would have caused inequality to rise. On the other hand, the effect of prices was highly equalizing, as it neutralized the effect of composition and lead to sharp declines, specially in above the median inequality, which contributed the most to the overall decline.

Figure 20: Full sample: Contribution of observable and unobservable prices and quantities to the evolution of the change in inequality (90-10 percentile log wage differential, QR JMP decomposition)



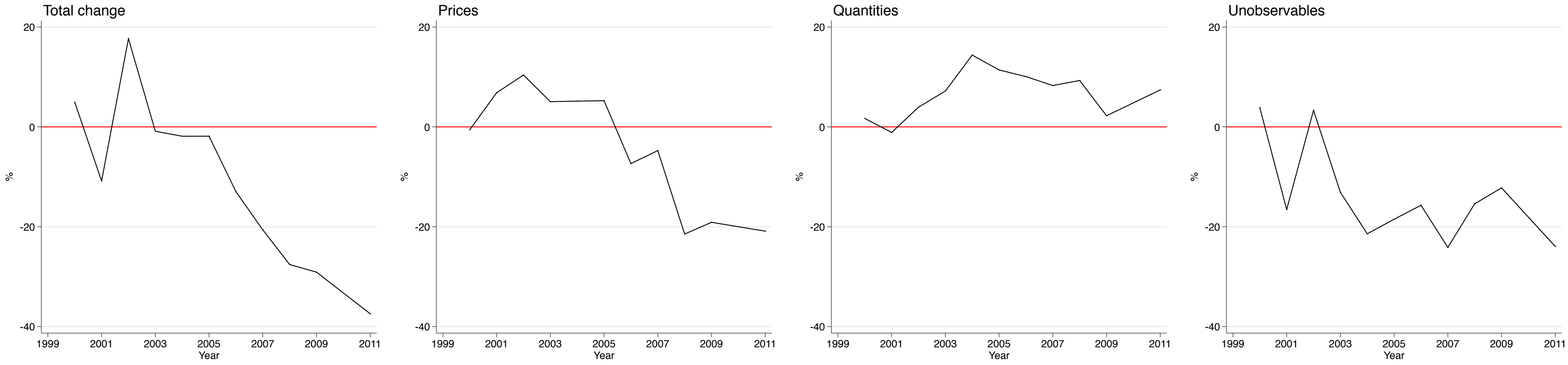
Source: Fundación ARU series of harmonized household surveys. Sample: 18-65 years old workers with positive salary. Outliers were dropped from the sample. Outliers were nominated using the BACON algorithm ($\alpha = 0.0001$). Note: The covariates include 4 education groups (incomplete high school, high school graduate, some college and college graduate), 10 experience groups and all the interactions among them.

Figure 21: Full sample: Contribution of observable and unobservable prices and quantities to the evolution of the change in inequality (90-50 and 50-10 percentile log wage differentials, QR JMP decomposition)



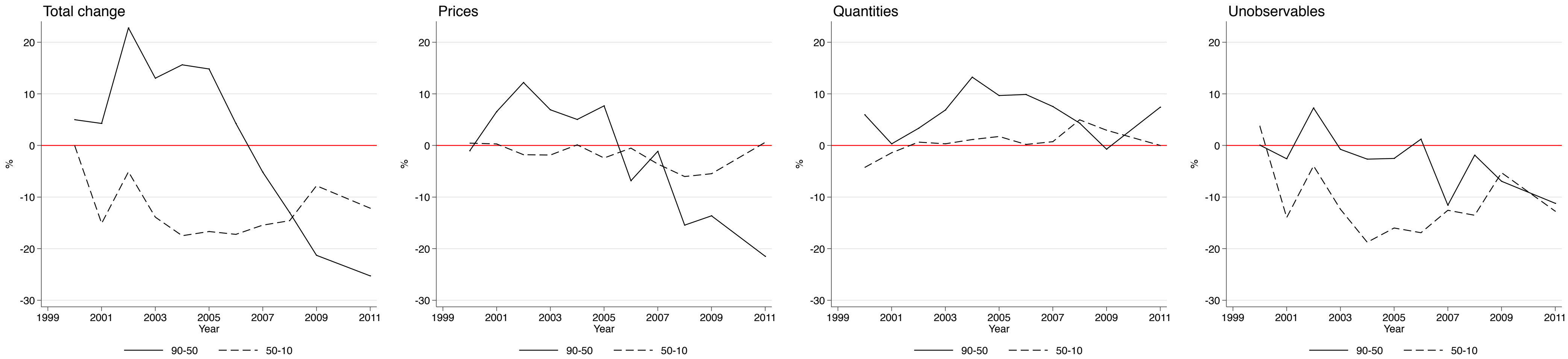
Source: Fundación ARU series of harmonized household surveys. Sample: 18-65 years old workers with positive salary. Outliers were dropped from the sample. Outliers were nominated using the BACON algorithm ($\alpha = 0.0001$). Note: The covariates include 4 education groups (incomplete high school, high school graduate, some college and college graduate), 10 experience groups and all the interactions among them.

Figure 22: Male workers: Contribution of observable and unobservable prices and quantities to the evolution of the change in inequality (90-10 percentile log wage differential, QR JMP decomposition)



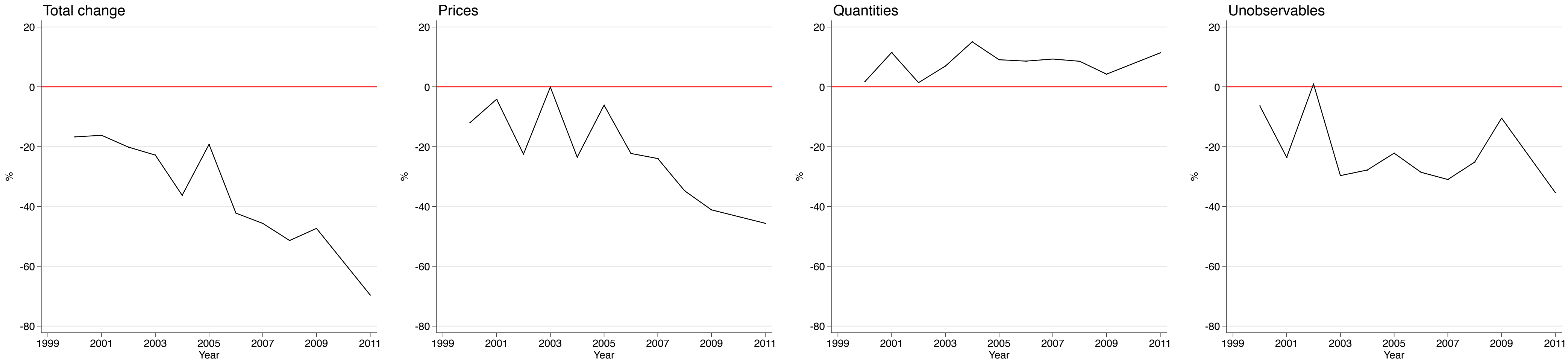
Source: Fundación ARU series of harmonized household surveys. Sample: 18-65 years old workers with positive salary. Outliers were dropped from the sample. Outliers were nominated using the BACON algorithm ($\alpha = 0.0001$). Note: The covariates include 4 education groups (incomplete high school, high school graduate, some college and college graduate), 10 experience groups and all the interactions among them.

Figure 23: Male workers: Contribution of observable and unobservable prices and quantities to the evolution of the change in inequality (90-50 and 50-10 percentile log wage differentials, QR JMP decomposition)



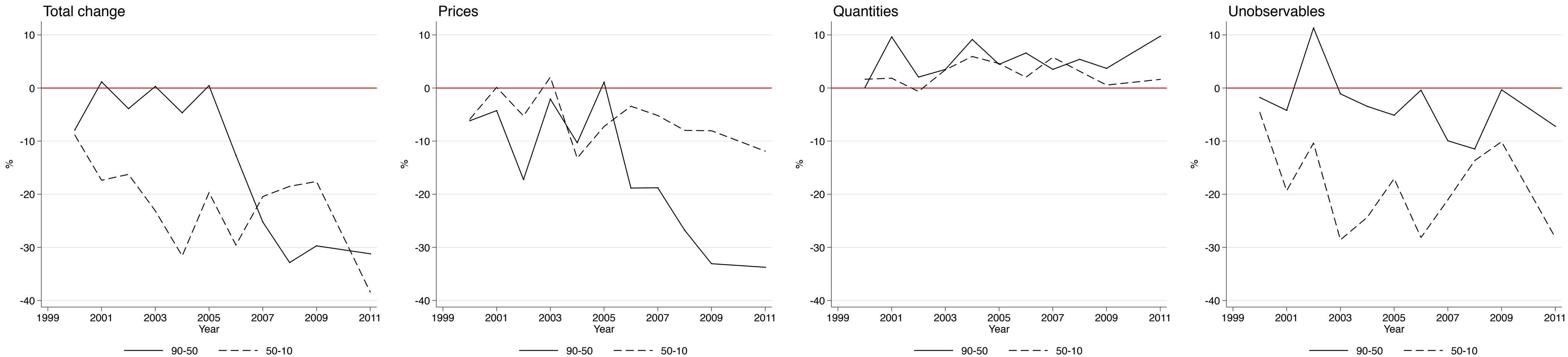
Source: Fundación ARU series of harmonized household surveys. Sample: 18-65 years old workers with positive salary. Outliers were dropped from the sample. Outliers were nominated using the BACON algorithm ($\alpha = 0.0001$). Note: The covariates include 4 education groups (incomplete high school, high school graduate, some college and college graduate), 10 experience groups and all the interactions among them.

Figure 24: Female workers: Contribution of observable and unobservable prices and quantities to the evolution of the change in inequality (90-10 percentile log wage differential, QR JMP decomposition)



Source: Fundación ARU series of harmonized household surveys. Sample: 18-65 years old workers with positive salary. Outliers were dropped from the sample. Outliers were nominated using the BACON algorithm ($\alpha = 0.0001$). Note: The covariates include 4 education groups (incomplete high school, high school graduate, some college and college graduate), 10 experience groups and all the interactions among them.

Figure 25: Female workers: Contribution of observable and unobservable prices and quantities to the evolution of the change in inequality (90-50 and 50-10 percentile log wage differentials, QR JMP decomposition)



Source: Fundación ARU series of harmonized household surveys. Sample: 18-65 years old workers with positive salary. Outliers were dropped from the sample. Outliers were nominated using the BACON algorithm ($\alpha = 0.0001$). Note: The covariates include 4 education groups (incomplete high school, high school graduate, some college and college graduate), 10 experience groups and all the interactions among them.

Table 6: QR JMP decomposition of changes in inequality 2000-2011

A. Full sample

Year	90-10 Total change	90-10 Character	90-10 Prices	90-10 Residua	90-50 Total change	90-50 Character	90-50 Prices	90-50 Residua	50-10 Total change	50-10 Character	50-10 Prices	50-10 Residuals
2000	-1.37	.9	-2.23	-.04	2.91	3.02	-2.31	2.2	-4.28	-2.12	.08	-2.24
2001	-12.48	2.49	.31	-15.28	3.5	1.25	4.09	-1.84	-15.98	1.25	-3.78	-13.44
2002	8.24	5.28	-.74	3.7	15.89	4.77	1.67	9.45	-7.65	.51	-2.42	-5.74
2003	-8.88	6.94	3.45	-19.27	9.79	4.48	5.27	.04	-18.67	2.46	-1.82	-19.31
2004	-12.19	14.27	-.71	-25.76	9.87	12.67	.79	-3.59	-22.06	1.6	-1.49	-22.17
2005	-7.31	11.51	-2.82	-16	8.26	9.4	.74	-1.88	-15.57	2.12	-3.56	-14.13
2006	-18.42	11.07	-10.22	-19.27	-2.37	6.12	-8.62	.13	-16.05	4.95	-1.6	-19.4
2007	-32.42	5.71	-12.42	-25.71	-10.85	5.62	-9.24	-7.23	-21.57	.09	-3.18	-18.48
2008	-26.72	8.58	-19.15	-16.15	-14.35	5.82	-15.56	-4.6	-12.37	2.76	-3.58	-11.55
2009	-33.5	3.18	-26.16	-10.52	-18.66	3.76	-17.51	-4.9	-14.85	-.58	-8.65	-5.62
2011	-48.54	4.53	-28.5	-24.57	-27.83	2.85	-23.69	-6.99	-20.71	1.67	-4.81	-17.57

B. Males

Year	90-10 Total change	90-10 Character	90-10 Prices	90-10 Residua	90-50 Total change	90-50 Character	90-50 Prices	90-50 Residua	50-10 Total change	50-10 Character	50-10 Prices	50-10 Residuals
2000	4.94	1.69	-.58	3.83	4.99	5.95	-1.03	.07	-.05	-4.26	.45	3.76
2001	-10.84	-1.11	6.83	-16.55	4.26	.31	6.54	-2.59	-15.1	-1.42	.29	-13.97
2002	17.68	3.95	10.4	3.32	22.78	3.32	12.19	7.27	-5.11	.64	-1.79	-3.95
2003	-.87	7.18	5.05	-13.11	13.03	6.86	6.91	-.75	-13.9	.32	-1.86	-12.36
2004	-1.87	14.38	5.16	-21.41	15.62	13.24	5.04	-2.65	-17.49	1.14	.12	-18.76
2005	-1.86	11.41	5.24	-18.5	14.82	9.67	7.67	-2.52	-16.68	1.74	-2.43	-15.99
2006	-12.97	10.08	-7.36	-15.7	4.26	9.88	-6.84	1.22	-17.23	.2	-.52	-16.91
2007	-20.61	8.28	-4.74	-24.14	-5.17	7.55	-1.14	-11.58	-15.44	.73	-3.6	-12.56
2008	-27.57	9.29	-21.46	-15.4	-12.99	4.32	-15.44	-1.87	-14.58	4.97	-6.02	-13.53
2009	-29.1	2.23	-19.11	-12.22	-21.29	-.72	-13.64	-6.94	-7.81	2.95	-5.47	-5.29
2011	-37.43	7.41	-20.88	-23.96	-25.28	7.41	-21.48	-11.21	-12.16	0	.6	-12.75

C. Females

Year	90-10 Total change	90-10 Character	90-10 Prices	90-10 Residua	90-50 Total change	90-50 Character	90-50 Prices	90-50 Residua	50-10 Total change	50-10 Character	50-10 Prices	50-10 Residuals
2000	-16.73	1.69	-12.05	-6.37	-7.91	.04	-6.17	-1.78	-8.82	1.65	-5.88	-4.59
2001	-16.21	11.48	-4.14	-23.55	1.16	9.63	-4.26	-4.21	-17.37	1.85	.12	-19.34
2002	-20.15	1.4	-22.5	.95	-3.89	2.05	-17.25	11.31	-16.26	-.66	-5.24	-10.36
2003	-22.83	6.92	-.07	-29.68	.3	3.5	-2.09	-1.1	-23.13	3.42	2.03	-28.58
2004	-36.26	15.05	-23.51	-27.81	-4.66	9.13	-10.32	-3.46	-31.61	5.93	-13.19	-24.34
2005	-19.24	9.07	-6.13	-22.18	.45	4.46	1.11	-5.12	-19.69	4.61	-7.24	-17.06
2006	-42.22	8.6	-22.27	-28.56	-12.66	6.59	-18.83	-.41	-29.57	2.01	-3.43	-28.15
2007	-45.65	9.3	-23.97	-30.98	-25.22	3.51	-18.79	-9.94	-20.44	5.79	-5.18	-21.04
2008	-51.37	8.55	-34.77	-25.16	-32.86	5.4	-26.78	-11.48	-18.51	3.15	-7.98	-13.67
2009	-47.32	4.25	-41.13	-10.45	-29.72	3.7	-33.08	-.34	-17.6	.55	-8.05	-10.11
2011	-69.61	11.36	-45.62	-35.35	-31.21	9.74	-33.75	-7.2	-38.4	1.62	-11.88	-28.15

Source: Fundación ARU series of harmonized household surveys. Sample: 18-65 years old full time workers with positive salary. Outliers were dropped from the sample. Outliers were nominated using the BACON algorithm ($\alpha = 0.01$). Note: The covariates include 4 education groups (incomplete high school, high school graduate, some college and college graduate), 10 experience groups and all the interactions among them.

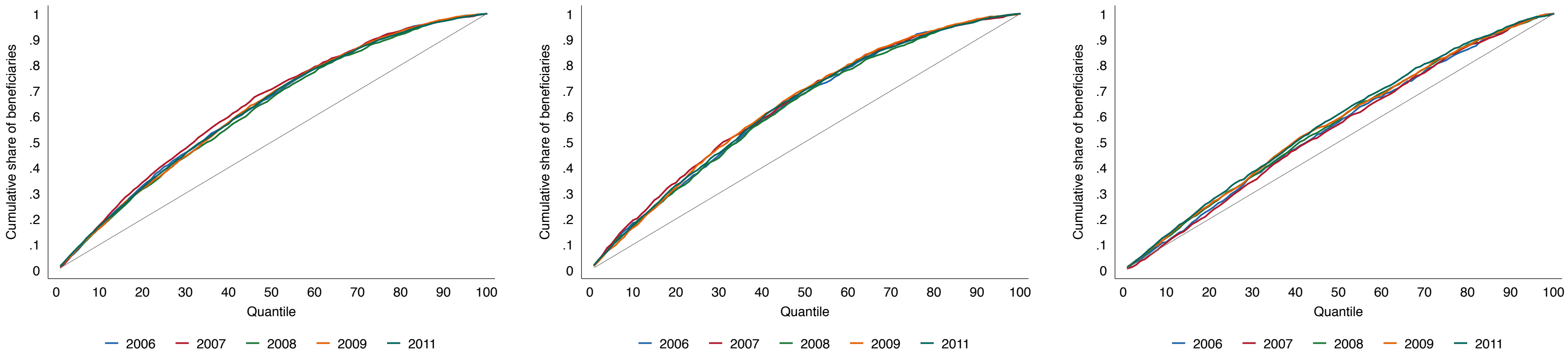
6. Public policy issues

The year 2005 marked the end of *neo-liberal* governments and the beginning of the new left regime, lead by Evo Morales. His administration expanded and modified existing conditional cash transfer programs as part of a new redistributive policy. Specifically, the *Juancito Pinto* and *Juana Azurduy* programs were created as conditional cash transfers, the first one to promote elementary school asistance and permanence, and the second one to improve health care for pregnant women and their children, until they turn 5. An already existing non-contributory social security program, *Bonosol* was modified and renamed to *Renta Dignidad*.

We now analyze the targeting of these programs. Figures 26 and 27 show the concentration curves by area for the *Juancito Pinto* and *Renta Dignidad* transfers, respectively. *Juancito Pinto* is a progresive transfer, as nearly 70% of the transfer reaches the first half of the distribution, but it fails to achieve the targeting of similar programs in other countries. *Renta Dignidad* is a regresive transfer, as having access to contributory social security is not a restriction to receive *Renta Dignidad*, it only reduces by 25% the amount of the transfer.

Regarding the generosity of the transfer, we estimate the relevance of the transfer as a share of the total income, shown on figures 28 and 29.*Juancito Pinto*'s value is approximately 30 US dollars per year, and as seen on figure 28, it is at most 50% of total household income for the bottom percentile of the distribution. It's share remains close to zero from the 10th percentile on. In the rural area, it's relevance in total household income may be as high as 80%, but after the 10th percentile, this percentage is drastically reduced as well. *Renta dignidad* is a much more generous transfer, with a value of a little under 30 US dollars per month, for people over 60 years old. In urban areas, it may be as much as 50% of total household income for the bottom quantiles, and 10% of total income for households in the median of the income distribution. But as we've shown in previous sections, this is not enough to promote changes in inequality.

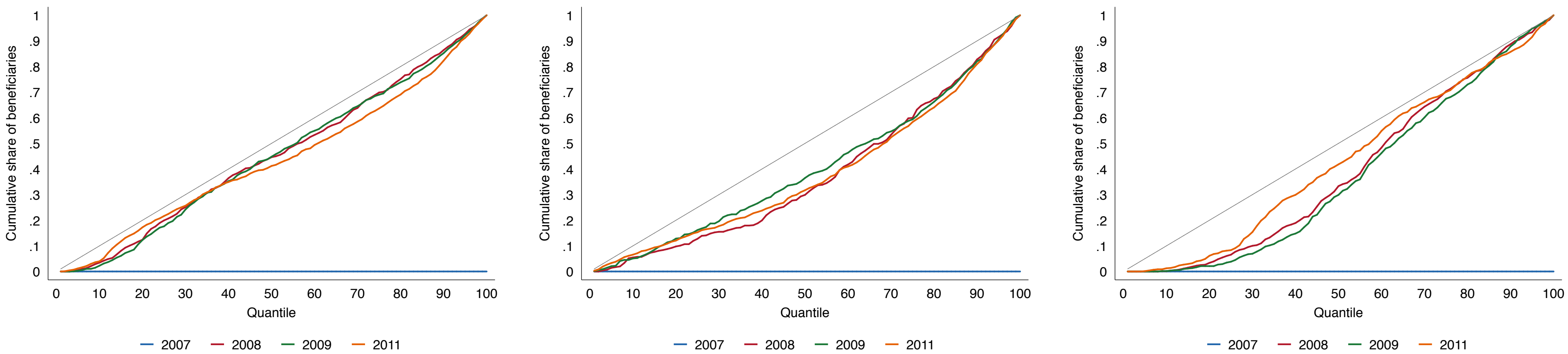
Figure 26: *Juancito pinto* concentration curve by area



National | Urban | Rural

Source: Fundación ARU series of harmonized household surveys. Note: Zeros and outliers were dropped from the sample. Outliers were nominated using the BACON algorithm ($\alpha = 0.0001$).

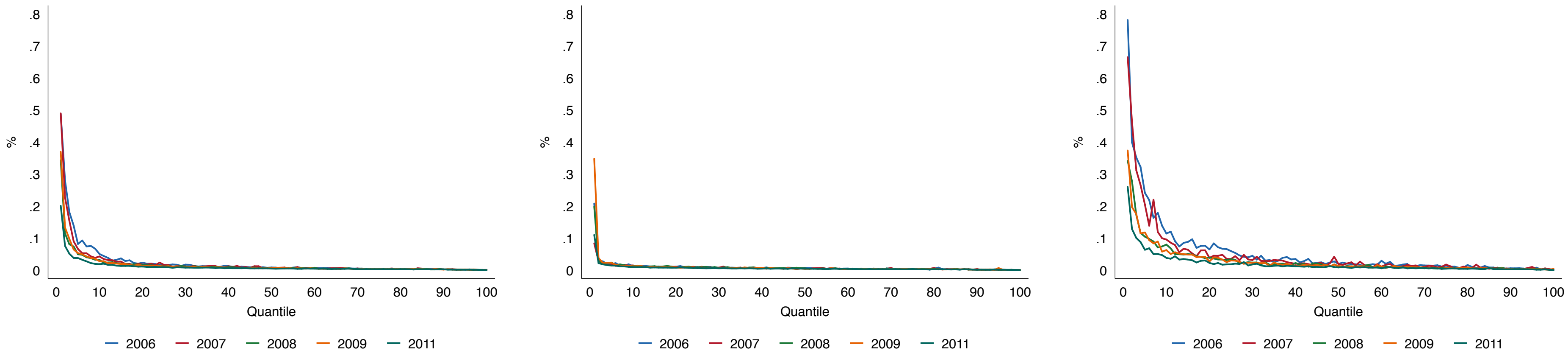
Figure 27: *Renta dignidad* concentration curve by area



National | Urban | Rural

Source: Fundación ARU series of harmonized household surveys. Note: Zeros and outliers were dropped from the sample. Outliers were nominated using the BACON algorithm ($\alpha = 0.0001$).

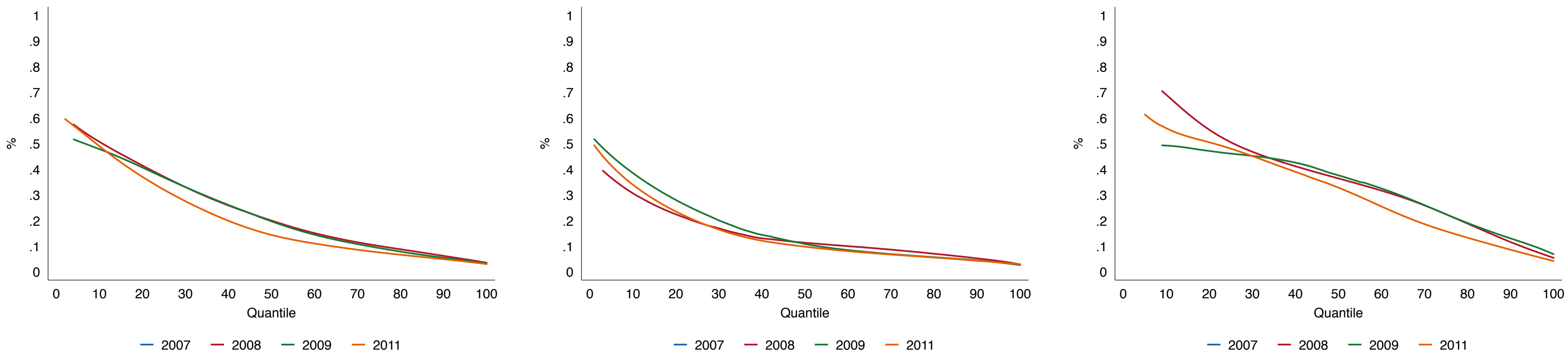
Figure 28: *Juancito pinto* as share of household income by area



National Urban Rural

Source: Fundación ARU series of harmonized household surveys. Note: Zeros and outliers were dropped from the sample. Outliers were nominated using the BACON algorithm ($\alpha = 0.0001$).

Figure 29: *Renta dignidad* as share of household income by area (smoothed)



National Urban Rural

Source: Fundación ARU series of harmonized household surveys. Note: Zeros and outliers were dropped from the sample. Outliers were nominated using the BACON algorithm ($\alpha = 0.0001$).

7. Conclusions

This paper set to analyze the determinants of the fast paced inequality decline in Bolivia during the 2000s, a period in which growth was high for the country's usual levels, and conditional cash transfer programs were implemented and modified. We find that the relevance of government transfers to the evolution of inequality is insignificant. The labor earnings component of per capita household income was the driver of the decline. Furthermore, we find that neither the intensity of labor, nor labor market participation decisions, nor compositional shifts in the labor force are responsible for the decline. Reductions in skill premia, through labor market prices account for the majority of the decline, which was more intense in the top half of the wage distribution. Regarding government transfers, we find that they fail to be as progressive as similar programs in other countries, and in some cases they are regressive. The amount of the transfer fails to produce any noticeable change in inequality.

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