

## WORKING PAPER

INAPP WP n. 4

# **More insecure and less paid? The effect of perceived job insecurity on wage distribution**

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SOMMARIO: 1. Introduction. – 2. Previous literature on perceived job-insecurity. – 3. Empirical specification; 3.1 – B-O decomposition and a semi-parametric estimation; 3.2 The Inverse Probability Weighting approach as a non-parametric estimation. – 4. Data. – 5. Results; 5.1 Counterfactual decomposition. – 6. Discussion and conclusions. – Appendix. – References

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## ABSTRACT

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# **More insecure and less paid? The effect of perceived job insecurity on wage distribution**

This article employs a Counterfactual Decomposition Analysis (CDA) using both a semi-parametric and a non-parametric method to examine the pay gap, over the entire wage distribution, between secure and insecure workers on the basis of perceived job insecurity. Using the 2015 INAPP Survey on Quality of Work, our results exhibit a mirror J-shaped pattern in the pay gap, with a significant sticky floor effect, i.e. the job insecurity more relevant at the lowest quantiles. This pattern is mainly due to the characteristics effect, while the relative incidence of the coefficient component accounts roughly for 22 up to 36% of the total difference, being more relevant at the bottom of the wage distribution.

**KEYWORDS:** Job (in)security, Counterfactual distribution, Semi-parametric methodology, Non-parametric methodology, Wage gap, Blinder/Oaxaca, Quantile regression, Italy

**JEL CODES:** J31, J82, C14

## 1. Introduction

On 26 February 1997 Alan Greenspan, the former chairman of the US Federal Reserve, in his Congressional hearing, explaining why “the rate of pay increase still was markedly less than historical relationships with labour market conditions would have predicted” said: “Atypical restraint on compensation increases has been evident for a few years now and appears to be mainly the consequence of greater worker insecurity [...] The unanswered question is why this insecurity persisted even as the labour market, by all objective measures, tightened considerably”<sup>1</sup>.

Contemporary society is characterized by high levels of uncertainty which saturate almost all domains of everyday life (Bauman 2007), including the labour market. From a general perspective, the intensified global economic competition, occurred in recent decades, has put strong pressure on many organizations, often changing their structure. In fact, in order to face difficulties and maintain a high level of effectiveness and competitiveness, most organizations have undertaken drastic measures such as merging, downsizing, acquisitions, layoffs, that have frequently led to reducing the workforce or changing its composition (e.g. higher proportion of temporary workers).

In recent decades great concern has been given to rising wage inequality and Job Insecurity (JI henceforth) in many developed countries. The difficult macroeconomic environment since 2007 has been characterized by slower nominal wage growth and lower job quality, due to greater labour market insecurity in most OECD countries (OECD 2016). This macro scenario has also changed the nature of work, moving from a traditional secure perspective into a more insecure and instable one. The current risk is that this situation may be exacerbated by technological change and the rise of the so called “gig economy”, considered as one of the sign of this epochal modification (Friedman 2014). As occupational risk – such as becoming unemployed or having a temporary contract – increases, the feelings and the perceptions of JI among the employees also surge. As a matter of fact, nowadays JI is considered one of the most powerful stressor at work (Sverke and Hellgren 2002).

The psychological, somatic and behavioral consequences of perceived JI on individuals have been widely investigated (Sverke and Hellgren 2002), but the evidence on the relationship between subjective JI and wage is scant. Empirical articles evaluating the effect of perceived JI on wage have focused on its average level (Blanchflower 1991; Maurin and Postel-Vinay 2005; Cambell *et al.* 2007). The most relevant aspects concerning its distribution, which in this type of analysis are of more interest to a policy maker, have been left out.

To the best of our knowledge, our article is the first attempt to estimate the association between perceived JI and wage along the whole wage distribution. We fill this gap of current economic literature, using the 2015 INAPP Survey on Quality of Work (InappQoW). This article employs a Counterfactual Decomposition Analysis (CDA) using both a semi-parametric and a non-parametric method to examine the pay gap over the entire wage distribution between two groups of workers on the basis of perceived job insecurity. In addition, we estimate whether and to what extent this pay gap is attributed more to differences in labour market characteristics between the two groups of

<sup>1</sup> See the Testimony of Chairman Alan Greenspan Federal Reserve's semiannual monetary policy report Before the Committee on Banking, Housing, and Urban Affairs, U.S. Senate February 26, 1997. <https://www.federalreserve.gov/boarddocs/hh/1997/february/testimony.htm>.

workers or to differences in rewards that the two groups receive for their characteristics in the Italian labour market.

Our results show that the mean estimates of the JI pay gap are likely to conceal important differences along the wage distribution for secure and insecure workers. The pay gap exhibits an interesting *mirror J-shaped* pattern along the whole wage distribution, with the lowest value around the 80<sup>th</sup> percentile, thus giving evidence of a significant sticky floor effect. Such pattern is mainly due to the characteristics effect, while the relative incidence of the coefficient component is more relevant at the bottom of the wage distribution.

The article is organized as follows: section two reports previous literature on the perceived job-insecurity. Section three describes the semi-parametric and the non-parametric decomposition methods. In Section four, data are illustrated. Empirical results are shown in section five, while section six concludes.

## 2. Previous literature on perceived job-insecurity

Currently, JI is a topic that crossways a growing literature in different disciplines such as psychology, sociology, political science and only marginally economics (Burchell 2009; Erlinghagen 2008; Gallie *et al.* 2017; Helbling and Kanji 2018; Koutentakis 2008; Lubke and Erlinghagen 2014), with several definitions. There are many objective situations in which a job position can be at risk and insecure. For instance, having a temporary contract that will end soon or being hired in an organization which is facing hard times of crisis and will possibly undertake massive dismisses are surely conditions of “objective” JI and occupational risk. Nevertheless, JI represents a fundamental “subjective” experiences (Greenhalgh and Rosenblatt 1984; Sverke and Hellgren 2002). In fact, in psychological literature JI is defined as the perceived threat and perceived probability of an involuntary job loss and the worries and concerns that relates to the future continuity of the current job (De Witte 1999; Hartley *et al.* 1990; Sverke and Hellgren 2002; Sverke *et al.* 2004). If, on one hand, the “subjective” perception of JI is strongly linked to the “objective” situation, on the other hand empirical and theoretical research has shown that these two aspects do not completely overlap (De Cuyper and De Witte 2007) and that, as we will note later, the “subjective” experience of JI has consequences that are independent from “objective” JI (Sverke and Hellgren 2002). This is why perceived JI is more interesting, as well as more suitable, to investigate.

Accordingly, the perception of JI principally rely on the “objective” conditions in which individuals work, the most important predictors being macro and socio-demographical variables (Ashford *et al.* 1989; Sverke and Hellgren 2002). Individual perception of JI is related to the national level of unemployment and the economic situation (De Weerd *et al.* 2004; Nätti *et al.* 2005). Moreover, also background characteristics which indicate a weak labor market situation are related to individual perception of JI. Research shows that low skilled individuals, blue collar-workers, workers in the industrial sector, employees which face organizational change, and those that have a temporary job contract, typically experience a higher level of perceived JI (Näswall and De Witte 2003; Keim *et al.* 2014). These kinds of workers, in fact, have in general a higher probability of losing their job and being fired.

Despite that, individual psychological variables may affect perception of JI which shows considerable amount of variance that is not accounted for by the objective situation. Different individuals embedded in the same objective situation do in fact perceive different level of JI since the very same objective situation can be appraised in various ways by different workers (Hartley *et al.* 1990; Klandermans and van Vuuren 1999). Moreover, while some individuals may perceive high level of JI even when the objective situation is secure and their job continuity is not at risk (for example permanent workers employed in public sector), on the contrary others may not feel particularly insecure about their jobs (for example those with higher level of employability) even though their objective situation is at risk (Klandermans and van Vuuren 1999).

A recent study investigated the relationship between individual JI and JI climate over time among 419 employees working in Flanders (Låstad *et al.* 2016). Findings appear to indicate that perceptions of individual JI were related with a climate of JI at workplace six months later, whereas no evidence was found for the opposite effect, namely JI climate do not seems to have a primary effect on individual JI. The authors suggest, therefore, that JI might origin in the individual's perceptions and expands only afterwards to comprise perceptions of a more general JI climate at the workplace.

This subjective variability in the perception of JI is very interesting since it has being shown to have a substantial impact on a number of individual and organizational outcomes, with important implications, over and above the "objective" JI (e.g. Cheng and Chan 2008; Gilboa *et al.* 2008; Sverke and Hellgren 2002).

Individuals with higher perceived JI have in general a worst health: those people report higher levels of physical complaints and stress, and poorer psychological well-being (Chirumbolo and Hellgren 2003; De Witte 1999; De Witte *et al.* 2015; De Witte *et al.* 2016). Subjective JI negatively impact also other personal outcomes in individuals' life: Higher perceived JI is related to poorer family relationships (Larson *et al.* 1994; Mauno and Kinnunen 1999), lower life satisfaction (De Cuyper *et al.* 2008; Lim 1997), reduced self-esteem (Kinnunen *et al.* 2003), impaired inclination towards daily consumption and limited major life decisions (Lozza *et al.* 2017).

Perception of high JI is also negative for the optimal functioning of the organizations. Employees that are worried with their situation at the workplace will be detracted from their focus on work, impairing their performance (Reisel *et al.* 2007), and will develop withdrawal attitudes and cognitions, reducing their commitment to the job and the organization itself. These patterns of findings were confirmed by many empirical studies (for review see Cheng and Chan 2008; De Witte 2005; Gilboa *et al.* 2008; Sverke *et al.* 2002).

In particular, investigations showed that higher perceived JI is related to lower organizational commitment and job satisfaction (e.g., Ashford *et al.* 1989; Callea *et al.* 2016; Chirumbolo and Hellgren 2003; Davy *et al.* 1997; De Cuyper and De Witte 2006; Hellgren *et al.* 1999), lower organizational citizenship behavior (Chirumbolo *et al.* 2017a; Piccoli *et al.* 2017; Reisel *et al.* 2010), lower work engagement (Chirumbolo *et al.* 2017a; De Cuyper *et al.* 2008; Stander and Rothmann 2010), worst self-rate task performance (Chirumbolo and Areni 2010; Chirumbolo *et al.* 2017a; LePine *et al.* 2005; Piccoli *et al.* 2017; Reisel *et al.* 2007), less identification with the organization (Chirumbolo *et al.* 2017b). On the other hand, higher perceived JI is usually related to more turn over intentions (Chirumbolo and Hellgren 2003; Dekker and Schaufeli 1995) and more deviant or counterproductive behaviors in the workplace (Chirumbolo 2015; Lim 1997; Reisel *et al.* 2010). It is worth to note that the vast majority of the aforementioned results highlighted the impact of

subjective JI controlling for the most important background and socio-demographical variables (such as gender, age, tenure, contract type, occupational status and the like).

Focusing on the economic literature, few papers have investigated the effect of perceived JI on the average level of wages. Maurin and Postel-Vinay (2005) demonstrate that perceived job security and wage are two substitute components in the functioning of European labour markets. Hubler and Hubler (2010) show that perceived and objective JI has a negative effect on wages in both the UK and Germany. Cambell *et al.* (2007) find that in Britain the fear of unemployment has a negative and significant effect on the mean level of wages. In Blanchflower (1991) it is shown that the concern for unemployment depresses pay significantly. Workers who expect to be redundant receive, on average, 9% less in the UK and 22% less in the US. It is important to note that when trying to assess the effects of policy variables, policy maker is more interested in the effects on the whole distribution of a variable, rather than on its average. This is particularly relevant in the case of social policies tailored to deal with wage inequality. Thus, a study investigating the effects on the average income actually leaves out the most relevant aspects concerning its distribution. We add to the existing literature, evaluating the effects of the JI on the income distribution as well as on its average. With regard to Italy, in the context of the great economic and financial crisis – it has shown both a quite large increase in JI and a decline in the hourly real wage, even more clearly than the other OECD countries. (OECD 2016). Some articles evaluated the wider labour market reform package adopted at the end of 2014 – Law 183 of 2014, known as the “Jobs Act” – aimed at both reducing labour market segmentation between fixed-term and open-ended job contracts and stimulating job creation (Cirillo *et al.* 2017; Sestito and Viviano 2018).

Catalano and Pezzolla (2017) using a Dynamic Stochastic General Equilibrium (DSGE) model to evaluate the so-called Jobs-Act find that the positive impact on GDP and aggregate demand comes at the expense of a reduction in the labour income share and the average wage.

With respect to income support measures, some authors noted that, although improved compared to the past (see the scheme, called *Reddito di Inclusione*, introduced at the beginning of 2018), the Italian Welfare State needs further improvements to cope with the demographic and technological changes in progress (Sacchi 2018).

Focusing on the empirical studies on the wage effect, attention has been devoted on the pay gap between permanent and temporary contracts (Berton *et al.* 2012; Bosio 2014), while the effect of perceived JI on wage has been neglected. Our paper adds to the current literature by exploiting both a semi-parametric and a non-parametric decomposition approach to provide new insights into the nature and sources of the pay gap due to perceived JI across dependent workforce in Italy.

### **3. Empirical specification**

#### **3.1 B-O decomposition and a semi-parametric estimation**

By means of the Blinder-Oaxaca (B-O) decomposition a researcher can explain how much of the difference in the mean wage across two groups is due to group differences in the levels of explanatory variables, and how much is due to differences in the magnitude of regression coefficients (Oaxaca 1973; Blinder 1973). If S and I are the two groups of secure and insecure

workers, the mean wage difference to be explained ( $\Delta\bar{y}$ ) is simply the difference in the mean wage for observations in those two groups, denoted  $\bar{y}_S$  and  $\bar{y}_I$ , respectively:

$$\Delta\bar{y} = \bar{y}_S - \bar{y}_I \quad (1)$$

In the context of a linear regression, the mean wage for group  $W=I,S$  can be expressed as  $\bar{y}_W = \bar{X}'_W \hat{\beta}_W$ , where  $\bar{X}_W$  contains the mean values of explanatory variables and  $\hat{\beta}_W$  the estimated regression coefficient. Hence,  $\Delta\bar{y}$  can be rewritten as:

$$\Delta\bar{y} = \bar{X}'_S \hat{\beta}_S - \bar{X}'_I \hat{\beta}_I \quad (2)$$

The twofold approach splits the mean outcome difference with respect to a vector of non-discriminatory coefficients  $\hat{\beta}_R$ . The wage difference in (2) can then be written as:

$$\Delta\bar{y} = (\bar{X}'_S - \bar{X}'_I)' \hat{\beta}_R + \bar{X}'_S \left( \hat{\beta}_S - \hat{\beta}_R \right) + \bar{X}'_I \left( \hat{\beta}_R - \hat{\beta}_I \right) \quad (3)$$

In eq. (3) the first term is the explained component while the sum between the second and the third term is the unexplained component.

While the Ordinary Least Squares (OLS) method provides estimates for the conditional mean exclusively, the Quantile Regression (QR) technique allows for the estimation of the whole conditional wage distribution. Moreover, QR estimates capture changes in the shape, dispersion and location of the distribution, while OLS estimates do not. This can be a source of misleading relevant information on the wage distribution for secure and insecure workers. Put in another way, the QR method (Koenker and Bassett 1978), seems to be more interesting, and more appropriate in this context: the  $\theta^{\text{th}}$  quantile of a variable conditional on some covariates can be accounted for and the effect of those covariates at selected quantiles of the distribution can be estimated.

If  $y_i$  is the dependent variable and  $x_i$  the vector of the chosen explanatory variables. The relation is given by:

$$y_i = x_i \beta(\theta) + \varepsilon_i \quad \text{with} \quad F_{\varepsilon}^{-1}(\theta | X) = 0 \quad (4)$$

where  $F_{\varepsilon}^{-1}(\theta | X)$  represents the  $\theta^{\text{th}}$  quantile of  $\varepsilon$  conditional on  $x$ . The estimated  $\theta^{\text{th}}$  quantile is obtained by solving the following equation:

$$\min_{\beta(\theta)} \left\{ \sum_{(i: y_i \geq x_i \beta(\theta))} \theta |y_i - x_i \beta(\theta)| + \sum_{(i: y_i < x_i \beta(\theta))} (1-\theta) |y_i - x_i \beta(\theta)| \right\} \quad (5)$$

and  $\beta(\theta)$  is chosen to minimize the weighted sum of the absolute value of the residuals.

Once the QR coefficients have been estimated, the differences at the selected quantiles of the wage distribution between the two groups can be divided into one component based on the differences in characteristics and another based on the differences in coefficients across the wage distribution. As argued by Melly (2005), in the classic Blinder-Oaxaca (B-O) decomposition procedure, the exact split of the average wage gap between two groups is due to the assumption that the mean wage conditional on the average values of the regressors is equal to the unconditional mean wage. In other words, if one chooses to frame the QR with the B-O methodology, he/she will elicit biased results. For this reason we chose to apply a procedure to single out the two above mentioned components from the decomposed differences at given quantiles of the unconditional distribution. Firstly, the conditional distribution is estimated through the Q; secondly it is integrated over the range of covariates.

Representing with  $\hat{\beta} = (\hat{\beta}(\theta_1), \dots, \hat{\beta}(\theta_j), \dots, \hat{\beta}(\theta_J))$  the vector of quantile regression parameters estimated at J different quantiles  $0 < \theta_j < 1$  with  $j=1, \dots, J$  and integrating over all of the quantiles and observations, an estimator of the  $\tau$ th unconditional quantile of the (log monthly) wage is given by:

$$q(\tau, x, \beta) = \inf \left\{ q : \frac{1}{N} \sum_{i=1}^N \sum_{j=1}^J (\theta_j - \theta_{j-1}) \mathbb{1} \left( x_i \hat{\beta}(\theta_j) \leq q \right) \geq \tau \right\} \quad (6)$$

where  $\mathbb{1}(\cdot)$  is the indicator function. Thus, the counterfactual distribution can be estimated by replacing either the computed parameters of the distribution of characteristics for secure or insecure workers. The difference at each quantile of the unconditional distribution can be decomposed into the two above mentioned components as follows:

$$q(\theta, x^i, \beta^i) - q(\theta, x^s, \beta^s) = [q(\theta, x^i, \beta^i) - q(\theta, x^i, \beta^s)] + [q(\theta, x^i, \beta^s) - q(\theta, x^s, \beta^s)] \quad (7)$$

The right hand term in the first brackets constitutes the difference in rewards that the two groups of workers receive for their labour market characteristics (i.e. the counterfactual distribution), while that in the second brackets is the effect of differences in labour market characteristics between secure and insecure workers. This is a semi-parametric-method because the QR framework does not need any distributional assumption while at the same time allows the same covariates to have an influence all over the conditional distribution.

To estimate the standard errors and confidence intervals, the bootstrap method can be used to replicate the above procedure. In this study 200 replications were performed.

### 3.2 The Inverse Probability Weighting approach as a non-parametric estimation

In order to correct for selection bias in the self-perception of JI for the two groups of workers, we also estimate the wage distributions by adopting a non-parametric framework, which allows for an analysis without imposing any shape at the outset.

Indeed, after performing the Oaxaca-Blinder and Melly's decompositions, we adopt a variant of the Inverse Probability Weighting (IPW) approach firstly proposed by Di Nardo, Fortin and Lemieux (DFL 1996) and estimate quantiles for two counterfactual distributions, one if every worker were secure

at his/her job, the other if they were all insecure. The IPW approach has been proved to be efficient (see Hirano *et al.* 2003) and particularly suitable when the aim of the researcher is, as in our case, the decomposition of the overall difference in the distributions of the outcome variable into its explained and unexplained component often called “aggregated” decomposition<sup>2</sup>. This non parametric method, needs milder assumptions than those on which methods based on the decomposition at quantiles, are built (for a detailed discussion on advantages and limitations of these methods see Firpo *et al.* 2011). Furthermore, with the IPW, we are not obliged to assume the same (parametric) model across quantiles unlike in Melly’s (2005).

In the first stage the conditional probability of being (in)secure at work, given a set of characteristics, is estimated by using a probit model of the following form:

$$\Pr(s = 1 | x) = \phi(x) \quad (8)$$

where  $s$  is the dummy variable assuming value 1 if the individual  $i = 1, 2, \dots, N$  (where  $N$  is the sample size) is secure at work and  $x$  is the same vector of variables used for the B-O and the QR decompositions<sup>3</sup>. In other words the  $x$  is the same vector of variables used and expected to be associated with the probability of being secure at work. The predicted values from model (8) are used for building up the following re-weighting functions:

$$\theta_0 = \frac{1 - \Pr(s = 1)}{1 - \Pr(s = 1 | x)} \quad (9)$$

$$\theta_1 = \frac{\Pr(s = 1)}{\Pr(s = 1 | x)} \quad (10)$$

Those functions are later used in the otherwise non-parametric Parzen-Rosenblatt kernel density estimator to build up two so-called counterfactual densities of wages, i.e. the density that would prevail if none of the employees were secure at work and the density if every worker were secure:

$$\hat{f}_{N,h(w)} = \frac{1}{N} \sum_{i=1}^N \frac{\hat{\theta}_j}{h} K\left(\frac{w - w_i}{h}\right) \quad j=0,1 \quad (11)$$

where  $w$  is the (natural log of the) wage and  $K$  is the kernel density function that satisfies:

$$\int_{-\infty}^{\infty} K(p) dp = 1^4$$

<sup>2</sup> Another type is the “detailed” decomposition, where the interest lies in estimating the contribution of each covariate to the overall difference.

<sup>3</sup> Results from the probit model are shown in table A1 in Appendix.

<sup>4</sup> Many kernel functions can be used to the scope. In our exercise we chose the Gaussian kernel evaluated at  $(w - w_i)$  given the bandwidth  $h$ . Our choice of the kernel is due to its property of monotonicity of peaks and valleys w.r.t. changes in the smoothing parameters, which proves to be useful when comparing distributions

Eq. (11) is the empirical counterpart of the two following distributions:

$$f^{ns}(w) = \int \theta_{ns} g^{ns}(w|x) l(x|s=0) dx \quad (12)$$

and

$$f^s(w) = \int \theta_s g^s(w|x) l(x|s=1) dx \quad (13)$$

for insecure and secure workers respectively.

In Eq. (12) and (13)  $\theta_{ns}$  and  $\theta_s$  are the true re-weighting parameters,  $g^{ns}(w|x)$  and  $l(x|s=0)$  as well as  $g^s(w|x)$  and  $l(x|s=1)$  are the conditional densities of wages and the distributions of the  $x$  characteristics associated to the subsamples for which  $s=0$  and  $s=1$  respectively. The two distributions are then compared to compute the total difference conditional on the  $x$  characteristics, while its explained part of is obtained by comparing the first of those distributions (that of insecure workers) with the actual density of wages

$$f(w) = \int g(w|x) l(x) dx \quad (14)$$

#### 4. Data

The data used in this article are from the Fourth INAPP Survey on Quality of Work (InappQoW) that has been carried out in 2015 on a sample of 15,000 workers. INAPP realizes this periodical survey every four years, with the aim of measuring the concept of work quality in Italy. The project is inspired to the European Working Conditions Survey carried out by Eurofound.

We first excluded self-employed workers. The sample was then restricted to employees between 18 and 64 years. The final sample consisted of 4,155 secure and 1,239 insecure workers.

In order to measure subjective (perceived) JI included within the wage equations estimated in section 5, we refer to a specific question which was asked in the InappQoW. Individuals who are currently in employment are asked: "In the next 12 months I could not have more work, in spite of myself". Individuals were required to respond "Yes" or "Not".

The logarithm of the monthly net wage is regressed on a set of covariates representing:

- individual characteristics: age and its squared, gender, household ability to make ends meet (3 categories indicating "simply", "with some difficulties", and "with many difficulties" education (eight categories based on the highest level achieved), education of father (eight categories based on the highest level achieved), work experience;

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(Sheather 2004). For what concerns the bandwidth, our choice has fallen on the Cross Validation (CV) method: it is suitable as there is no need to make assumptions about the smoothness to which the unknown density belongs (Loader 1999).

- job characteristics: part-time/full-time, temporary/permanent, mobility in change job (four categories showing how many changes since the first job, “never changed”, “1/2 changes job”, “3/5”, “more than 5”, stability of job security over time (three categories given by the response to the question “by comparing your current work situation with that of January 2008, do you think the job stability has worsened, equalled or improved?”), training received in the last year, supervisory position, telework, welfare/social security contributions payment, routine tasks prevailing at work, skill mismatch, job-stress (three categories for the question “consider your stressful work?”, ranging from “never” to “always or most of the time”);
- firm characteristics: size (measured by the number of workers in the same local unit), location in the Southern Italy (*Mezzogiorno*), sector of economic activity (17 dummy variables).

Table 1 shows the descriptive statistics for the sample of secure and insecure employees used in the empirical analysis. Figure 1 plots the kernel estimates of the wage density for both groups. It can be noted that the top of the monthly net wage density for secure workers is reached at a higher wage than that for insecure workers. Furthermore, the wage distribution for secure worker is clearly shifted to the right with respect to the insecure workers.

**Table 1.** Summary statistics

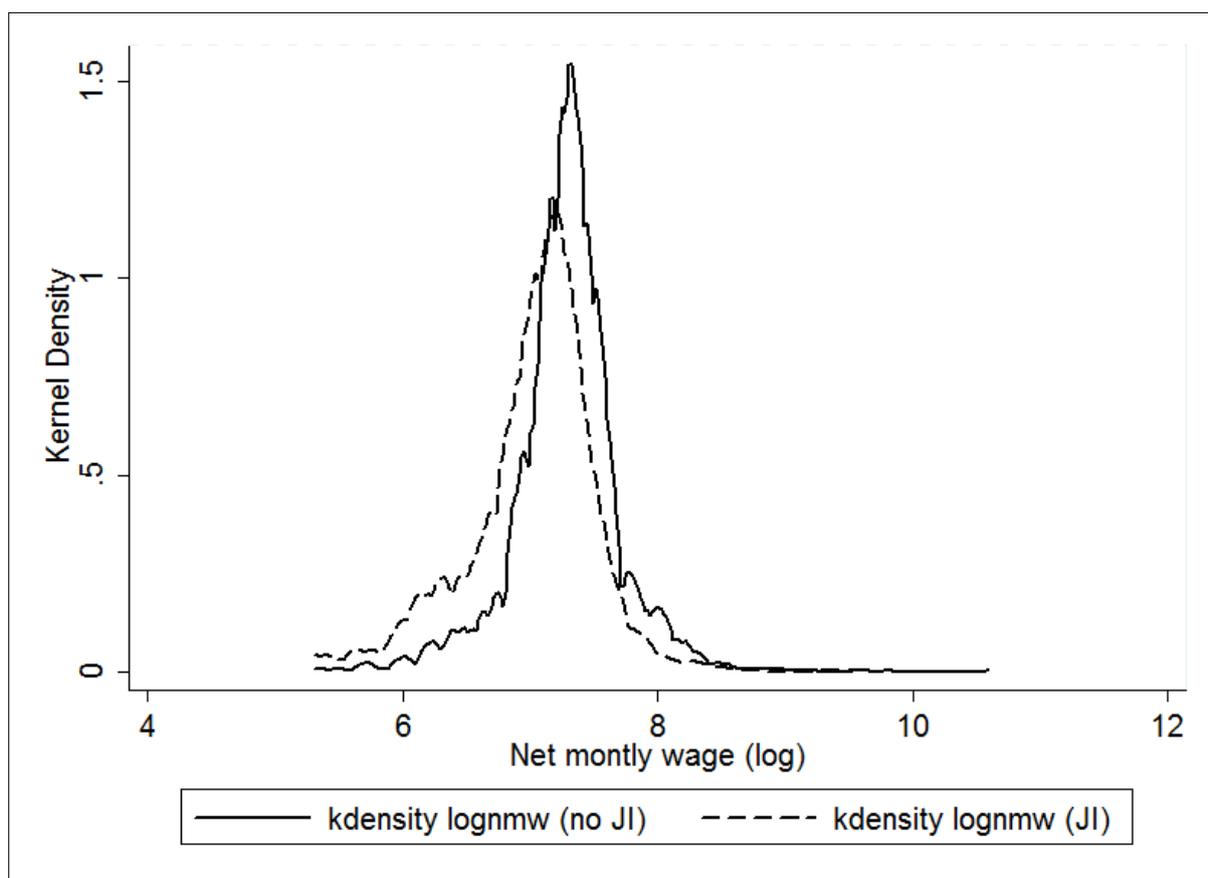
Variable	Job insecurity: no					Job insecurity: yes				
	Obs	Mean	Std. Dev.	Min	Max	Obs	Mean	Std. Dev.	Min	Max
lognmw	4897	7,267	0,411	5,298	10,597	1683	7,017	0,499	5,298	9,547
age	6477	46,277	11,134	18	64	2194	42,583	11,725	18	64
dmale	6477	0,516	0,500	0	1	2194	0,536	0,499	0	1
make_ends_meet	6388	1,199	0,655	0	2	2169	0,925	0,678	0	2
edu_fath	6113	1,853	1,036	0	4	2069	1,808	1,011	0	4
work_exp	6477	23,883	11,672	0	55	2194	20,934	12,707	0	55
pasted	6477	4,046	1,527	0	8	2194	3,626	1,468	0	8
dfull	6477	0,845	0,362	0	1	2194	0,716	0,451	0	1
dperm	6287	0,939	0,240	0	1	1959	0,734	0,442	0	1
mobility	6456	1,038	1,016	0	3	2184	1,357	1,071	0	3
stability	5823	1,089	0,635	0	2	1788	0,607	0,720	0	2
dtraining	6477	0,591	0,492	0	1	2194	0,448	0,497	0	1
supervisor	6477	0,375	0,484	0	1	2194	0,340	0,474	0	1
telework	6477	0,160	0,367	0	1	2194	0,102	0,303	0	1
contr	6447	0,976	0,154	0	1	2161	0,932	0,252	0	1
routine	6477	0,689	0,463	0	1	2194	0,786	0,410	0	1
mismatch	6477	0,195	0,396	0	1	2194	0,273	0,446	0	1
stress	6477	1,136	0,543	0	2	2194	1,131	0,572	0	2
unionsize	6477	253,912	785,857	1	9000	2194	172,809	659,531	1	9000
mezz	6477	0,239	0,426	0	1	2194	0,279	0,449	0	1
sectors	6477	9,877	4,761	1	17	2194	8,752	5,015	1	17
N. Observations			4155					1239		
Insecure workers (%)								29%		

Source: Fourth Inapp Survey on Quality of Work (InappQoW), 2015

Note: Sampling weights applied

As a first robustness check for the difference between the two distributions, the non-parametric Kolmogorov-Smirnov test based on the concept of stochastic dominance, is used to check for differences in all moments of the wage distribution. The concept of first order stochastic dominance allows one to establish a ranking for compared distributions. The results of the Kolmogorov-Smirnov test for the first order stochastic dominance shown in table 2 confirm that the net monthly wages of secure workers stochastically dominate, at the 1 per cent significance level, those of insecure workers.

**Figure 1.** Wage distribution for workers with JI and workers with no JI



Source: Fourth Inapp Survey on Quality of Work (InappQoW), 2015

**Table 2.** Kolmogorov-Smirnov test for comparison between workers with JI and workers with no JI

	Combined	JI=no	JI=yes
KS <sub>2</sub>	0,2563 (0.000)		
KS <sub>1</sub>		-0,2563 (0.000)	0,000 (1.000)

Notes: *p*- values in parentheses

## 5. Results

As a first step, we estimate the Mincerian wage equations – separately for secure and insecure workers. The estimation results are presented in tables 3A and 3B. In particular we show, for the two groups, respectively, the OLS coefficients as well as the conditional coefficients at nine representative quantiles:  $\theta_{10}$ ,  $\theta_{20}$ ,  $\theta_{30}$ ,  $\theta_{40}$ ,  $\theta_{50}$ ,  $\theta_{60}$ ,  $\theta_{70}$ ,  $\theta_{80}$ ,  $\theta_{90}$ .

The OLS results for those who are secure at work show that their salary is higher when they grow older, if they are men, if they do not have any difficulty in making ends meet<sup>5</sup>, if workers and their fathers have attained at least the lowest school degree (elementary school)<sup>6</sup>, if they have more work experience (even though this variable is slightly significant) and unsurprisingly if they have a full time contract, a permanent job, or supervise other workers. High mobility (more than 5 changes) is found to have a not significant negative effect on the salary of the first group of workers. Stability of the job condition is also non statistically significant. Attending training courses at work has a positive effect on their salary (increasing it by about 5.8 percentage points). Interestingly, workers who sometimes work remotely from home with their own PCs are found to earn 8.2% more than those who in the secure case do not. Routinary tasks negatively affect wage of secure workers (-5.5%). Being stressed at work is found to be associated with higher wages as well as a larger size of the firm, while being a Southern worker is not statistically significant.

For what concerns the insecure group of workers unlike the former group, their age is found statistically significant. Fathers' educational effect on their wage is again positive. Mobility has a negative significant effect on salary starting from 3/5 change: more than 5 changes has the highest negative effect. Again, having a full time job with permanent contract, with some form of job training and remote work is positively correlated to the wage level. Being stressed has a lower positive effect on salaries than in the secure group (+7.8%). Job mismatch has a significant negative effect unlike the former regression. Finally, also in this case, the territorial predictor (i.e. being a Southern worker) is not found to have a significant effect on "unsafe" workers.

When we depart from the analysis at the conditional mean and perform simultaneous quantile regressions, the effect of age is confirmed to be positive at all the quantiles examined, even though with some difference in statistical significance: for example it is not significant at the highest decile of the insecure group.

The gender wage gap, the educational attainment, the quality of the job contract (full-time and permanent), job training possibilities remain significant and positive regardless the technique used. Somewhat similar results are found for the categorical variable "make ends meet". Fathers' education is positively related to the wage and this positive contribution increases at the highest deciles: this fact hints at a hysteresis in the wage distribution across generations. The routinary task is negative and significant across the distribution and it is generally increasing. Mismatch is negative and significant only for the lowest deciles of the insecure group.

<sup>5</sup> The effect from category 0 to 1 and from 1 to 2 is increasing, thus suggesting a non-linear relation with the wage.

<sup>6</sup> The effect of the direct (i.e. of the worker) educational attainment is found to increase salary of about 5.3 percentage points, while the indirect (i.e. of their fathers) increases the salary of 2% percentage points.

**Table 3A.** OLS and Quantile Regressions estimates. Job Insecurity: no

	OLS	q10	q20	q30	q40	q50	q60	q70	q80	q90
age	0.015* (0.014)	0.031** (0.007)	0.021*** (0.007)	0.010 (0.007)	0.017** (0.007)	0.015** (0.007)	0.009 (0.008)	0.018** (0.009)	0.018 (0.012)	0.022* (0.012)
age_sq	-0.000 (0.000)	-0.000** (0.000)	-0.000*** (0.000)	-0.000 (0.000)	-0.000* (0.000)	-0.000* (0.000)	-0.000 (0.000)	-0.000* (0.000)	-0.000 (0.000)	-0.000 (0.000)
male	0.153*** (0.019)	0.162*** (0.034)	0.155*** (0.023)	0.138*** (0.024)	0.136*** (0.032)	0.129*** (0.022)	0.133*** (0.024)	0.154*** (0.019)	0.161*** (0.025)	0.162*** (0.022)
make_ends_meet_1	0.101*** (0.020)	0.160*** (0.034)	0.122*** (0.031)	0.079*** (0.023)	0.086*** (0.021)	0.099*** (0.021)	0.086*** (0.016)	0.079*** (0.022)	0.069** (0.027)	0.047 (0.037)
make_ends_meet_2	0.185*** (0.026)	0.209*** (0.028)	0.177*** (0.040)	0.150*** (0.030)	0.141*** (0.030)	0.143*** (0.028)	0.134*** (0.025)	0.131*** (0.026)	0.164*** (0.044)	0.217*** (0.061)
edu_fath	0.020* (0.011)	0.005 (0.018)	0.004 (0.009)	0.012* (0.007)	0.016** (0.007)	0.013** (0.005)	0.013* (0.008)	0.019 (0.013)	0.016 (0.013)	0.043*** (0.014)
work_exp	0.005*** (0.002)	0.007** (0.003)	0.006*** (0.001)	0.006*** (0.002)	0.003** (0.002)	0.004* (0.002)	0.003* (0.002)	0.003* (0.002)	0.003 (0.002)	0.003 (0.002)
pasted	0.053*** (0.007)	0.055*** (0.010)	0.055*** (0.009)	0.050*** (0.007)	0.041*** (0.003)	0.050*** (0.006)	0.049*** (0.007)	0.046*** (0.008)	0.057*** (0.012)	0.059*** (0.012)
full	0.408*** (0.025)	0.574*** (0.037)	0.496*** (0.040)	0.483*** (0.027)	0.428*** (0.033)	0.382*** (0.025)	0.344*** (0.023)	0.344*** (0.020)	0.315*** (0.022)	0.273*** (0.046)
perm	0.093*** (0.026)	0.099* (0.055)	0.153*** (0.041)	0.112*** (0.024)	0.122*** (0.023)	0.097*** (0.019)	0.082*** (0.020)	0.080** (0.031)	0.041 (0.045)	0.035 (0.040)
mobility_1	-0.060*** (0.023)	-0.026 (0.033)	-0.032 (0.028)	-0.022 (0.023)	-0.032 (0.024)	-0.067*** (0.026)	-0.070*** (0.026)	-0.078*** (0.026)	-0.083** (0.040)	-0.066 (0.045)
mobility_2	-0.068*** (0.023)	-0.109*** (0.040)	-0.054* (0.032)	-0.040 (0.028)	-0.028 (0.028)	-0.051** (0.024)	-0.051*** (0.019)	-0.054** (0.022)	-0.077** (0.037)	-0.053* (0.029)
mobility_3	-0.029 (0.028)	-0.066 (0.053)	-0.043 (0.036)	-0.022 (0.028)	-0.005 (0.031)	-0.023 (0.023)	-0.042 (0.030)	-0.017 (0.032)	-0.034 (0.045)	-0.027 (0.043)
stability	-0.011 (0.012)	-0.021 (0.025)	-0.004 (0.020)	-0.004 (0.017)	-0.010 (0.015)	-0.013 (0.014)	-0.018* (0.010)	-0.020 (0.015)	0.005 (0.012)	-0.001 (0.020)
training	0.058*** (0.017)	0.090*** (0.025)	0.064*** (0.020)	0.044** (0.020)	0.038* (0.022)	0.040* (0.023)	0.044*** (0.013)	0.047** (0.021)	0.056* (0.031)	0.015 (0.041)
supervisor	0.098*** (0.019)	0.029 (0.028)	0.060*** (0.022)	0.081*** (0.013)	0.082*** (0.014)	0.098*** (0.018)	0.115*** (0.013)	0.112*** (0.008)	0.111*** (0.025)	0.161*** (0.025)
telework	0.082*** (0.029)	0.077 (0.074)	0.051 (0.035)	0.038 (0.026)	0.058** (0.023)	0.057 (0.039)	0.084** (0.042)	0.083*** (0.032)	0.085* (0.046)	0.059 (0.041)
contr	0.098 (0.063)	0.190* (0.111)	0.121 (0.097)	0.133** (0.058)	0.058 (0.055)	0.058 (0.052)	0.063 (0.057)	-0.021 (0.051)	-0.002 (0.030)	0.034 (0.055)
routine	-0.055*** (0.020)	-0.061* (0.035)	-0.045 (0.037)	-0.047 (0.031)	-0.065*** (0.015)	-0.069*** (0.024)	-0.075*** (0.023)	-0.070** (0.032)	-0.072*** (0.019)	-0.074*** (0.024)
mismatch	-0.030 (0.019)	0.003 (0.021)	-0.030 (0.019)	-0.023 (0.020)	-0.025 (0.024)	-0.035* (0.022)	-0.034 (0.025)	-0.023 (0.021)	-0.037 (0.025)	-0.019 (0.040)
stress	0.078*** (0.017)	0.147*** (0.027)	0.101*** (0.025)	0.077*** (0.013)	0.050*** (0.017)	0.055*** (0.013)	0.056*** (0.019)	0.045** (0.021)	0.043** (0.021)	0.082*** (0.025)
unionsize	0.000** (0.000)	0.000 (0.000)	0.000 (0.000)	0.000* (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000** (0.000)
mezzogiorno	-0.033 (0.021)	-0.050 (0.050)	-0.024 (0.047)	-0.027 (0.039)	-0.023 (0.031)	-0.014 (0.029)	-0.019 (0.030)	-0.024 (0.036)	-0.024 (0.033)	-0.026 (0.036)
_cons	5.508*** (0.21)	4.569*** (0.352)	5.012*** (0.250)	5.471*** (0.146)	5.571*** (0.120)	5.670*** (0.147)	5.863*** (0.151)	5.817*** (0.174)	5.934*** (0.263)	5.892*** (0.369)
Sectors	Yes									
N	1239									
R-Squared	0,557	0,446	0,403	0,375	0,351	0,337	0,325	0,315	0,316	0,332

Notes: Standard errors in parentheses; robust standard errors are computed for OLS coefficients while the quantile regression standard errors are obtained by bootstrapping (200 repetitions). 17 dummies for sectors included, but not reported. \*\*\*p < 0.01, \*\*p < 0.05, \*p < 0.1

**Table 3B.** OLS and Quantile Regressions estimates. Job Insecurity: yes

	OLS	q10	q20	q30	q40	q50	q60	q70	q80	q90
age	0.013** (0.005)	0.025** (0.010)	0.019** (0.007)	0.019*** (0.005)	0.017*** (0.004)	0.020*** (0.003)	0.019*** (0.005)	0.018*** (0.006)	0.010 (0.010)	0.005 (0.007)
age_sq	-0.000 (0.000)	-0.000** (0.000)	-0.000* (0.000)	-0.000*** (0.000)	-0.000*** (0.000)	-0.000*** (0.000)	-0.000** (0.000)	-0.000* (0.000)	-0.000 (0.000)	0.000 (0.000)
male	0.126*** (0.010)	0.112*** (0.010)	0.103*** (0.009)	0.113*** (0.008)	0.111*** (0.008)	0.099*** (0.011)	0.109*** (0.013)	0.115*** (0.009)	0.125*** (0.014)	0.143*** (0.015)
make_ends_meet_1	0.082*** (0.013)	0.093*** (0.022)	0.072*** (0.018)	0.067*** (0.015)	0.068*** (0.012)	0.064*** (0.016)	0.069*** (0.014)	0.073*** (0.014)	0.070*** (0.014)	0.039* (0.023)
make_ends_meet_2	0.173*** (0.014)	0.156*** (0.025)	0.141*** (0.014)	0.131*** (0.018)	0.137*** (0.015)	0.139*** (0.020)	0.139*** (0.019)	0.146*** (0.019)	0.156*** (0.018)	0.141*** (0.031)
edu_fath	0.018*** (0.005)	0.004 (0.010)	0.008 (0.007)	0.015*** (0.005)	0.016*** (0.004)	0.014*** (0.005)	0.016** (0.007)	0.019*** (0.007)	0.021*** (0.006)	0.020** (0.008)
work_exp	0.002* (0.001)	0.002 (0.001)	0.002*** (0.001)	0.002*** (0.001)	0.003*** (0.001)	0.003*** (0.001)	0.002** (0.001)	0.002* (0.001)	0.001 (0.001)	0.000 (0.001)
pasted	0.059*** (0.004)	0.050*** (0.005)	0.052*** (0.004)	0.048*** (0.003)	0.049*** (0.004)	0.052*** (0.003)	0.054*** (0.002)	0.057*** (0.003)	0.061*** (0.003)	0.076*** (0.007)
full	0.393*** (0.016)	0.586*** (0.036)	0.494*** (0.029)	0.418*** (0.023)	0.383*** (0.016)	0.356*** (0.012)	0.333*** (0.011)	0.307*** (0.012)	0.295*** (0.015)	0.268*** (0.026)
perm	0.060* (0.032)	0.119 (0.082)	0.072** (0.035)	0.059*** (0.019)	0.068*** (0.020)	0.063*** (0.014)	0.073*** (0.016)	0.070*** (0.020)	0.079* (0.044)	0.029 (0.050)
mobility_1	-0.018 (0.011)	-0.021 (0.016)	-0.033*** (0.008)	-0.035*** (0.013)	-0.025** (0.012)	-0.023* (0.013)	-0.019 (0.015)	-0.011 (0.019)	-0.013 (0.014)	-0.019 (0.017)
mobility_2	-0.022* (0.012)	-0.029** (0.014)	-0.033*** (0.009)	-0.043*** (0.012)	-0.037*** (0.014)	-0.036** (0.014)	-0.022 (0.019)	-0.024 (0.015)	-0.007 (0.016)	0.003 (0.023)
mobility_3	-0.036** (0.017)	-0.039 (0.024)	-0.049*** (0.018)	-0.061*** (0.013)	-0.057*** (0.016)	-0.047*** (0.017)	-0.036 (0.022)	-0.033** (0.014)	-0.013 (0.010)	-0.015 (0.029)
stability	0.010 (0.007)	0.006 (0.007)	-0.002 (0.007)	0.003 (0.009)	-0.004 (0.007)	-0.002 (0.007)	0.005 (0.009)	0.001 (0.008)	0.011 (0.009)	0.020** (0.009)
training	0.043*** (0.009)	0.027* (0.015)	0.038*** (0.012)	0.033*** (0.010)	0.034*** (0.008)	0.037*** (0.007)	0.028** (0.012)	0.025** (0.010)	0.034*** (0.011)	0.033*** (0.013)
supervisor	0.118*** (0.009)	0.085*** (0.009)	0.075*** (0.005)	0.087*** (0.006)	0.090*** (0.008)	0.092*** (0.011)	0.099*** (0.014)	0.115*** (0.014)	0.147*** (0.016)	0.187*** (0.021)
telework	0.058*** (0.013)	0.044* (0.025)	0.045*** (0.014)	0.044*** (0.014)	0.055*** (0.012)	0.050*** (0.009)	0.063*** (0.011)	0.068*** (0.012)	0.071*** (0.015)	0.057** (0.023)
contr	0.074 (0.049)	0.129 (0.162)	0.025 (0.030)	0.046** (0.020)	0.057* (0.034)	0.071** (0.033)	0.085** (0.039)	0.071* (0.042)	0.049 (0.046)	0.082 (0.087)
routine	-0.059*** (0.010)	-0.051*** (0.017)	-0.045*** (0.013)	-0.053*** (0.011)	-0.057*** (0.007)	-0.053*** (0.009)	-0.062*** (0.011)	-0.062*** (0.010)	-0.054*** (0.010)	-0.078*** (0.017)
mismatch	-0.029** (0.011)	-0.050*** (0.016)	-0.021*** (0.007)	-0.014*** (0.004)	-0.011* (0.006)	-0.004 (0.005)	-0.008 (0.011)	-0.006 (0.014)	-0.003 (0.014)	-0.011 (0.025)
stress	0.041*** (0.009)	0.029*** (0.008)	0.030** (0.012)	0.037*** (0.010)	0.030*** (0.011)	0.025* (0.015)	0.018 (0.015)	0.022* (0.014)	0.026** (0.013)	0.033** (0.014)
unionsize	0.000*** (0.000)	0.000*** (0.000)	0.000*** (0.000)	0.000*** (0.000)	0.000*** (0.000)	0.000** (0.000)	0.000*** (0.000)	0.000*** (0.000)	0.000*** (0.000)	0.000* (0.000)
mezzogiorno	-0.011 (0.010)	-0.024 (0.016)	-0.009 (0.011)	-0.023* (0.012)	-0.006 (0.010)	0.003 (0.013)	0.011 (0.011)	0.012 (0.012)	0.014 (0.013)	-0.011 (0.028)
_cons	5.732*** (0.143)	4.838*** (0.313)	5.487*** (0.150)	5.683*** (0.079)	5.755*** (0.066)	5.748*** (0.062)	5.784*** (0.073)	5.881*** (0.117)	6.094*** (0.271)	6.320*** (0.194)
Sectors	Yes									
N	4155									
R-Squared	0,493	0,370	0,334	0,315	0,300	0,285	0,286	0,293	0,303	0,341

Notes: See table A1

### 5.1 Counterfactual decomposition

Table 4 reports decomposition results for the mean and for several quantiles of the wage distribution. The observed wage gaps between secure and insecure workers is shown in column (1). Columns (2) – (6) refer to the semi-parametric estimate described in section 3.1, while columns (7) – (11) show the non-parametric estimate. The estimated least are also reported for comparison. Figure 2 plots the decomposition results at each of the 99 different quantiles, with a 95% bootstrap confidence interval. All estimates are significantly different from 0 at the 1% significance level.

The B-O decomposition shows a difference between mean wages of the two groups of 282 euros (1509 vs. 1227 euros). Thus the secure group earns almost 23 pp more than the insecure workers. The difference in endowments account for  $\frac{1}{4}$  of this gap (0.15 out of 0.21 when computed in natural logs). The difference in coefficients accounts for the remaining  $\frac{3}{4}$ .

**Table 4.** Decompositions of changes in JI wage gap and counterfactual distribution, using semi-parametric and fully non-parametric estimation

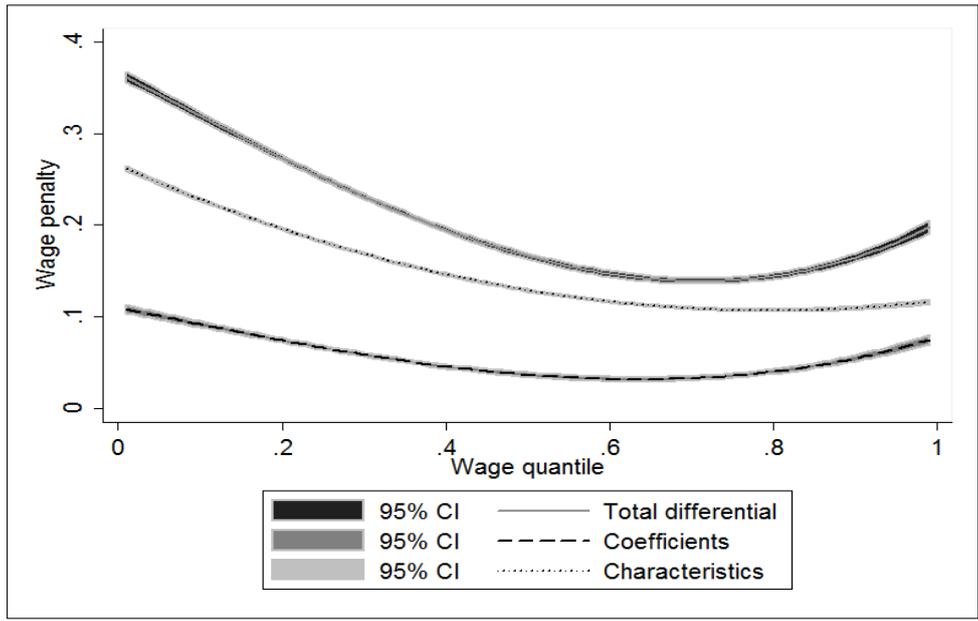
	Raw	Semi-parametric estimate					Non-parametric estimate				
	(1)	(2) Tot. Diff.	(3) Char.	(4) %	(5) Coeff.	(6) %	(7) Tot. Diff.	(8) Char.	(9) %	(10) Coeff.	(11) %
Mean	0.266	0.207	0.155	75%	0.052	25%	0,240	0,172	72%	0,068	28%
$\theta=.10$	0.596	0,338	0.231	68%	0.107	32%	0,349	0,223	64%	0,126	36%
$\theta=.20$	0.363	0,273	0.202	74%	0.071	26%	0,300	0,216	72%	0,083	28%
$\theta=.30$	0.262	0,219	0.167	76%	0.052	24%	0,260	0,194	75%	0,066	25%
$\theta=.40$	0.241	0,183	0.139	76%	0.044	24%	0,232	0,175	76%	0,057	24%
$\theta=.50$	0.223	0,164	0.126	77%	0.038	23%	0,212	0,162	76%	0,051	24%
$\theta=.60$	0.208	0,155	0.118	76%	0.037	24%	0,198	0,152	77%	0,046	23%
$\theta=.70$	0.194	0,149	0.112	75%	0.038	25%	0,189	0,146	77%	0,043	23%
$\theta=.80$	0.145	0,146	0.108	74%	0,038	26%	0,184	0,143	78%	0,041	22%
$\theta=.90$	0.201	0,153	0.108	71%	0.045	29%	0,189	0,148	78%	0,041	22%

Notes: Bootstrap standard errors for semi-parametric estimates are obtained with 200 replications. Mean values for the semi-parametric estimation are obtained with the B-O decomposition. All coefficients are significant at 1%

When the decomposition approach is extended to the whole wage distribution, it becomes evident that the contribution of differences in returns is larger than that of different covariates at each of the estimated quantiles. Moreover, the relative incidence of the coefficient component accounts roughly for 22 up to 36% of the total difference, being more relevant at the bottom of the wage distribution, thus showing a greater relevance of JI for low wages.

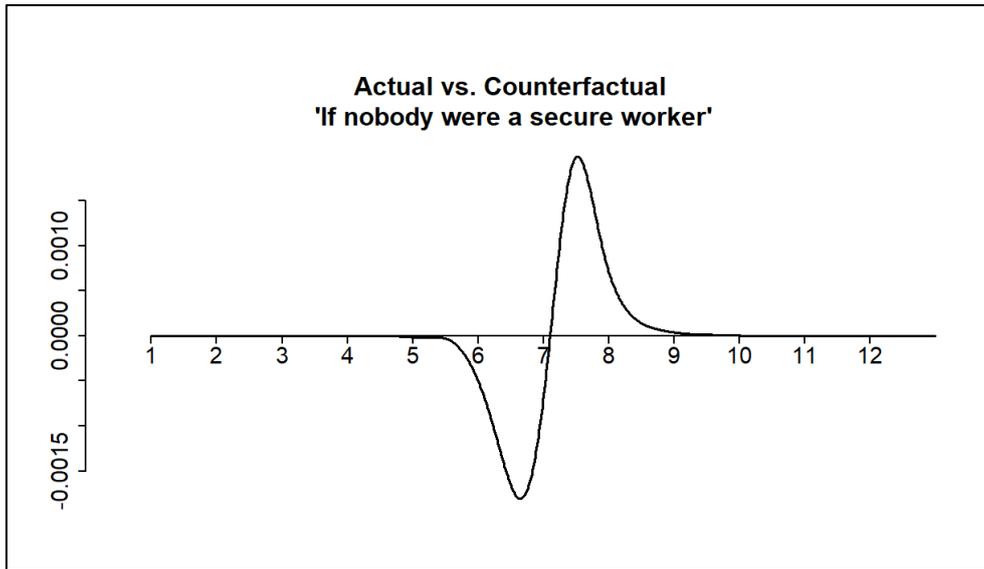
Figure 2 indicates that the insecure group of workers suffers from a statistically significant pay gap along all the wage distribution – as can be seen from the confidence band far from crossing the horizontal axis - after controlling for the predictors illustrated above. What is more, the pay gap seems *mirror J-shaped*, with the presence of a so called “sticky floor” (i.e. a situation in which the 10<sup>th</sup> percentile wage gap is significantly higher than the estimated wage gap at the 50<sup>th</sup> percentile). Indeed, as figure 2 clearly shows, the 10<sup>th</sup> percentile is not contained within the 95% confidence bands constructed for the 50<sup>th</sup> percentile (the median) which also presents a rather low (even though not the lowest) overall value in the wage gap between the two groups. The pattern is slightly shifted over the right side, with the lowest value reached around the 80<sup>th</sup> percentile.

**Figure 2.** Decomposition of differences in distribution using quantile regression



Source: Fourth Inapp Survey on Quality of Work (InappQoW), 2015

**Figure 3.** IPW, smoothed difference between actual and counterfactual (if nobody were a secure worker) distribution of wages



Source: Fourth Inapp Survey on Quality of Work (InappQoW), 2015

Results from the non-parametric model – table 4, columns (7) - (11) – indicate that the estimate is not substantially distorted by a selection bias, thus strengthening the sticky floor effect found with the semi-parametric method<sup>7</sup>. Figure 3 shows the smoothed difference between the actual and the the

<sup>7</sup> The insight here is that, being the dependent variable a self-perceived JI, it already probably contains a sort of self-selection term: therefore the distortion due to self-selection is low.

counterfactual distribution “if nobody were a secure worker”. It is clear that the impact is higher on the left tail of the distribution, consistently with the hypothesis that the wage gap between secure and insecure workers on the basis of perceived JI is higher for lowest quantiles.

## 6. Discussion and conclusions

Using the last wave of the INAPP Survey on Quality of Work, this paper employs both a semi-parametric and a non parametric decomposition method to examine the relationship between perceived JI and wage at the mean and over the entire conditional wage distribution of the Italian dependent workforce.

Results show the clear presence a *mirror J-shaped* pattern for the wage gap between secure and insecure workers, together with a significant sticky floor phenomenon. The counterfactual decomposition also highlights a very high endowments effect on the wage gap. Indeed, characteristics of the insecure group of workers account roughly for 2/3 up to 3/4 of the total difference along the wage distribution, with a higher incidence at lowest quantiles. This evidence suggests that a highly imperfect competitive labour market is at work in Italy, where greater JI may lead to workers accepting lower wages (Blanchflower 1991).

The reluctance of workers to leave their insecure and underpaid job reinforces the hysteresis of precariousness in the current labour market conditions, regardless of the recuperation in employment numbers achieved in the post-crisis period.

Our article has some policy indications emerged for the Italian welfare state. Indeed, to fill the wage gap, there is a need for social policies tailored to deal with income support measures. Moreover, endowments of the “unsafe group of workers” (i.e. their predictor levels in the regressions performed) should be raised. For this to happen, well-functioning and “well-intertwined” labour market and educational institutions are needed in order to strengthen the quality of job contracts (full-time and permanent being of course strongly correlated with the high level of the salary), increase employees’ educational attainment, promote job training, reduce routine and mismatch during the job. This challenge appears all the more important as high wage gaps increase inequality while at the same time jeopardizing Italian social fabric.

## Appendix

**Table A1.** First stage IPW. Estimated probability of being insecure

	Coef.	Robust Std. Err.
_cons	0.799*	-0,474
age	0,010	0,019
age_sq	0,000	0,000
male	-0,067	0,043
make_ends_meet_1	-0.222***	0,049
make_ends_meet_2	-0.490***	0,060
edu_fath	0,010	0,021
work_exp	-0.007**	0,004
pasted	-0,011	0,016
full	-0.173***	0,053
perm	-0.871***	0,067
mobility_1	0.128**	0,053
mobility_2	0.276***	0,051
mobility_3	0.375***	0,065
stability	-0.585***	0,028
training	-0.130***	0,040
supervisor	-0,004	0,041
telework	-0,043	0,061
contract	-0,129	0,130
routine	0,042	0,045
mismatch	0.112**	0,045
stress	0.089**	0,035
unionsize	0,000	0,000
mezzogiorno	0,058	0,047

\*\*\*p < 0.01, \*\*p < 0.05, \*p < 0.1

AIC = 5958.5

Number of obs = 6902

Pseudo R2 (McFadden) = 0.3926

Notes: 17 dummies for sectors included, but not reported

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