Wage inequality on the rise: The role of workers' characteristics[1]

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Abstract

Wage inequality has been an important factor behind the rise in income inequality around the world in recent decades. The leading explanation for increased wage inequality has been the increasing returns to human capital, usually attributed to changing technology and globalization. This paper studies the rise in wage inequality in Uruguay, a small open developing economy. In contrast with popular explanations, our results highlight a strong and gradual inequalizing effect of changes in workers' characteristics such as increased schooling and age, decline of public sector employment and contraction of employment in manufacturing together with increased employment in services.

Keywords: wage inequality, quantile regressions, inequality decomposition, Uruguay.

JEL Classification: J31, D31.

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1. Introduction

Wage inequality has been on the rise in the last three decades in most developed countries (OECD 2011): wages of those at the top and bottom of the wage distribution started diverging early in the 1980s in English-speaking countries and in the 1990s this trend became generalized across most other developed countries (OECD 2011).[5] In Latin America, usually characterized as the most unequal region in the world, wage inequality also rose in the 1980s and 1990s, particularly in the region's most populous countries (Gasparini and Lustig, 2011).

Notwithstanding the effort of outstanding scholars, there is no consensus yet on the causes of the observed increase in wage dispersion. On the one hand, since the early 1990s the observed correlation between the evolution of wage inequality and returns to education and experience led scholars to attribute rising wage inequality to increases in the price of human capital (Katz and Murphy, 1992; Juhn, Murphy and Pierce, 1993). A similar literature on Latin America followed, associating growing wage inequality with rising returns to college education during the 1990s (Manacorda et al., 2005; Avalos and Savvides, 2006; Behrman et al., 2000; Sánchez-Páramo and Schady, 2003; Contreras and Gallegos, 2011; Binelli, 2008). Within a standard price theory setup, rising returns to human capital are a consequence of excess demand for skills, which has in turn mainly been attributed to (skill biased) technological change and/or globalization (Katz and Murphy, 1992; Juhn, Murphy and Pierce, 1993; Acemoglu, 2002; Goldin and Katz, 2008). Although research along these lines has received serious critiques (Card and DiNardo, 2002; Lemieux, 2006), it has probably remained

[5] Though wage inequality is an important object of study per se, understanding its dynamics and drivers provides important insights on income inequality in general. Some scholars mention wage inequality as an important or even as the main driver of income inequality (OCDE 2011), although other factors may be important as well (Gottschalk and Moffitt (2009) stress increased earnings instability as a driver behind higher inequality measures). The extent to which the following discussion on the wage inequality literature and our contribution can be extended into the realm of income inequality will be left to the reader.

the leading explanation behind increased wage inequality around the world (IMF, 2007; Goldin and Katz, 2008; Mankiw, 2013).

On the other hand, a series of other influential papers has proposed a set of competing hypotheses to explain rising wage inequality, from which we may distinguish two main groups. The first group has highlighted, since the mid-1990s, the changing role of institutions as drivers of the evolution of wage inequality (DiNardo, Fortin and Lemieux, 1996; Piketty and Saez, 2006; Lemieux, MacLeod and Parent, 2009).[6] The second group emphasizes the role of changes in the distribution of workers according to certain observable characteristics such as education, experience, gender or economic sector of activity (Lemieux, 2006; Machado and Mata, 2005; Melly, 2005; Lacuesta and Izquierdo, 2012). This explanation, highlighting the role of composition effects, started to emerge more recently and it is fair to say that it is far less popular than the other two.

The present paper contributes to the discussion between these competing hypotheses by providing evidence that highlights the role of composition effects as a driver of wage inequality in Uruguay, a small open developing economy. The relevance of our contribution is twofold. First, evidence on the evolution and causes of wage inequality in developing countries is still relatively scarce (OECD, 2011) and thus our paper contributes to completing a missing part of the story on global wage inequality. Being a small and open economy that experienced rapid increases in wage inequality in the 1990s and 2000s, evidence for Uruguay might be a starting point to look for candidates in order to explain the evolution of wage inequality in similar economies in the developing world. Second, state-of-the-art econometric techniques (Melly, 2005; Chernozhukov, Fernandez-Val and Melly, 2013) allows us to discuss why previous studies may have understated the relevance of changing workers characteristics to

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[6] The hypothesis of changing institutions focuses for instance in the impact of minimum wages (DiNardo, Fortin and Lemieux, 1996; Lee 1999), norms (Piketty and Saez, 2006) and pay regimes (Lemieux, MacLeod and Parent, 2009) among labor market institutions.

understand the evolution of wage inequality. The improved measurement of this composition effect gives a rationale for why previous studies may have underestimated the role of changing workers characteristics among the set of competing hypotheses mentioned above.

We believe there are two important factors that may explain the relatively late arrival and low popularity of composition effects as an explanation of wage inequality changes. First, and as it will become clear later, the correct identification of *composition* effects was limited by shortcomings of available econometric techniques (Lemieux, 2006; Melly, 2005). Second, as prices change faster than quantities, composition effects are more likely to be noticeable after a while and only in studies adopting more of a long-run perspective.

Our paper can thus be placed among the group of recent papers highlighting the role of composition effects by providing evidence for a small developing economy, Uruguay, which experienced rapid wage inequality increases during the 1990s and 2000s. To do this, we apply a decomposition technique based on the estimation of quantile regressions, which was proposed by Melly (2005). The decomposition approach allows us to capture, given a certain set of workers' characteristics, whether changes in wage inequality were due to shifts in wage differentials between groups of workers (price effects), variations in the distribution of personal attributes (characteristics effect), or to other changes within groups of workers (residual effect). The methodology's main advantage over previous techniques based on OLS regressions – such as Juhn, Murphy and Pierce (1993) – is the improved way in which it measures the characteristics effect (Melly, 2005; Machado and Mata, 2005; Autor, Katz and Kearney, 2005). To illustrate this, consider the case in which within wage dispersion differs among groups of workers. In this case, changes in the distribution of workers between those groups will affect the overall dispersion of wages. The methodology applied by Juhn, Murphy and Pierce (1993) does not capture this adequately because their procedure does not condition residuals on characteristics. Since quantile regressions allow characteristics to affect the whole distribution of wages -and not only the mean as in OLS regressions-, use of this approach to estimate the counterfactual distribution of wages leads to a better identification of how changes in the composition of the workforce affect the overall dispersion of wages.

Another traditional approach to decomposing changes in wage distributions, which has the advantage of capturing phenomena such as the example in the previous paragraph, is the non-parametric technique developed by DiNardo, Fortin and Lemieux (1996). The drawback of their approach is that it does not discern between within-group effects and between-group effects. The quantile regression decomposition approach can be seen as integrating the methods of Juhn, Murphy and Pierce (1993) and DiNardo, Fortin and Lemieux (1996), since it simultaneously permits the identification of between-group and within-group wage differentials as well as composition effects. The importance of applying this methodology should now be clearer: coming back to the discussion on the competing hypothesis behind changes in wage inequality, this methodology has the potential to provide clearer answers regarding the predominant factor behind a particular trend in wage inequality.

Previous empirical work on wage inequality in Uruguay using the Juhn, Murphy and Pierce (1993) methodology found that the price effect played a key role in changes in inequality between 1986 and 1999 (Arim and Zoppolo, 2000). In a similar fashion to what happened in the US, this emphasis on price effects as driving forces of inequality trends has been generally accepted by local academia, and is believed to be linked to the many structural reforms implemented in the country in the 1990s –covering labor markets, commercial integration and exchange rate policies.[7] However, research conducted for other countries based on the same methodology used here tends to emphasize the inequalizing role played by certain changes in workers' characteristics, like the rise in schooling and experience levels as well as de-unionization (Machado and Mata, 2005; Melly, 2005; Autor, Katz and Kearney, 2005).

The paper begins by briefly describing the evolution of wage inequality in Uruguay and introducing the three candidates driving factors: prices, characteristics and residuals (section 2). Then we introduce the methodology and empirical strategy (section 3) and the data used (section 4). In section 5, we set out the main results of the decomposition exercise and then we close the paper with a summary of the main findings and a brief discussion of some of their implications (section 6).

2. Wage inequality in Uruguay, 1986-2007

2.1 *General country context*

As a preamble before discussing the evolution of wage inequality, some context on the main economic events would be helpful. After a decade of military rule, Uruguay returned to democracy in 1985. The first years of the period thus correspond to a phase of political adjustment that went by without major economic reforms but with smaller relevant changes, such as the end of union prohibition and the partial reinstatement of centralized wage bargaining probably improved worker's bargaining power. Starting in 1991, a new government put forth a more ambitious economic reform package based on three fronts. On the labor front, the government dismantled centralized wage bargaining and reduced the share of public employment, which

[7] Section 2 includes a more in-depth discussion of these reforms.

declined from 28.8% in 1990 to 24.9% in 1997 (see Table A.2). On the commercial front, the government implemented an aggressive liberalization scheme that included drastic reduction of tariffs and other regulations concerning imports and exports.[8] These policies shifted relative prices and meant a negative shock to (previously protected) industrial production and a positive one to the financial sector. As a result, employment in manufacturing fell from 21.9% of the total workforce in 1990 to 13.4% in 2004, while the employment share of finance and related sectors went up from 5.0% to 7.5% in those years (see Table A.2). On the exchange rate front, the government chose to fight inflation with a stabilization plan based on an exchange rate anchor implemented via a crawling peg to the US dollar. The scheme was quite successful in fighting inflation, but added pressure to tradable industries as it led to a negative evolution of competitiveness vis-à-vis competing economies.[9]

By the end of the 1990s, bad economic performance of neighboring Brazil and Argentina (respectively entered recession in 1998 and 1999) together with real exchange rate misalignments led to a stagnating economic situation, that was aggravated by supply shocks[10] as well as contagion from the Argentinian 2001 financial crisis that eventually forced an abandonment of the exchange rate anchor and a full-scale devaluation. After a recession in 2002 and a double-digit contraction in GDP in 2003, the country recovered through export-led growth. Starting in 2005, a new center-left government introduced major economic reforms comprising taxation, labor relations (re-instating the centralized wage bargaining mechanism dismantled in 1991), public health and foreign investment, among others.

[8] These changes went hand in hand with the implementation of MERCOSUR, a free trade area comprising Argentina, Brazil, Paraguay and Uruguay.

[9] For a more detailed description of these processes see Olesker (2001).

[10] Supply shocks included floods and droughts. Agricultural based exports collapsed and high end markets (as US and EU) stopped demanding Uruguayan meat after a surge in foot-and-mouth disease affected cattle as well.

2.2 *The evolution of wage inequality*

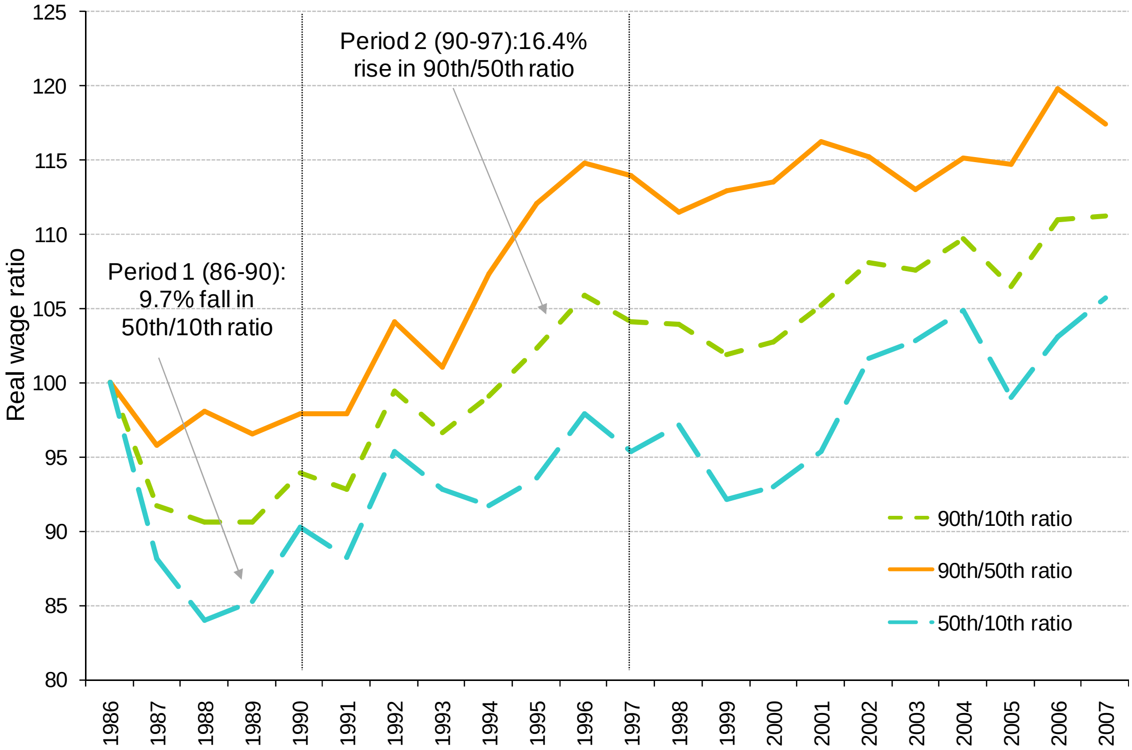
Against this background, a look at hourly wages shows that wage inequality, measured by the Gini Index, rose 11% between 1986 and 2007. This increase can be split into three periods with different trends, largely uncorrelated with the evolution of the average real wage (see Figure 1 in Appendix). Period 1 was a time of moderate inequality reduction (-3.4%) covers 1986 to 1990. Period 2 saw strongly increasing inequality (12.2%) over 1990 to 1997. Inequality rose much more slowly (2.2%) during Period 3, from 1997 to 2007.[11] Wage inequality may vary due to changes in different parts of the distribution: the relation between the 90th, 50th and 10th percentile of the wage distribution provides more information on the mentioned changes. We then look at the ratios between the 90th and 50th and between the 50th and 10th percentiles of the wage distribution as proxies of the evolution of inequality above and below the median wage. These measures show that: a) the slight reduction of inequality in Period 1 is explained by the decrease in wage dispersion in the lower tail of the distribution; b) in Period 2 inequality rose sharply due to a strong increase in the dispersion of wages in the upper tail; and c) in Period 3 the 90th/50th ratio slightly rose and the increase in overall inequality is explained mainly by the evolution of the 50th/10th ratio.

Place Table 1 here

As the overall rise in wage inequality mainly corresponds to its increase in Period 2 (1990 to 1997), and within this period inequality rose mainly above the median, then the rise in wage dispersion in the upper tail seems to be the main factor behind rising wage inequality throughout the whole period. This will be a central feature to be explained in the decomposition exercise shown in section 5.

FIGURE 1 – EVOLUTION OF 90TH/10TH, 90TH/50TH AND 50TH/10TH WAGE RATIOS (IN LOGS)

[11] This characterization of the evolution of wage inequality is robust to the Index chosen: both Entropy 0 and Theil indexes behave in the same way (see Table 1).



Source: Data from Uruguay Household Survey (ECH). Base = 100 (1986).
Notes: Calculations based on hourly wages for the universe of urban workers in Uruguay. All ratios expressed take 1986 as the base year 100.

2.3 *Three candidates to explain rising inequality: prices, characteristics and residuals.*

Our methodology allows us to identify three drivers of the evolution of wage inequality: changes in prices, changes in the distribution of workers' characteristics and changes in residuals or within-group inequality. To carry out the decomposition exercise, we will use a set of six covariates: gender, education, region, potential experience, public/private sector, and industry. The choice of these covariates is based on evidence showing changes in their prices and distribution across the workforce for the period. A companion paper (Alves, Brum and Yapor, 2011) fully presents and discusses these phenomena; here we provide a brief summary that will be useful later, when interpreting the decomposition results.

Regarding changes in prices, Table A.1 in the Appendix displays coefficients from an OLS regression of log hourly wages on a large set of characteristics for selected years.[12] Results show a clear reduction in the period in wage differentials by sex and region, and in the premium to financial sector workers.[13] This could suggest an overall contribution of the price effect to the reduction of wage inequality. However, returns to education -the largest coefficients-, remained stable for lower levels of schooling and increased for higher levels (i.e. for workers having more than high school) in the 1986-2007 comparison.[14]

In terms of changes in the distribution of workers' characteristics, Table A.2 in the Appendix reveals a slow but steady increase in the levels of schooling and age of the workforce,[15] rising participation of women in the labor market, and a relative reduction in public employment and manufacturing employment (in favor of services). Some of these changes can be understood in the context of the economic changes referred to above such as reduction of public employment and deindustrialization.

Tracking changes in workers' characteristics is key for our analysis, as our methodology will better assess their impact on wage inequality. Particularly, these changes can affect the wage distribution by two channels, each of them given by the interaction of changes in workers' characteristics with between- and within-group wage differentials. The first channel corresponds to the case in which a subset of workers that has a wage differential in relation to another subset changes its size, thereby affecting overall inequality. For instance, since financial sector workers usually enjoy a

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[12] See Alves, Brum and Yapor (2011) for a detailed analysis. Although the evolution of "prices" in the decomposition exercise will be captured by the quantile regression corresponding to the median, here we look at the OLS coefficients to provide a closer link to the rest of the literature (for instance to allow the comparison with Arim and Zoppolo (2000) which is the main antecedent of the work). Moreover, OLS coefficients and median quantile regression coefficients have a similar evolution over the period (Alves, Brum and Yapor 2011).

[13] A similar quantitative reduction in the gender gap has also been noted by Amarante and Espino (2004).

[14] Returns to education first declined in the late 1980s and recovered in the early 1990s. These results are quantitatively similar to those by Arim and Zoppolo (2000).

[15] A rise in schooling and experience might be inconsistent with a fixed retirement age for the population. For an explanation on how this is possible see footnote 27, which explains in detail the particularities of the retirement age in Uruguay.

positive wage differential over other sectors even when controlling for usual observable characteristics, a rise in the number of workers in the sector may lead to higher overall wage inequality.[16] Given the aforementioned changes in workers' characteristics, this example might actually correspond to the case of Uruguay for the period. Another composition change that may have also contributed to higher inequality is the rise in schooling and age, as the wage structure of the country is characterized by large returns to education and potential experience.

A second channel corresponds to the case in which within-group inequality varies for different groups. Typically, wage inequality is lower in some industries than others and among younger and less educated workers than among older and more educated workers (Mincer, 1974; Chay and Lee, 2000; Melly, 2005). Also, the public sector has relatively lower within-group wage dispersion than the private sector (Melly, 2005). Again, the descriptive evidence for the case of Uruguay suggests that changes in public/private employment may have affected inequality in this way. To investigate this channel further we follow Melly (2005) and look at the difference between 90th and 10th quantile regression estimates.[17] This is our measure of within-group inequality: a statistically significant positive difference for example means that the wage differential associated to a given characteristic is different between those at the top and those at the bottom of the wage distribution. Table A.3 in the Appendix[18] shows significant and positive 90th-10th differentials for almost all education levels, with values that grow with the levels. This means that wage dispersion is higher among the more educated. The difference is also significant and positive for the financial sector in the 1990s, and negative and huge for public sector workers throughout the whole period. In this

[16] This is just an example to facilitate the understanding of how composition effects may affect overall wage inequality. However, it should be made clear that it is not always the case that an increased share of a group with a positive wage differential will lead to greater overall inequality. More generally, as it will become clearer in the methodological section, the final impact depends on the interaction between the joint densities of workers´ characteristics and wage conditional distributions.

[17] In terms of the notation we develop in the next section, Table A.3 reports the $\hat{\beta}(90) - \hat{\beta}(10)$ difference.

[18] 5.000 replications were performed to obtain bootstrapped standard errors and p-values.

context, changes in the workforce distribution within these groups will affect inequality given that groups with higher within-group inequality are increasing/decreasing in size. Then, the previously documented patterns of rising age and schooling, declining public sector participation and increase of the employment share in the financial sector could have implied increases in overall inequality.[19]

The same interquantile differences between quantile regression coefficients in Table A.3 provides information on the evolution of residual wage inequality, which arises from wage differences within a given group of workers defined according to the set of characteristics enumerated above. The positive premium enjoyed by high wage male workers with respect to high wage females and that enjoyed by low-wage construction and public sector workers all went up in the period. On the other hand, the wage premium enjoyed by high wage earners living in the capital city of the country went up, and so did the wage dispersion within each of the different education levels. Given all these changes pointing in different directions, it is hard if not impossible at this point to say what could have happened with residual wage inequality during the period. Many of these changes are nonetheless interesting themselves and might be useful later when interpreting the results of the decomposition exercise.

Up to this point, the statements made in the last paragraphs are only hypotheses; the results presented in section 5 will shed some light on *how much* of the total rise of wage inequality in Uruguay is due to each effect. This could allow for a better understanding and valuation of the different explanations proposed in the literature for this phenomenon.

3. Methodology

[19] These findings are similar to those highlighted for the United States by Melly (2005).

This section briefly presents the methodology used to analyze the determinants of the changes in the wage distribution. The methodology consists in estimating quantile regressions to decompose these changes in price, characteristics and residual effects, and was developed by Melly (2005), based on Machado and Mata (2005). Here, we present the basic elements of the method; the interested reader should refer to Section 2 in Melly (2005) and Section 2 in Machado and Mata (2005) for more detailed expositions.

In this paper, we will consider a linear functional form which relates a quantile of the distribution of wages with the characteristics of individuals through a vector of parameters.[20] The estimation of this vector of parameters is not trivial, and for that purpose Koenker and Basset (1978) developed a particular algorithm. Traditional regression methods like OLS estimate a conditional mean function, and then the estimated parameters of an equation are obtained by minimizing the sum of squared errors. Thus, this class of estimators accounts for the *average* impact of changes in the independent variables on the dependent variable. Quantile regressions allow for the estimation of parameters for *different* pre-defined points of the distribution (that is, different quantiles). Koenker and Basset (1978) suggested the following minimization problem, which uses a special weighting method in order to, as OLS does, minimize errors:[21]

$$\min_{\beta} \frac{1}{n}\left\{ \sum_{i:w_i > x_i'\beta} \theta |w_i - x_i'\beta| + \sum_{i:w_i < x_i'\beta} (1-\theta)|w_i - x_i'\beta| \right\} \qquad (1)$$

[20] The vector of parameters is $\beta(\theta)$ and the θ th quintile in this linear version is $Q_\theta(w \mid x_i) = x_i'\beta(\theta)$.

[21] Angrist et al. (2006) have shown that quantile regression minimizes a weighted mean-squared loss function for specification error.

In this formulation, the vector of parameters $\beta(\theta)$ for the chosen quantile represents the linear relation between the dependent variable and the independent variables at that quantile of the distribution of wages. The estimators obtained with this method will be well-behaved and have good properties in the absence of endogeneity and even in the presence of heteroskedasticity (Koenker, 2005; Angrist, Chernozhukov and Fernandez-Val, 2006).

Beginning with the quantile regression-based decomposition technique, essentially the work of Machado and Mata (2005), Autor, Katz and Kearny (2005) and Melly (2005), start from the distribution of individuals' characteristics and the estimation of quantile coefficients to obtain the unconditional distribution of wages, which is then used to conduct counterfactual exercises. The difference between the three different papers lies in the *procedure* used to obtain the unconditional distribution. In this paper, we follow the methodology developed by Melly (2005), due to the properties of consistency and asymptotic normal distribution of his estimator, and because its implementation is computationally simpler and less demanding (Chernozhukov, Fernandez-Val and Melly 2013).[22]

Intuitively, in the same way that the Oaxaca-Blinder decomposition yields counterfactual estimations for the mean wage, the procedure of Melly (2005) consists of estimating counterfactual quantiles of wages that characterize the whole wage distribution, and therefore allows for decomposition of its changes at any point. A detailed description of the steps followed by the author to obtain the estimator of the population quantile can be found in Melly (2005); a brief explanation is presented next. Basically, the procedure consists in finding the infimum of the unconditional distribution function at the quantile Q by the population quantile τ :

[22] Also, the procedure in Melly (2005) is equivalent to the one in Machado and Mata (2005) when the number of simulations approaches infinity.

$$\hat{Q}(\tau) = \inf\left\{\frac{1}{N}\sum_{i=1}^{N}\sum_{j=1}^{J}1\left(x_i'\hat{\beta}(\theta_j) \le Q\right) \ge \tau\right\} \qquad (2)$$

Since the estimator is expressed in terms of both characteristics and parameters obtained by the estimation of quantile regressions, it is straightforward to see its applicability to perform a decomposition analysis of changes in the wage distribution. In this sense, the fundamental contribution of Autor, Katz and Kearney (2005) and Melly (2005) with respect to Machado and Mata (2005) is the development of between-group and within-group inequality estimators, from the parameters of quantile regressions. Thus, Autor, Katz and Kearny (2005) define a between-group inequality indicator ($\hat{\beta}^{b}$ from now on) as the vector of parameters that corresponds to the median quantile, $\hat{\beta}(50)$. They also suggest a within-group inequality measure ($\hat{\beta}^{w}$ from now on), as the difference between the vector of estimated coefficients and the estimated median:

$$\hat{\beta}^{w}(\theta) = \hat{\beta}(\theta) - \hat{\beta}^{b} \text{ for } \theta \in (0,1).\text{[23]} \qquad (3)$$

The complete distribution of wages is now defined in terms of three components: the matrix of individuals' characteristics (X), the vector of between-group prices ($\hat{\beta}^{b}$), and the matrix of within-group prices ($\hat{\beta}^{w}$). Let us denote the θ th quantile of the distribution wages when characteristics (X) are distributed as in period s, between-group inequality ($\hat{\beta}^{b}$) is as in period t and within-group inequality ($\hat{\beta}^{w}$) as in period u, by:

[23] By definition, it holds that $\hat{\beta}^{w}(50) = 0$.

$$\hat{Q}_{\theta}(X_s, \hat{\beta}_t^b, \hat{\beta}_u^w)\text{ [24]} \qquad (4)$$

After the characterization of the unconditional wage distribution, Autor, Katz and Kearney (2005) and Melly (2005) implement a decomposition methodology similar to that of Juhn, Murphy and Pierce (1993), in which the observed change in inequality between two periods, t and s, is decomposed into three effects: price, characteristics and residuals. In this case, the observed change between periods t and s in the θ-th wage quantile is defined as:

$$\Delta Q_{\theta} = \hat{Q}_{\theta}(X_s, \hat{\beta}_s^b, \hat{\beta}_s^w) - \hat{Q}_{\theta}(X_t, \hat{\beta}_t^b, \hat{\beta}_t^w) \qquad (5)$$

The first component of this variation is given by the change in workers' characteristics between two periods ($\Delta Q_{\theta}^x = \hat{Q}_{\theta}(X_s, \hat{\beta}_t^b, \hat{\beta}_t^w) - \hat{Q}_{\theta}(X_t, \hat{\beta}_t^b, \hat{\beta}_t^w)$. In this case, if between-group and within-group prices remain constant, the difference in wages for the θ-th quantile represents the contribution of this shift in characteristics to total wage variation. Similarly, a second component of total wage variation can be obtained only if changes in between-group prices ($\Delta Q_{\theta}^b = \hat{Q}_{\theta}(X_s, \hat{\beta}_s^b, \hat{\beta}_t^w) - \hat{Q}_{\theta}(X_s, \hat{\beta}_t^b, \hat{\beta}_t^w)$) are considered, while the third component is obtained considering only the variation of residuals ($\Delta Q_{\theta}^w = \hat{Q}_{\theta}(X_s, \hat{\beta}_s^b, \hat{\beta}_s^w) - \hat{Q}_{\theta}(X_s, \hat{\beta}_s^b, \hat{\beta}_t^w)$). These three components are equal to the total observed change, that is:

$$\Delta Q_{\theta}^x + \Delta Q_{\theta}^b + \Delta Q_{\theta}^w = \Delta Q_{\theta} \qquad (6)$$

[24] To obtain the quantiles for the counterfactual exercise in practical terms, see the four-step procedure presented in Melly (2005).

It should be noted that the order in which the decomposition takes place implies a certain set of weights, which reflects which elements are maintained at their initial or final levels while the others vary. Therefore, the change attributed to each component will depend on which of the remaining components vary first (Autor, Katz and Kearney 2005). It is desirable then, as we do in this paper, to contrast the results of the decomposition when performed in different orders for the purpose of assessing any impact of this on the results. In our case, the order of the decomposition yields no significant changes in the results.[25]

Before turning to our main results, it is necessary to stress an important limitation of the methodology which generally affects most decomposition methodologies. The separation of quantity and price effects does not consider general equilibrium issues: shifts in prices are assumed to not be affecting workers' characteristics and vice versa. For instance, when it is concluded that much of the increase in inequality in a period is attributable to changes in prices, it is assumed that any change in workers' characteristics that may have occurred in the same period did not affect those prices.

In terms of the specific regression we will use when performing the decomposition exercise, in our main specification we estimate the following extended Mincer equation (Mincer 1974):

$$\ln w_{it} = \beta_0 + \sum_j \beta_{eduj} eduj_{it} + \sum_{n=1}^{3} \beta_{\exp^n} \exp_{it}^n + \beta_{sexo} sex_{it} + \beta_{mvd} mvd_{it} + \beta_{rama} rama_{it} + \beta_{priv} priv_{it} + u_{it} \quad (7)$$

[25] Both Autor, Katz and Kearney (2005) and Melly (2005) carried out the decomposition in different orders, which did not change their results. In this paper we chose to perform the decomposition in three orders. In the first, the results of which are presented in the body of the paper, we first varied within-group coefficients, then between-group coefficients, and finally characteristics. In the second, we varied first the characteristics, then the between-group coefficients and finally the within-group coefficients. In the third, we first varied between-group coefficients, then within-group coefficients and finally the characteristics. Our results are robust to these different orders and are available upon request.

with $\ln w_i$ being the log of hourly real wage, edu_i a set of dummy variables indicating schooling (in seven levels),[26] $\exp_i^n$ potential experience (linear, quadratic and cubic),[27] sex_i a dummy variable indicating sex (1=men; 0=women); mvd_i a dummy variable indicating geographic location (1=Montevideo; 0=interior), $rama_i$ a dummy variable indicating sector of activity (ISIC Rev 2.); $priv_i$ a dummy variable indicating private (1) or public (0) employment and u_i an error term.

We included education and potential experience based on standard human capital arguments, and gender to capture discrimination and/or differentials present throughout world and certainly in Uruguay. Half of the total population lives in the capital city (Montevideo), where all central government and headquarters for private firms are based, thus the importance of the Montevideo-Interior term in our study. Wage setting mechanisms differ between private and public sector,[28] which justifies the inclusion of a private/public distinction. The previously mentioned structural reforms induced important changes in the economic structure and thus we chose to include industry as well.

Finally, we also estimate a simplified version of the equation that includes only human capital variables (education and experience). This allows us to partially isolate the effect of changes in prices and characteristics of these two key variables from those of the other variables.

4 – Data

[26] The seven levels are: under seven years of schooling (primary education and less), seven to nine (lower secondary education and less), ten and eleven (high school dropout), twelve (complete secondary education), thirteen to fifteen (college dropouts and technical education), sixteen (bachelor degree) and over sixteen (graduate school and longer university degrees). We chose this classification after careful analysis of the wage-education structure in Uruguay (see Alves et al., 2009, for more details).

[27] Potential experience is measured as the lesser of (age minus years of education minus six) and (age minus fourteen).

[28] For instance, a law forbids firing public employees across most of the public sector and makes it extremely complicated and expensive for the remaining part. Thus, union power and tactics differ, affecting wage outcomes.

The data comes from the Uruguayan Continuous Household Survey (Encuesta Continua de Hogares, ECH) for the period 1986-2007, carried out by the official statistics agency of the country, the Instituto Nacional de Estadistica (INE). The ECH is a nationally representative survey capturing common information on demographics, education, work and income, etc. In particular, we use declared monthly labor income and declared weekly worked hours[29] to construct hourly wages, our key variable. We focus on public and private wage earners, which is equivalent to setting to the side the self-employed, retirees, business owners and rentiers. We also restrict the sample to individuals that are 18 years old or higher, up to 75 years old.[30] The survey is representative of all localities of more than 5,000 inhabitants, which comprises 85% to 90% of the country's total population during the period. The number of observations, after sample restrictions, is above 15,000 in all years (see Table A.2 in the Appendix).[31]

5. Main Results

In this Section we present the main results of the decomposition exercise. To do this we will first focus on results on the whole period and then go through each of the three sub-periods. Recalling Section 2, we know that wage inequality fell in Period 1 (1986-90), and increased strongly in Period 2 (1990-97) and moderately in Period 3 (1997-2007). The analysis of the $90^{th}/50^{th}$ and $50^{th}/10^{th}$ ratios showed that: 1) the reduction in

[29] The specific question deals with the weekly hours a worker usually works, thus diminishing the impact of minor shocks to hours worked. Also, the incorrect declaration of working hours leads to the existence of individuals with abnormally high or low hourly wages. We removed observations with less than six working hours per week from our sample. We also restrict attention to those individuals with less than 120 working hours per week.

[30] Retirement age is a complex topic in Uruguay. The minimum legal age to retire in Uruguay is 60 years old. Nevertheless, individuals are required to have worked for at least 30 or 35 years (depending on the profession) in order to retire. This implies that individuals might choose to retire at different ages depending on when they entered the labor force and how many times and for how long they left it (for unemployment, illness, birth, etc.). Also, individuals might choose to keep working beyond the minimum age as this raises retirement income. Finally, the law allows some individuals to keep working even after retiring (specifically in the education sector, for teachers), while others choose to keep working beyond retirement in the informal sector, to complement retirement income. All these elements explain our decision of considering individuals up to age 75. Also, they help in explaining why higher levels of education can go hand in hand with higher levels of experience, a situation that could happen if individuals get more years of schooling and choose to retire later on.

[31] In 2006, the Survey become representative of the whole country; we restrict our attention to localities of 5,000 and more inhabitants to make the series compatible.

inequality in Period 1 corresponded mainly to changes below the median; 2) the great increase in inequality in Period 2 corresponded mainly to changes above the median; 3) the slight rise in inequality in Period 3 was due almost exclusively to changes below the median. We have also pointed to some important changes in the labor market in the period: 1) regarding characteristics, average schooling and age slowly and steadily increased, female participation also rose, employment in the public sector went down while workers migrated from manufacturing to services; 2) regarding prices, wage differentials by sex, region and to financial sector workers went down, while returns to education remained stable for lower levels of schooling and rose for higher levels; 3) regarding residuals, within-group dispersion is higher among the more educated and financial sector workers and lower for public sector workers. These are the main empirical elements to take into account when looking at the results of the decomposition exercise.

Table 2 presents the summary of the main decomposition results.[32] The sharp rise in wage inequality throughout the period measured by the Gini index was mainly due to changes in workers' characteristics, which accounts for almost 60% of the total rise in wage inequality. Residuals (within-group wage dispersion) also made a sizeable contribution to the rise in total wage inequality, while the price effect was almost negligible and insignificant. Table 2 also shows that characteristics and residuals had a differentiated impact above and below the median: shifts in workers' characteristics represented 75% of the total rise in the $90^{th}/50^{th}$ ratio, while residuals[33] were almost the sole drivers of the rise in the $50^{th}/10^{th}$ ratio.

[32] Standard errors in Table 2 were calculated by bootstrap with 100 replications. Chernozhukov et al. (2013) prove the validity of the bootstrap method to do inference in a variety of decomposition methods, among which Melly (2005) is included.

[33] For an excellent discussion on the interpretation of residual effects, see Lemieux (2006).

In order to fully exploit the potential of the technique for decomposing changes along the whole distribution of wages, in Figure 2 we represent the total change in log hourly wages for each of 400 estimated quantiles and how each of the three effects contributes to that change.[34] We can see that changes in workers' characteristics contributed to the rise in wages along the entire distribution, a fact that is coherent with the increase in workers' experience and schooling referred to above.[35]

The decomposition for the three sub-periods also provides interesting results. Within Period 1, the reduction in inequality responds mainly to a change in prices that counters the inequalizing effect of changes in characteristics. These effects are present above and below the median and are consistent with a period in which a return to democracy increased workers' bargaining power and changes in wages favoring low-wage workers reduced overall inequality, countering the slow inequalizing changes in characteristics.

In Period 2, characteristics, prices and residuals contributed to the increase in inequality above the median (all significant at 1% levels), which represented two-thirds of the overall increase in inequality in the period (measured by the $90^{th}/10^{th}$ ratio). Changes in prices and characteristics still contributed to the increase in inequality below the median as well. These changes are consistent with major changes seen in the period, in which manufacturing lost workers to services, wage differentials rose for the more educated (linked to three macro reforms and the dismantling of wage-setting mechanisms), and characteristics such as public sector employment and workforce

[34] Melly (2005) works with a benchmark of 200 quantile regressions. With a number of observations that is similar to ours in order of magnitude, he also shows that results are identical if using either 10, 100, 200 or 400 regressions (see Figure B3 in Melly (2005) online appendix).

[35] The graph should be read as follows. The horizontal axis represents quantiles in the wage distribution, and the vertical axis represents log points. The top left panel of Figure 2 shows the decomposition of the changes in wage inequality for the period 1986-2007. Looking at the line showing the total, the 90^{th} percentile corresponds to a value of around 0.29, which means that from 1986 to 2007 at the 90^{th} percentile, wages increased by approximately 0.29 log points. The value for the 10^{th} percentile is approximately 0.12. The difference between these quantiles is 0.17, which corresponds to the reported figure in Table 2 (Panel A). Through our counterfactual exercise, Figure 2 captures the contribution of changes in characteristics, prices and residuals to total change in wages across the entire distribution, giving a clearer picture of the evolution of inequality.

education and age slowly but steadily kept changing in an inequalizing fashion (see Section 2). The decomposition exercise for the 400 estimated quantiles (see Figure 2) shows once again that the price effect had an impact across the whole distribution, while changes in characteristics begin to be associated with higher inequality at the 45th percentile and residuals mostly contribute from the 80th percentile onwards.

In Period 3, changes in characteristics increased wage inequality according to the 90th/50th ratio (significant at 1% levels) while the rise in the 50th/10th ratio mainly corresponds to changes in residuals (significant at 1% levels). Figure 2 shows the price effect to be homogeneous across the distribution, while the negative effect of residuals is concentrated below the 20th percentile.[36] The effect of characteristics is positive for the whole distribution though slightly higher at the top end.

Looking at the bigger picture, although unimportant when looking at the whole period, the price effect becomes relevant as a driver of changes in inequality *trends* within each period: changes in prices *reduced* inequality in Period 1 and *increased* inequality in Period 2. As stated before, a plausible explanation for these movements in wage differentials would be the collective wage bargaining mechanisms that were reinstated in 1985 and then dismantled in 1992 in a context of increasing demand for skilled workers probably due to technical change incorporation and capital goods imports expansion (Arim and Zoppolo, 2000).[37] On the other hand, changes in characteristics constantly pressed inequality upwards throughout the period, being then the main explanatory factor behind the rise of wage inequality in the whole period.[38]

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[36] Which means, a reduction in within-group wage inequality was concentrated in the bottom part of the distribution; this is consistent with the effect of the reinstatement of the wage setting mechanisms combined with an explicit intention of the new government of improving life conditions of the poor.

[37] A full inquiry into the underlying causes behind changing wage differentials goes beyond the purpose of this work.

[38] The results presented so far are consistent with the findings of Arim and Zoppolo (2000). These authors also find that price changes played a key role as determinants of the wage inequality shift seen in the early 1990s. However, whereas they find that the characteristics effect contributed to the rise of wage inequality in the upper tail of the distribution during their period of study (1986-2000), our results show a much more permanent and important contribution of this effect.

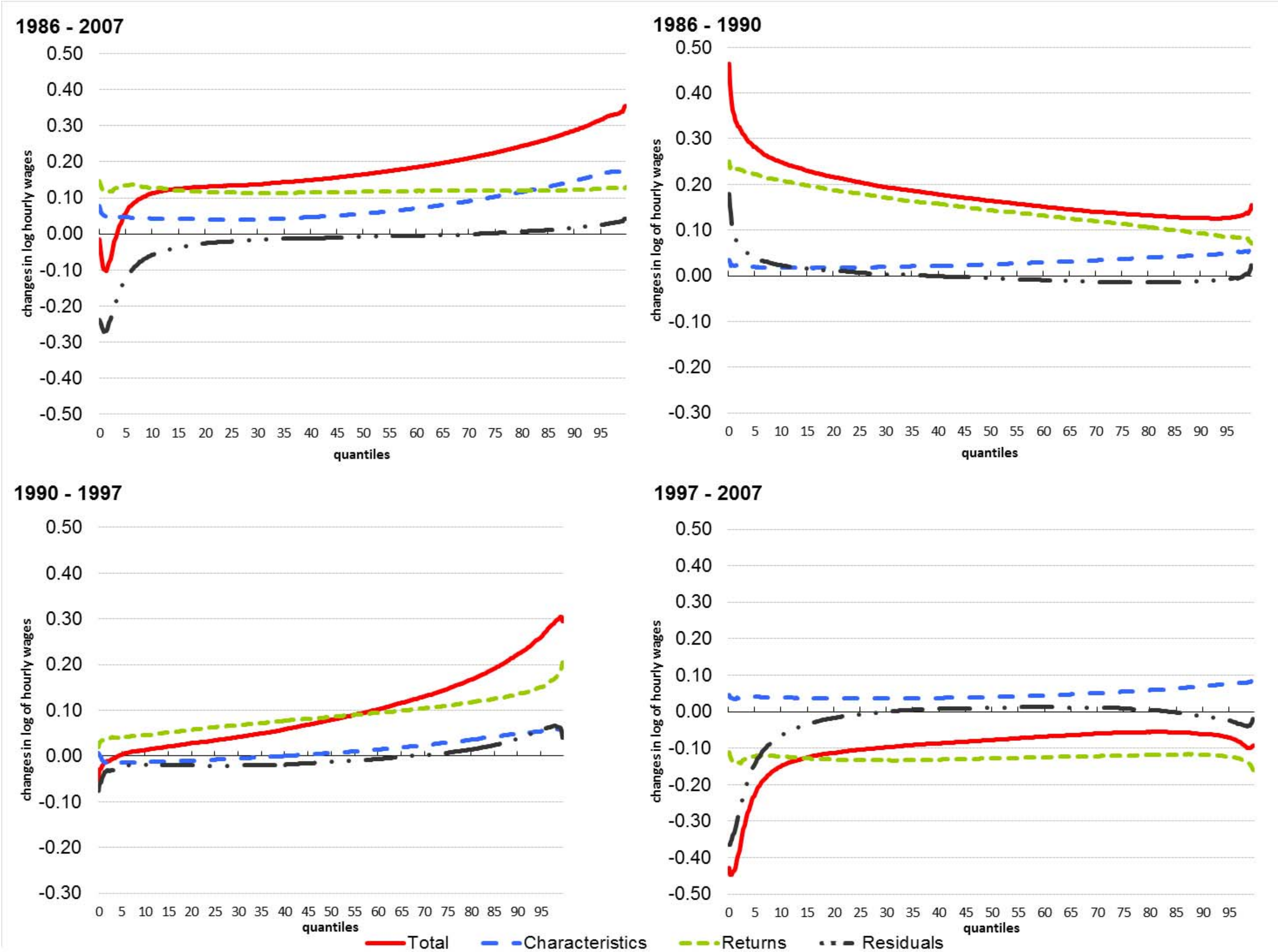
Place table 2 here

The relative primacy of changes in workers' characteristics in explaining rising wage inequality in Uruguay led us to further explore whether these impacted the unconditional distribution of wages either by interacting with between- or within-group wage differentials. In Section 2, we discussed how a change in the relative share of a certain group of workers may impact overall wage inequality either because this group's average wage is different from other groups or because this group is internally highly unequal. To assess this question, we will follow Chernozhukov, Fernandez-Val and Melly (2013), who suggest implementing a variance decomposition of the effect of characteristics of between-group and within-group effects.[39] Results of the variance decomposition in Table 3 show that changes in characteristics acted through both channels in almost identical proportions. Roughly half of the effect was due to the increased share of groups with significant wage differentials relative to other groups (like the increase in the employment share of the financial sector) and half was due to the increased share of groups with higher within-group inequality (like the decrease in public sector employment).

Place Table 3 here

[39] We thank an anonymous referee for this valuable suggestion. See Chernozhukov et al. (2013), in particular Appendix D of the supplemental material, for details on the variance decomposition.

FIGURE 2 - DECOMPOSITION OF CHANGES IN WAGE QUANTILES (400 QUANTILES)



Sources: Calculations based on hourly wages for the universe of urban workers in Uruguay. Data from Uruguay Household Survey (ECH).

In a further effort to identify which elements are behind price and characteristic effects, that is, to find out *which* characteristics and prices were the main drivers of increasing inequality, we repeated the decomposition exercise with an alternative specification of the estimated Mincer equation that includes only human capital variables, that is, potential experience and schooling levels. Table A.4 in the Appendix shows the comparison of results for both specifications. One important finding is that for the whole period, the inequalizing effect of prices is higher using the human capital specification (especially above the median). This confirms that changes in returns to experience and schooling had a strong impact on wage inequality, which would have been partially offset by changes in returns to other variables and/or by changes in the composition of workers. Regarding the role of characteristics, results indicate a positive but smaller impact in this alternative specification in comparison with our benchmark specification; this can be taken as an indication that changes in the distribution of other characteristics of the workers also had a concentrating effect. If a link were to be established between changes in the composition of the workforce and the internal dispersion of groups of workers, the main elements mentioned in Section 2 would be the fall of public employment and the rise in the services sector, particularly the financial sector.[40]

To sum up, we find that while price effects were responsible for the changes in inequality trends within the 1986-2007 period, changes in workers' characteristics exerted a constant inequalizing pressure and played the main role in increasing wage inequality in Uruguay in the period.[41] As we mentioned in the Introduction, this type of

[40] The contrast between the results also shed light on the dynamics within each Period. In Period 1, the rise in schooling levels and potential experience of the workforce appears not to have had a significant impact on wage dispersion above or below the median. Then, the overall effect of changes in characteristics –the main driver of rising wage inequality in the period– responded mainly to the rest of the variables, especially above the median. In Period 2, the price effect –the main factor behind the inequality changes in the period– included changes in returns to both human capital and the other considered variables. The same pattern is observed for the characteristics effect above the median using the human capital specification. Within Period 3, changes in schooling and potential experience contributed to the increase in wage dispersion above the median while changes in other characteristics contributed in the same direction but to a lesser extent.

[41] As a robustness check of these results, we proceeded to repeat the decomposition exercise on a more homogeneous sample. Our original sample includes students, women and part-time workers, which implies different degrees and modes of attachment to the labor market, and thus more diverse and complex relations between workers' characteristics and wage determination mechanisms. We then repeated the exercise

phenomenon in which short-run changes in inequality are driven by price effects and composition effects act slowly and become visible only in longer-run analyses should be a first order issue in wage inequality studies. This feature, together with methodological limitations, may also explain why early studies dismissed the relevance of composition effects.

6. Conclusions

Changes in the distribution of workers in groups defined by a set of standard characteristics is the key factor explaining rising inequality in Uruguay between 1986 and 2007. These changes had a slow and gradual effect: they started in the second half of the 1980s due to the increase in schooling levels and experience of the labor force. This trend persisted, and its concentrating effect was reinforced in the 1990s by the rise in the share of employment in financial services in total employment, as well as by the fall in the share of public employment.

These results and the accompanying methodological discussion should call researchers' attention to how changes in the workforce composition may lead to first order impacts in wage inequality. To search for these changes, we should look at various and very distinct phenomena. Demographic factors such as an aging population may lead to greater wage dispersion due to forces such as learning, sorting and matching (Neal and Rosen, 2000).[42] Cultural and economic changes such as the massive incorporation of women into the labor market are strong candidates too. On the other hand, as the example of Uruguay shows, big changes in countries' economic structures such as deindustrialization or reductions in the share of public employment can lead also to substantive impacts in the levels of wage inequality.

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considering only a subsample of non-student male workers with 30+ working hours per week. Results of the decomposition exercise for this smaller subsample goes in line with our main results. Tables and graphs are available upon request.

[42] Wage dispersion increases with age for example because workers and firms learn about workers "true" ability (learning) or alternatively they learn about which are good and bad firm-worker matches (matching models). For an excellent exposition see Neal and Rosen (2000).

We would like to finish with a call to caution. Decomposition approaches as the one used in this paper have a serious limitation in terms of being partial equilibrium analysis. In particular, the interpretation on the relevance of composition effects lies in the strong assumption that prices do not react, or at least have not reacted yet, to those changes in quantities. The effect of increased human capital endowment in a country may be taken as a first order example of this. It is true that within a certain structure of returns to education the process of human capital accumulation may lead to greater wage inequality in a typical case of pure composition effects. However, it is reasonable to assume that, over a certain time range, human capital prices will react to those changes in the supply side and then the final effect of human capital accumulation may have a different sign than the one given by the decomposition exercise.

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TABLE 1 – WAGE INEQUALITY IN URUGUAY, 1986 - 2007

Period	*Gini*	*Theil*	*Entropy 0*	*90/10*	*90/50*	*50/10*
1986-1990	-3.4%	-5.4%	-9.3%	-6.1%	-2.1%	-9.7%
1990-1997	12.4%	27.0%	25.4%	10.9%	16.4%	5.6%
1997-2007	2.2%	4.4%	8.5%	6.8%	3.0%	10.9%
1986-2007	11.0%	25.4%	23.6%	11.2%	17.4%	5.7%

Source: Calculations based on hourly wages for the universe of urban workers in Uruguay. Data from Uruguay Household Survey (ECH).
Notes: 90/10, 90/50 and 50/10 ratios based on log wages.

TABLE 2 – DECOMPOSITION OF INEQUALITY MEASURES

	Total	Characteristics	Prices	Residuals
		Panel A: 1986 - 2007		
Gini	0.037***	0.023***	0.005*	0.009***
	(0.003)	(0.002)	(0.003)	(0.003)
90/10	0.165*	0.097	-0.001	0.069
	(0.098)	(0.060)	(0.075)	(0.080)
90/50	0.120***	0.089***	0.013	0.018
	(0.023)	(0.016)	(0.019)	(0.019)
50/10	0.046	0.008	-0.014	0.051**
	(0.029)	(0.014)	(0.013)	(0.025)
		Panel B: 1986 - 1990		
Gini	-0.017***	0.006***	-0.019***	-0.004
	(0.004)	(0.001)	(0.002)	(0.003)
90/10	-0.124	0.027	-0.109	-0.041
	(0.076)	(0.029)	(0.086)	(0.054)
90/50	-0.038*	0.019***	-0.048***	-0.009
	(0.023)	(0.008)	(0.014)	(0.017)
50/10	-0.086***	0.008	-0.061***	-0.032
	(0.025)	(0.008)	(0.014)	(0.020)
		Panel C: 1990 - 1997		
Gini	0.046***	0.012***	0.021***	0.013***
	(0.004)	(0.002)	(0.003)	(0.004)
90/10	0.208***	0.061	0.096	0.051
	(0.085)	(0.045)	(0.079)	(0.071)
90/50	0.142***	0.041***	0.051***	0.050***
	(0.025)	(0.012)	(0.015)	(0.021)
50/10	0.065***	0.020**	0.044***	0.001
	(0.024)	(0.010)	(0.014)	(0.020)
		Panel D:1997 - 2007		
Gini	0.007**	0.007***	0.001	-0.001
	(0.003)	(0.002)	(0.003)	(0.003)
90/10	0.081	0.025	0.007	0.049
	(0.097)	(0.054)	(0.077)	(0.076)
90/50	0.016	0.028***	0.013	-0.025
	(0.026)	(0.012)	(0.019)	(0.021)
50/10	0.066***	-0.003	-0.006	0.075***
	(0.026)	(0.013)	(0.013)	(0.024)

Source: Calculations based on hourly wages for the universe of urban workers in Uruguay.
Data from Uruguay Household Survey (ECH).
Notes: Robust standard errors in parenthesis. Statistical significance at 1% (***) 5% (**) and 10% (*) levels. 90/10, 90/50 and 50/10 ratios based on log wages.

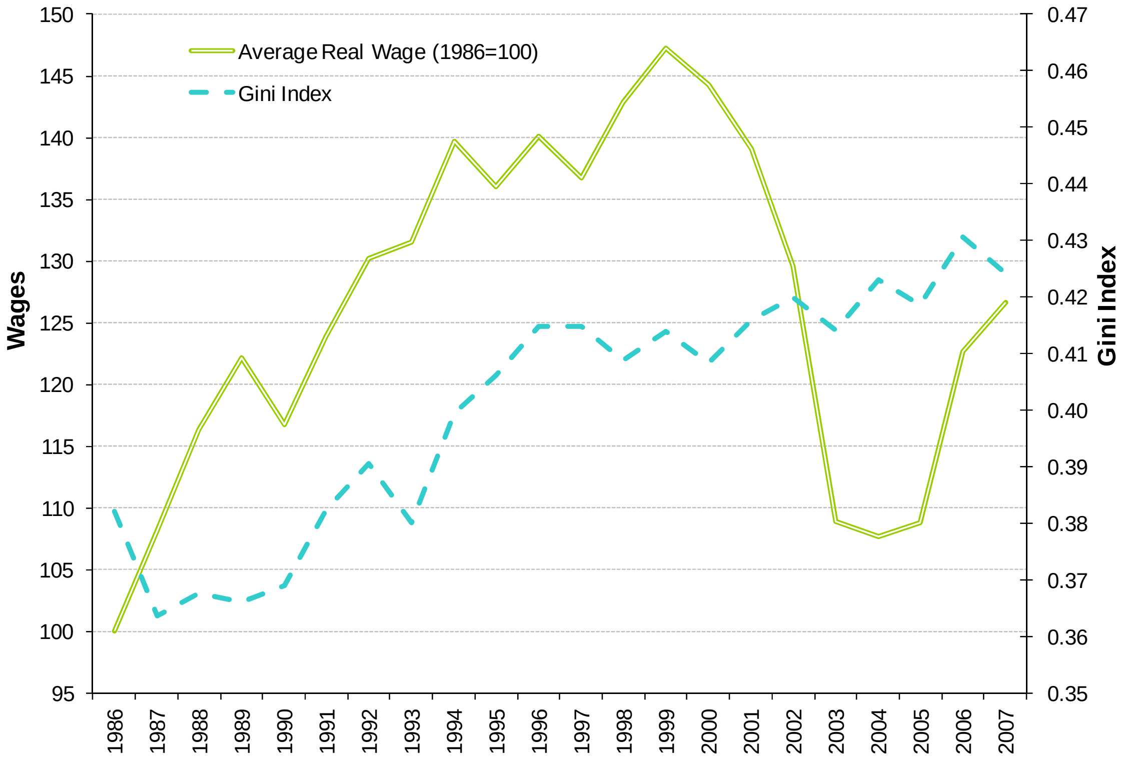
TABLE 3 – VARIANCE DECOMPOSITION OF THE IMPACTS OF CHANGES IN WORKERS' CHARACTERISTICS ON WAGE INEQUALITY: 1986-2007

	Between-group	Within-group	Total
(Var 2007-Var 1986) / Var1986	11.9%	7.2%	19.1%
% relevance of each component	49.7%	50.3%	100.0%

Source: Calculations based on hourly wages for the universe of urban workers in Uruguay.

Appendix – Auxiliary Tables and Figures

FIGURE A.1 - EVOLUTION OF GINI AND MEAN REAL WAGE



Source: Calculations based on hourly wages for the universe of urban workers in Uruguay. Data from Uruguay Household Survey (ECH).

TABLE A.1 - OLS WAGE REGRESSION RESULTS

	1986	1990	1997	2004	2007
Sex					
Males	0.290***	0.260***	0.222***	0.202***	0.215***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Potential Experience					
Linear	0.058***	0.056***	0.065***	0.070***	0.063***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Quadratic	-0.001***	-0.001***	-0.002***	-0.002***	-0.002***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Cubic	0.00001***	0.00001***	0.00001***	0.00001***	0.00001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Years of Education					
7 to 9 years	0.183***	0.166**	0.174***	0.176***	0.185***
	(0.002)	(0.011)	(0.000)	(0.000)	(0.000)
10 to 11 years	0.393***	0.371***	0.406***	0.331***	0.382***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
12 years	0.619***	0.589***	0.593***	0.521***	0.589***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
13 to 15 years	0.697***	0.677***	0.766***	0.830***	0.856***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
16 years	1.027***	0.892***	0.914***	0.995***	1.021***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
17+ years	1.114***	1.083***	1.182***	1.256***	1.264***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Region					
Montevideo	0.303***	0.252***	0.309***	0.234***	0.154***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Industry (see notes for reference)					
2	0.318***	0.226***	0.260***	0.155***	0.160***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
3	0.380***	0.266***	0.386***	0.399***	0.335***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
4	0.125***	0.172***	0.261***	0.150***	0.143***
	(0.002)	(0.000)	(0.000)	(0.000)	(0.000)
5	0.174***	0.127***	0.180***	0.073***	0.065***
	(0.000)	(0.008)	(0.000)	(0.004)	(0.000)
6	0.262***	0.147***	0.214***	0.224***	0.232***
	(0.000)	(0.002)	(0.000)	(0.000)	(0.000)
7	0.547***	0.428***	0.550***	0.280***	0.399***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
8	0.121***	0.062	0.183***	0.146***	0.117***
	(0.019)	(0.145)	(0.000)	(0.000)	(0.000)
Sector of employment					
Public sector	0.282***	0.116**	0.165***	0.296***	0.333***
	(0.000)	(0.025)	(0.000)	(0.000)	(0.000)

Source: Calculations based on hourly wages for the universe of urban workers in Uruguay. Data from Uruguay Household Survey (ECH).

Notes: Dependent variable is the log of hourly wages. P-values in parenthesis calculated from robust standard errors. Potential experience is the lesser of (age minus years of education minus six) and (age minus fourteen). Industry reference: 1) Agriculture, hunting, forestry, fishing, mining and quarrying (omitted); 2) Manufacturing; 3) Electricity, gas and water; 4) Construction; 5) Wholesale and retail trade and restaurants and hotels; 6) Transport, storage and communication; 7) Financing, insurance, real estate and business services; 8) Community, social and personal services.

TABLE A.2 - DISTRIBUTION OF THE WORKFORCE BY AGE, SEX, REGION, EDUCATION, INDUSTRY AND SECTOR

	1986	1990	1997	2004	2007
Years of education					
<7	42.4	37.4	29.9	24.6	22.5
7 to 9	20.9	21.6	24.8	29.5	29.2
10 and 11	17.5	18.6	16.9	15.1	17.1
12	7.5	9.1	11.4	10.3	9.3
13 to 15	3.5	4.7	7.6	8.5	10.2
16	3.7	3.9	5.2	6.6	5.8
17+	4.6	4.8	4.5	5.5	6
Age					
<25	34.4	31.8	33.7	28.5	28.9
25 to 34	35	37.1	35.4	35.3	36
35 to 49	25	25.5	25.2	29.9	28.3
50+	5.3	5.5	5.9	6.2	6.6
Years of Potential Experience					
<10	27.5	26.1	28.7	22.5	23.8
11 to 20	25	25.6	23.4	23.9	25.3
21 to 30	19.8	20.6	21.6	23.8	21.9
31 to 40	16.7	16.6	16.2	19	18.4
40+	11	11.1	10.5	10.8	10.6
mean (in years)	21.4	21.5	21.2	22.7	22.2
Sex					
Men	61.5	59	56.1	53.9	53
Women	38.5	41	44.4	46.1	47
Region					
Montevideo	52.7	55.9	56.2	54.2	49.6
Elsewhere	47.3	44.1	44.3	45.8	50.4
Sector of employment					
Private	67.1	71.2	74.4	74.6	77.8
Public	32.9	28.8	24.9	25.4	22.2
Industry (see notes for reference)					
1	2.7	2.2	3.4	4.2	4.6
2	20.7	21.9	16.5	13.4	14.4
3	2.3	2	1.7	1.2	1.2
4	3.8	5.8	4.7	4.4	5.5
5	13	13.3	15.7	16.7	18.5
6	7.4	6.3	6.3	6.4	6.6
7	4.8	5	6.9	7.5	6.8
8	45.2	43.6	45.3	46.2	42.5
Number of Observations					
N	15,468	16,000	17,306	15,812	38,735

Source: Calculations based on hourly wages for the universe of urban workers in Uruguay. Data from Uruguay Household Survey (ECH).
Notes: Dependent variable is the log of hourly wages. P-values in parenthesis calculated from robust standard errors. Potential experience is the lesser of (age minus years of education minus six) and (age minus fourteen). Industry reference: 1) Agriculture, hunting, forestry, fishing, mining and quarrying (omitted); 2) Manufacturing; 3) Electricity, gas and water; 4) Construction; 5) Wholesale and retail trade and restaurants and hotels; 6) Transport, storage and communication; 7) Financing, insurance, real estate and business services; 8) Community, social and personal services.

TABLE A.3 -INTERDECILE DIFFERENCES IN QUANTILE WAGE REGRESSION COEFFICIENTS: 90TH - 10ST PERCENTILES. RESULTS FOR LOG OF HOURLY WAGES AGAINST SELECTED CHARACTERISTICS

	1986	1990	1997	2007
Sex				
Male	-0.041	0.025	0.026	0.059***
	(0.125)	(0.308)	(0.317)	(0.001)
Potential Experience				
Linear	0.002	0.007	0.003	-0.014**
	(0.738)	(0.285)	(0.69)	(0.029)
Quadratic	-0.00002	-0.0001	0.0003	0.001***
	(0.948)	(0.633)	(0.446)	(0.005)
Cubic	0.000003	0.000002	-0.000003	-0.00001**
	(0.486)	(0.540)	(0.447)	(0.019)
Years of Education				
7 to 9 years	0.015	0.116***	0.043	-0.027
	(0.620)	(0.000)	(0.160)	(0.397)
10 to 11 years	0.056	0.126***	0.124***	-0.018
	(0.115)	(0.000)	(0.001)	(0.458)
12 years	0.076	0.180***	0.243***	0.036
	(0.107)	(0.000)	(0.000)	(0.333)
13 to 15 years	0.148**	0.218***	0.255***	0.053*
	(0.030)	(0.000)	(0.000)	(0.055)
16 years	-0.007	0.076	0.166***	-0.009
	(0.915)	(0.156)	(0.001)	(0.927)
17+ years	0.373***	0.395***	0.453***	0.282***
	(0.000)	(0.000)	(0.000)	(0.000)
Region				
Montevideo	-0.180***	-0.129***	-0.059**	-0.047**
	(0.000)	(0.000)	(0.021)	(0.018)
Industry (see notes for reference)				
2	0.030	-0.147*	-0.110	-0.063
	(0.720)	(0.065)	(0.163)	(0.477)
3	0.102	-0.084	-0.032	-0.093
	(0.352)	(0.414)	(0.811)	(0.371)
4	-0.109	-0.153*	-0.019	0.055
	(0.229)	(0.065)	(0.915)	(0.249)
5	-0.009	-0.225***	-0.092	-0.218***
	(0.919)	(0.004)	(0.238)	(0.002)
6	0.047	-0.140*	0.048	-0.045
	(0.597)	(0.089)	(0.562)	(0.685)
7	0.181*	0.067	0.337***	0.134
	(0.053)	(0.444)	(0.000)	(0.026)
8	0.127	0.007	0.106	0.047
	(0.122)	(0.933)	(0.192)	(0.337)
Sector of Employment				
Public sector	-0.383***	-0.437***	-0.374***	-0.522***
	(0.000)	(0.000)	(0.000)	(0.000)

Source: Calculations based on hourly wages for the universe of urban workers in Uruguay. Data from Uruguay Household Survey (ECH). P-values in parenthesis. All results based on regressions run with robust standard errors. Potential experience is the lesser of (age minus years of education minus six) and (age minus fourteen). Industry reference: 1) Agriculture, hunting, forestry, fishing, mining and quarrying (omitted); 2) Manufacturing; 3) Electricity, gas and water; 4) Construction; 5) Wholesale and retail trade and restaurants and hotels; 6) Transport, storage and communication; 7) Financing, insurance, real estate and business services; 8) Community, social and personal services.

TABLE A.4 – DECOMPOSITION OF INEQUALITY MEASURES (HUMAN CAPITAL SPECIFICATION)

	Total	Characteristics	Prices	Residuals
		Panel A: 1986 - 2007		
Gini	0.041***	0.013***	0.016***	0.012***
	(0.004)	(0.002)	(0.003)	(0.003)
90/10	0.172	0.056	0.058	0.058
	(0.108)	(0.056)	(0.072)	(0.087)
90/50	0.127***	0.053***	0.053***	0.022
	(0.023)	(0.014)	(0.019)	(0.021)
50/10	0.045	0.003	0.005	0.036
	(0.034)	(0.018)	(0.012)	(0.031)
		Panel B: 1986 - 1990		
Gini	-0.015***	0.003***	-0.010***	-0.008***
	(0.004)	(0.001)	(0.002)	(0.003)
90/10	-0.127	0.010	-0.044	-0.093
	(0.085)	(0.025)	(0.085)	(0.075)
90/50	-0.036	0.010	-0.027*	-0.019
	(0.024)	(0.006)	(0.016)	(0.017)
50/10	-0.091***	0.000	-0.017	-0.074***
	(0.028)	(0.007)	(0.011)	(0.029)
		Panel C: 1990 - 1997		
Gini	0.048***	0.005***	0.023***	0.020***
	(0.004)	(0.001)	(0.003)	(0.004)
90/10	0.207**	0.023	0.084	0.100
	(0.090)	(0.037)	(0.070)	(0.085)
90/50	0.150***	0.020*	0.059***	0.071***
	(0.024)	(0.011)	(0.017)	(0.023)
50/10	0.057*	0.004	0.025*	0.029
	(0.030)	(0.008)	(0.014)	(0.030)
		Panel D:1997 - 2007		
Gini	0.008***	0.006***	0.008***	-0.006**
	(0.003)	(0.001)	(0.003)	(0.003)
90/10	0.092	0.022	0.035	0.035
	(0.105)	(0.059)	(0.081)	(0.081)
90/50	0.014	0.023*	0.029	-0.038
	(0.027)	(0.012)	(0.019)	(0.024)
50/10	0.078***	-0.001	0.006	0.073***
	(0.032)	(0.016)	(0.013)	(0.027)

Source: Calculations based on hourly wages for the universe of urban workers in Uruguay. Data from Uruguay Household Survey (ECH).
Notes: Robust standard errors in parenthesis. Statistical significance at 1% (***), 5% (**) and 10% (*) levels.