PUBLIC POLICY INNOVATION

WORKING PAPER

INAPP WP n. 59

Routine biased technological change and wage inequality: the role of workers' perceptions

Silvia Vannutelli
Sergio Scicchitano
Marco Biagetti

MARZO 2021

Routine biased technological change and wage inequality: the role of workers' perceptions

Silvia Vannutelli
Department of Economics, Boston University, Boston
svann@bu.edu

Sergio Scicchitano
Istituto nazionale per l'analisi delle politiche pubbliche (INAPP), Roma
Corresponding author: s.scicchitano@inapp.org

Marco Biagetti
Università degli Studi della Tuscia, Viterbo
marco.biagetti2013@gmail.com

MARZO 2021

We thank Branko Milanovic, Pascual Restrepo, Paolo Severati, participants at 16th Annual Conference of the ESPAnet Europe, 30 August-1 September, 2018, Vilnius, at the II Astril Annual Conference "Technology, Employement, Institutions", University Roma Tre, 13-14 December, at the Tasks V: Robotics, Artificial Intelligence and the Future of Work, organized by IAB, BIBB and ZEW, Bonn, Germany, 7-8 February 2019, at the European Meeting on Applied Evolutionary Economics (EMAEE) 2019 "Economics, Governance and Management of AI, Robots and Digital Transformations", SPRU, University of Sussex, 3-6 June 2019, for useful comments. The views and opinions expressed in this article are those of the authors and do not necessarily reflect those of the Institutions.

ABSTRACT

Routine biased technological change and wage inequality: the role of workers' perceptions

The Routine Biased Technological Change (RBTC) has been called as a relatively novel technology-based explanation of social changes like job and wage polarization. In this paper we investigate the wage inequality between routine and non-routine workers along the wage distribution in Italy. Thanks to unique survey data, we can estimate the wage differential using both actual and perceived level of routine intensity of jobs to classify workers. We adopt semi-parametric decomposition techniques to quantify the importance of characteristics of workers in explaining the gaps. We also employ non-parametric techniques to account for self-selection bias. We find evidence of a significant U-shaped pattern of the wage gap, according to both definitions, with non-routine workers earning always significantly more than routine workers. Results show that workers' characteristics fully explain the gap in the case of perceived routine, while they account for no more than 50% of the gap across the distribution in the case of actual routine. Thus, results highlight the importance of taking into account workers' perceptions when analyzing determinants of wage inequality. Overall, we confirm that, after leading to job polarization, RBTC induced a similar polarizing effects on wages in Italy.

KEYWORDS: job analysis, wage inequality, technological innovation, wage

JEL CODES: J31, J82, C14

1. Introduction

In recent years, the US and many European countries experienced relevant social changes like increasing job polarization and a surge in wage inequality. A number of papers have provided a novel technology-based explanation of these employment dynamics, a theory widely known as Routine-Biased Technological Change (RBTC) (Autor *et al.* 2003; Goos and Manning 2007; Goos *et al.* 2014; Acemoglu and Autor 2011; Autor and Dorn 2013). According to this view, recent technological progress related to automation and computerization leads to the replacement of occupations intense in routine tasks, which are usually the occupations in the middle of the skill distribution. Moreover, the current Covid-19 pandemic seems to force the use of innovative technologies at an unprecedented pace (Hantrais *et al.* 2020; Paunov and Plenes-Satorra 2020). In this context, just a few papers have also documented how RTBC induced job polarization may translate into wage polarization (Autor and Handel 2013; Firpo *et al.* 2011). All the previous papers, however, are focused on the actual definition of routine and focus on the average wage level. In this work, we ask a set of different questions: What is the role of perceptions in determining the wage inequality between routine and non-routine workers? Does the pay gap change along the wage distribution when characterizing workers according to their perceived, rather than the actual level of routine? How much of the earnings' inequality is due to workers' characteristics?

Thanks to the availability of unique detailed professional dataset on tasks, skills and work attitudes, we are able to classify workers according to both the actual (objective) and their perceived (subjective) level of routinarity of jobs (AR and PR, respectively). The dataset was built merging two surveys.

The first one is the Fourth Survey on Quality of Work (Inapp-QoW), carried out by the National Institute for Public Policy Analysis (Inapp), from which we can evaluate the PR by refering to a specific question. Individuals were asked: "Do repetitive tasks prevail in your work?".

The second survey is the Italian Survey of Professions (ICP), which provides detailed information of the task-content of occupations at the 4-digit occupation level. ICP is the Italian equivalent of the US O*NET repertoire and it is based Italian occupations, not on those of the US: therefore it is able to capture the specific features of the Italian productive structure, which the O*NET is not able to grasp, thus avoiding potential biases.

The existing literature (Goos *et al.* 2014) is built instead on US O*Net data and crosswalks between US and European occupations, thus possibly reflecting US-specific technology and labour market. Notably, Italy is one of the few countries to have such a dictionary of occupations corresponding to the US O*NET and allows us to build the well-known Routine Task Index (RTI) of Autor and Dorn (2013), which is the most relevant and robust indicator of the AR. Then we merge the RTI to the QoW data set in order to show the effect of RBTC on wage, according to both actual and perceived level of routine intensity. The logarithm of monthly net wage is regressed on a set of covariates representing: (i) individual characteristics, (ii) job characteristics, (iii) firm characteristics.

To investigate on the sources of the observed gaps, we exploit both a semi-parametric method (following Melly 2005) and a non-parametric one, analogous to the one of Firpo *et al.* (2011). In particular we use a Counterfactual Decomposition Analysis (CDA) using quantile regression (QR) through which we are able to quantify the relative importance of characteristics of workers in explaining the observed wage inequality between routine and non-routine workers. More specifically, we estimate whether and to what extent this pay gap is attributed more to differences in labour market characteristics between the two groups of workers or to differences in rewards that the two groups receive for their characteristics in the Italian labour market. Our results show that average gaps are likely to conceal important differences along the wage distribution for routine and non-routine workers, the dispersion being more accentuated when using the subjective rather than the objective definition of routine. Beyond the mean, we find evidence of an interesting and significant U-shaped pattern of the wage inequality between non-routine and routine workers, according to both definitions, suggesting the presence of both "sticky floor" and "glass-ceiling" effects[1]. When we perform CDA we see that the contribution of differences in characteristics is larger than that of different returns at each of the estimated quantiles. Moreover, workers' characteristics almost fully explain the observed gap in the case of perceived routine, while they account for no more than 50% of the gap between actual routine and non-routine workers across the distribution. The difference in the behavior of the bottom part of the distribution seems to highlight the presence of negative self-selection, with workers with relatively "worse" characteristics concentrated into low-paid jobs that they perceived as being highly routine.

All in all, we provide evidence of the stable presence of a U-shaped wage inequality between non-routine and routine workers, which is robust to different estimation tecniques and different definitions of routine. This confirms that, after leading to job polarization, RBTC induced a similar polarizing effects on wages in Italy. Moreover, when estimating wage inequality according to the perceived definition of routine, the higher explanatory power of characteristics highlights the importance of taking into account workers' perceptions, as they significantly reduce the set of omitted variables that could explain the observed wage inequality, along the entire wage distribution. To the best of our knowledge, this is the first paper to empirically estimate the role of perceptions in the RBTC.

The rest of the paper is organized as follows: section two reviews previous related literature. section three describes the semi-parametric and the non-parametric decomposition methods. In section four, data are illustrated. Empirical results are discussed in section five, while section six concludes.

2. Literature Review

Starting with the seminal work of Katz and Murphy (1992), a large literature has discussed the impacts of technological change on the labour market, focusing on employment and wages (Autor *et al.* 1998; Autor *et al.* 2003; Autor *et al.* 2006; Li *et al.* 2006; Autor *et al.* 2008; Gashi *et al* 2010; Acemoglu and Autor 2011; Coupe 2019). The majority of works deal with the US and document a dramatic rise in wage inequality and job polarization, starting from the 1980s, whose primary cause is considered to be Skilled-Biased Technological Change (SBTC). The SBTC hypothesis assumes the presence of two

[1] *Sticky-floor* refers to a situation in which the 10^{th} percentile wage gap is higher than the estimated wage gap at the 50^{th} percentile. *Glass ceiling* refers to a situation in which the 90^{th} percentile wage gap is higher than the estimated wage gap at the 50^{th} percentile.

types of skill groups, producing two imperfectly substitutable goods, and technology is factor-augmenting only for the skilled factor. In this setting, demand for “skilled” jobs rise relative to that for “unskilled” jobs, and wage growth depends on skill level. This could explain the rapid growth in wage inequality observed during the 1980s, especially between college graduates and non-college graduates. However, the SBTC hypothesis cannot explain another empirically documented phenomenon, namely the growth in wage and demand for low wage occupation, a crucial determinant of the increased job and wage polarization observed in the last two decades (Acemoglu 1998; Acemoglu 2002a, 2002b; Card and DiNardo 2002; Weiss and Garloff 2009; Neves *et al.* 2018).

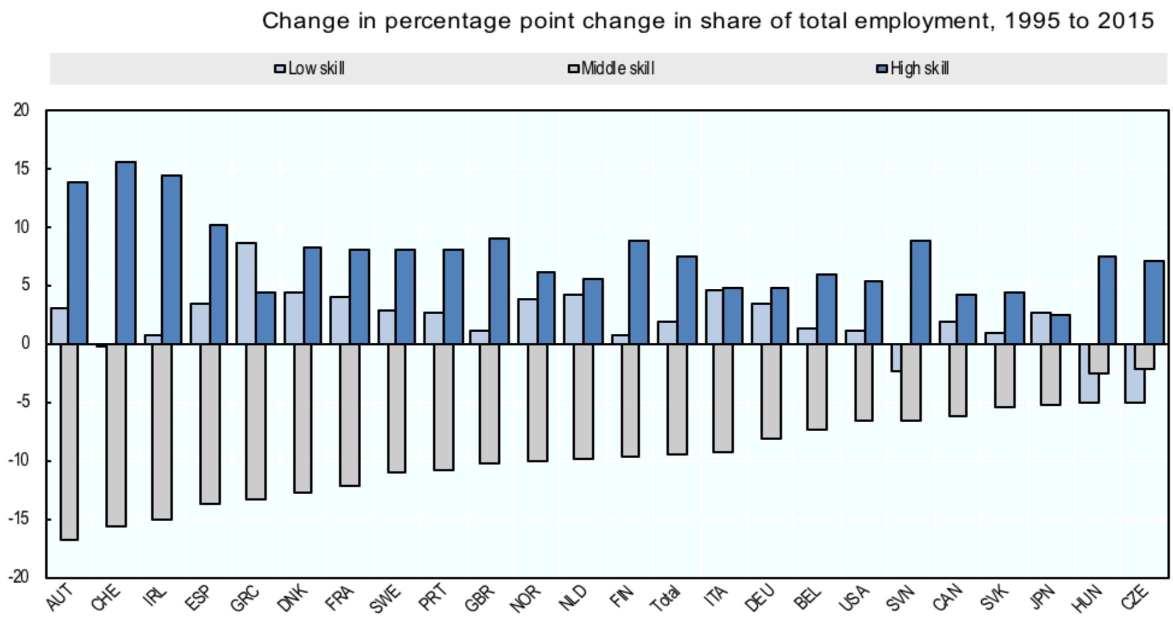
Autor *et al.* (2003) solve this puzzle by moving the focus from skills to tasks, suggesting the importance of looking at the task content of occupations. In their view, technological developments have enabled computers to perform repetitive, procedural – so-called “routine” – job tasks that were previously performed by human workers. This caused a substantial change in the returns to certain skills and a shift in the assignment of skills to tasks. Middle-skilled manufacturing and clerical workers that used to perform jobs characterized by a high number of routine tasks were increasingly replaced by cheaper machines. On the other side, those workers performing non-routine tasks who cannot easily automated benefit from complementarity with machines and improve their relative position on the labour market. This is true both for high-skill, creative occupations but also for low-skilled workers working in non-routine jobs, e.g. those employed in service occupations that involve assistance and care for others. In this view, commonly referred as Routine-Biased Technological Change (RBTC), rather than uniformly favoring skilled workers, technology has a “polarizing” effect on the labour market, leading to the “hollowing out” of the occupational distribution observed in the data and documented in numerous subsequent studies (Goos and Manning 2007; Autor *et al.* 2006, 2008; Spitz-Oener 2006; Smith 2008; Dustmann *et al.* 2009; Goos *et al.* 2014; Acemoglu and Autor 2011; Autor and Dorn 2013).

Italy and many other European countries have experienced similar trends of job polarization, as illustrated in figure 1, taken from the last OECD Employment Outlook (2017). Here, we see that both high skill and low skill occupations experienced similar rates of growth, as a share of total employment, between 1995 and 2015, of over 4.5%. On the other side, middle skill occupations experienced a corresponding decrease of around 10%.

Looking beyond past trends, some recent work has focused on estimating the share of jobs at medium and high risk of automation. The analysis, detailed in Arntz *et al.* (2016) looks at PIAAC (Program for the International Assessment of Adult Competencies) data, an OECD survey to monitor workers’ skills and tasks carried out in Italy by Inapp. In the analysis it is showed that around 10% of Italian jobs are considered to be at high risk of future automation, just slightly higher than the OECD average (9%). On the other side, looking at the share of jobs at significant risk of seeing the majority of the tasks they entail changed by technology, Italy is in a much worse position (33% against an OECD average of 25%). Using different data, Dengler and Matthes (2018) reach similar conclusions, showing that 15% of jobs are at risk of being automated in Germany. Moreover, the global rapid expansion of industrial robots seems to confirm a labour-substituting effect (Jung and Lim 2020).

It is not immediately clear if and to what extend RTBC-induced job polarization translates into wage polarization. In their model, Autor and Dorn (2013) explicit conditions under which job polarization is expected to be accompanied by wage polarization. They stress the importance of considering both production and consumption elasticities and the degree of complementarity/substitutability between high-skill and low-skill jobs and goods (mainly produced by routine tasks) and services (mainly produced by manual tasks). More in particular they introduce the well-known Routine Task Index (RTI) for the US economy, which is actually the most suitable indicator to evaluate the effects of RBTC on the labour market.

Figure 1. Job Polarization in Europe



Source: OECD Employment Outlook (2017). European Labour Force Survey, Labour force surveys for Canada (LFS), Japan (LFS), Switzerland (LFS), and the United States (CPS MORG)

Firpo *et al.* (2011) focus specifically on wage dynamics, with the aim to assess the contribution of occupations to the evolution of wage inequality in the US. They develop a Roy Model that explains observed US wage polarization as determined by changes in returns to tasks, exposure to offshoring of different jobs, and de-unionization.

Autor and Handel (2013) use a similar Roy self-selection framework to look at the relationship between tasks and wages both between and within occupations. The authors argue that the traditional Mincerian framework is not appropriate to measure “returns to tasks”, as tasks are not fixed workers’ attributes, like human capital, but rather they represent characteristics of jobs. Thus, workers can choose which tasks to perform by self-selecting into jobs requiring different tasks. Importantly, however, jobs are characterized by a bundle of unmodifiable and indivisible tasks.

The Roy model allows to take into account these aspects, by predicting workers’ self-selection into jobs that give them the highest return (wage), to the set of tasks they are able to perform given their skills. The authors provide an empirical test of model implications looking at a cross-sectional survey of self-reported task engagement within occupations. Thanks to the unique availability of person-level data on perceived level of routine tasks, we will also be able to compare wage dynamics for routine vs non-routine workers both between and within occupations.

Some papers have pointed out that non-routine workers earn more than routine workers, both at the occupation level (Acemoglu and Autor 2011; Goos *et al.* 2014) at the worker level (Agasisti *et al.* 2020;

Autor and Handel 2013; de la Rica *et al.* 2020). Regarding European countries, Naticchioni *et al.* (2014) conclude that there is a weal evidence that that automation is causing wage polarization in Europe. As to Italy, Basso (2020) recently finds no significant polarization of wages, but only a general impoverishment of the labour market due to the growth of low-skills occupations.

Moreover what is missing in the RBTC literature is to investigate the role workers perceptions regarding the degree of routinarity of their own job. This could be particularly relevant, as workers' perception can include information that is not captured by the “official” measures (like the RTI), in particular a more precise understanding of the work requirements. The economics literature has traditionally recognized the individuals’ subjective reports: it is just the case of the literature on educational and skill mismatch, where different ways for measuring the phenomenon are followed, from expert statements to respondents’ subjective assessments (McGuinness *et al.* 2018). In particular, self-assessed measures have been largely used in the last years (Dolton and Vignoles 2000; Green and Zhu 2010; Boll *et al.* 2016; Muñoz de Bustillo Llorente *et al.* 2018) as workers' perceptions are able to report a much more precise picture on the characteristics of work performed, compared to what indicators proposed by experts in the sector can do. The self-assessed approach has a subjective nature and consists in asking the workers about the educational requirement set by the firm to get the job or the level required for this job, according to their view and in comparing it with their actual level of education. For example, in the OECD’s Survey of Adult Skills (PIAAC), individuals are asked, relative to their own education, what level of education do they think would be necessary to satisfactorily do their job. In a similar way, we follow a subjective approach, by asking workers if their work can be considered routinary. To the best of our knowledge, this is the first study to analyze the routine non-routine wage inequality in Italy, by using a self-assessed approach other than an objective one, based on expert statements.

3. Empirical strategy

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 N and R are the two groups of non-routine and routine 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 $\bar{y}_n$ and $\bar{y}_r$, respectively:

$$\Delta\bar{y} = \bar{y}_n - \bar{y}_r \tag{1}$$

In the context of a linear regression, the mean wage for group W$= N, R$ 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:

$$\Delta\bar{y} = \bar{X}'_n\hat{\beta}_n - \bar{X}'_r\hat{\beta}_r \tag{2}$$

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:

$$\Delta\bar{y} = (\bar{X}_{\mathrm{n}} - \bar{X}_{\mathrm{r}})'\hat{\beta}_{\mathrm{n}} + \bar{X}'_{\mathrm{n}}(\hat{\beta}_{\mathrm{n}} - \hat{\beta}_{\mathrm{r}}) + \bar{X}'_{\mathrm{r}}(\hat{\beta}_{\mathrm{r}} - \hat{\beta}_{\mathrm{n}}) \quad (3)$$

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 routine and non-routine workers. Put in another way, the QR method (Koenker and Bassett 1978), seems to be more interesting, and more appropriate in this context: the ϑ^{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.

Being y_i the dependent variable and x_i the vector of the chosen explanatory variables, the relation is given by:

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

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

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

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

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

where 1(·) is the indicator function. Thus, the counterfactual distribution can be estimated by replacing either the computed parameters of the distribution of characteristics for routine or non-routine workers. The difference at each quantile of the unconditional distribution can be decomposed into the two above mentioned components as follows:

$$q(\theta, x^n, \beta^n) - q(\theta, x^r, \beta^r) = \left[q(\theta, x^n, \beta^n) - q(\theta, x^n, \beta^r) \right] + \left[q(\theta, x^n, \beta^r) - (\theta, x^r, \beta^r) \right] \tag{7}$$

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 routine and non-routine 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 routine position, 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 Lemiex (Di Nardo *et al.* 1996) and estimate quantiles for two counterfactual distributions, one if every worker were non routine at his/her job, the other if they were all routine. 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. 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 doing routine task at work given a set of characteristics is estimated by using a probit model of the following form:

$$\Pr(\mathrm{r} = 1 | \mathrm{x}) = \phi(\mathrm{x}) \tag{8}$$

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

$$\theta_0 = \frac{1 - \Pr(r = 1)}{1 - \Pr(r = 1 | x)} \tag{9}$$

$$\theta_1 = \frac{\Pr(r = 1)}{\Pr(r = 1 | x)} \tag{10}$$

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 non-routine at work and the density if every worker were routine:

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

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

$$\int_{-\infty}^{\infty} K(p)dp = 1$$ [2]

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

$$f^{nr}(w) = \int \theta_{nr} g^{nr}(w | x) l(x | r = 0) dx \tag{12}$$

and

$$f^{r}(w) = \int \theta_{r} g^{r}(w | x) l(x | r = 1) dx \tag{13}$$

for routine and non-routine workers respectively.

In eq. (12) and (13) θ_{nr} and θ_r are the true re-weighting parameters, $g^{nr}(w | x)$ and $l(x | r = 0)$ as well as $g^{r}(w | x)$ and $l(x | r = 1)$ are the conditional densities of wages and the distributions of the x characteristics associated to the subsamples for which $r=0$ and $r=1$ respectively. The two

[2] 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 (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).

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 non-routine workers) with the actual density of wages:

$$f(w) = \int g(w \mid x) l(x) dx \tag{14}$$

4. Data

Data used in this article are from a unique and innovative dataset recently built by merging two Italian surveys developed and administered by Inapp: QoW and ICP.
The first dataset we use is the Fourth Inapp Survey on Quality of Work (Inapp QoW), 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[3]. The Inapp QoW allows us to obtain information regarding the subjective (perceived) level of jobs' routinarity included within the wage equations estimated in section 5. In order to measure it, we refer to a specific question which was asked in the QoW. Individuals who are currently in employment are asked: "Do routinary tasks prevail in your work?". Individuals were required to respond "Yes" or "Not".
On the other side, to measure objective (actual) level of routinarity, we exploit detailed information on the task-content of jobs at the 4-digit occupation-level, using data drawn from the Inapp-Istat Survey of Professions (ICP). The ICP is a rather unique source of information on skill, task and work contents. In fact, the ICP is one of the few surveys replicating extensively American O*Net[4]. The latter is the most comprehensive repertoire reporting qualitative and quantitative information on tasks, work context, organizational features of work places at a very detailed level. Both the American O*Net and the Italian ICP focus on occupations (i.e. occupation-level variables are built relying on both survey-based worker-level information as well as on post-survey validation by experts' focus groups). The ICP survey has been realized twice (2007 and 2012) being based the whole spectrum of the Italian 5-digit occupations (i.e. 811 occupational codes). The interviews cover about 16.000 Italian workers ensuring representativeness with respect to sector, occupation, firm size and geographical domain (macro-regions). On average, 20 workers per each Italian occupation are interviewed providing representative information at the 5th digit. The survey includes more than 400 variables on skill, work contents, attitudes and tasks.

[3] Additional information are in Scicchitano *et al.* (2020).
[4] The US O*Net database is based on the Dictionary of Occupational Titles (DOT, hereafter) which since 1939 provided information on occupations with a specific focus on the skills required in the public employment service. The O*Net is based on the Standard Occupational Classification (SOC) providing for each elementary occupation variables on knowledge, skills, abilities and tasks. The key dimensions included in the O*Net are the following: *worker characteristics* – permanent characteristics affecting workers performance as well as their propensity to acquire knowledge and skills; *worker requirements* – workers characteristics matured by means of experience and education; *experience* – characteristics mostly related to past work experience; occupation – a large set of variables referring to requirements and specific features of the various occupations.

In line with the current literature (Autor *et al.* 2003; Autor and Dorn 2013; Goos *et al.* 2014), we measure the objective degree of task routineness according to the RTI index. Using the ICP questionnaire, we account for the same task-related dimensions used by Goos *et al.* (2014) and followers in their empirical studies.

In our case, however, we can improve the quality of data in Goos *et al.* (2014). They use the RTI index built by Autor and Dorn (2013) and mapped into their European occupational classification: a key point of our data is that our task and skill variables directly refer to the Italian economy. The ICP is able to capture the structure of the labour market, the level of technology and the industrial relations characterizing the Italian economics. In fact, the availability of ICP variables avoid potential methodological problems arising when information referring to the American occupational structure (i.e. contained in the US O*Net repertoire) are linked to labour market data referring to different economies as the European ones.

The existing literature on RBTC (Goos *et al.* 2014) use instead US O*Net data, making an artificial'bridge' between US and European (and Italian in particular) occupations which possibly reflects US-specific technology and labour market[5].

As in Autor *et al.* (2003), we build upon six dimensions allowing to qualify jobs according to their relative degree of routineness. Thus, the RTI adopted can be formalized as follows:

$$RTIk = RCk + RMk - (NRCAk + NRCIk + NRMk + NRMIAk) \tag{15}$$

Where for each 5-digit occupation k (k = 1,…,811) the RTI index is computed as the sum of the standardized values of the Routine Cognitive (RC) indicator capturing dimensions as the degree of repetitiveness and standardization of tasks as well as the importance of being exact and accurate; Routine Manual (RM) indicator proxying the degree of repetitiveness and of predetermination of manual operations minus the Non Routine Cognitive Analytical (NRCA) reporting the relevance of tasks related to think creatively as well as to analyse and interpret data and information; Non Routine Cognitive Interpersonal (NRCI) referring to the importance of social relationships, interaction, managing and coaching colleagues; Non Routine Manual (NRM) capturing the degree of manual dexterity needed to perform operations; Non Routine Manual Interpersonal Adaptability (NRMIA) referring to degree of social perceptiveness.

The indicator in (15) rises with the importance of routine task in each 4-digit occupation, while declines with the importance of abstract and non-routine tasks.

The detailed description of the RTI we use in our estimates is reported in table 1. Based on this information, we define a worker as being employed in an objectively routine job if he works in a job with an RTI index above the sample average.

The ICP variables used in this analysis are collected at the 5th digit of the Italian occupation classification and then aggregated at the 4th digit to realize the ICP-QoW matching. We first excluded armed forces self-employed workers. The sample was then restricted to employees between 18 and 64 years. The final sample consisted of 6,232 non-routine and 2,439 routine workers.

[5] See also Bonacini *et al.* (2021), Barbieri *et al.* (2020), Caselli *et al.* (2020), Cirillo *et al.* 2020, Esposito and Scicchitano (2020).

Table 1. The structure of the Routine Task Index

Routine cognitive (RC)

Importance of repeating the same tasks
Importance of being exact or accurate
Structured v. Unstructured work (reverse)

Routine manual (RM)

Pace determined by speed of equipment
Controlling machines and processes
Spend time making repetitive motions

Non-routine cognitive: Analytical (NRCA)

Analyzing data/information
Thinking creatively
Interpreting information for others

Non-routine cognitive: Interpersonal (NRCI)

Establishing and maintaining personal relationships
Guiding, directing and motivating subordinates
Coaching/developing others

Non-routine manual (NRM)

Operating vehicles, mechanized devices, or equipment
Spend time using hands to handle, control or feel objects, tools or controls
Manual dexterity
Spatial orientation

Non-routine manual: interpersonal adaptability (NRMIA)

Social Perceptiveness

The ICP variables used in this analysis are collected at the 5th digit of the Italian occupation classification and then aggregated at the 4th digit to realize the ICP-QoW matching. We first excluded armed forces self-employed workers. The sample was then restricted to employees between 18 and 64 years. The final sample consisted of 6,232 non-routine and 2,439 routine workers.

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

(i) 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 of father (eight categories based on the highest level achieved), education (eight categories based on the highest level achieved), work experience;

(ii) job characteristics: part-time/full-time, temporary/permanent, job mobility (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, perceived job insecurity (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”);

(iii) firm characteristics: size (categorical variable reflecting 5 quintiles in terms of number of workers in the same local unit), location in the Southern Italy (*Mezzogiorno*), sector of economic activity (17 dummy variables), skills (9 categories, reflecting the ISCO classification at first-digit level).

Table 2 displays summary statistics for the sample of non-routine and routine employees used in the empirical analysis, along with the t-statistic for the difference in the averages. In particular, column (1) reports averages for the whole sample, columns (2)-(4) look at the separate groups according to the subjective definition of routine, while columns (5)-(7) refer to the objective definition of routine. As it can be seen, for both definitions, the two groups of workers differ significantly in all of their average characteristics, except for their age.

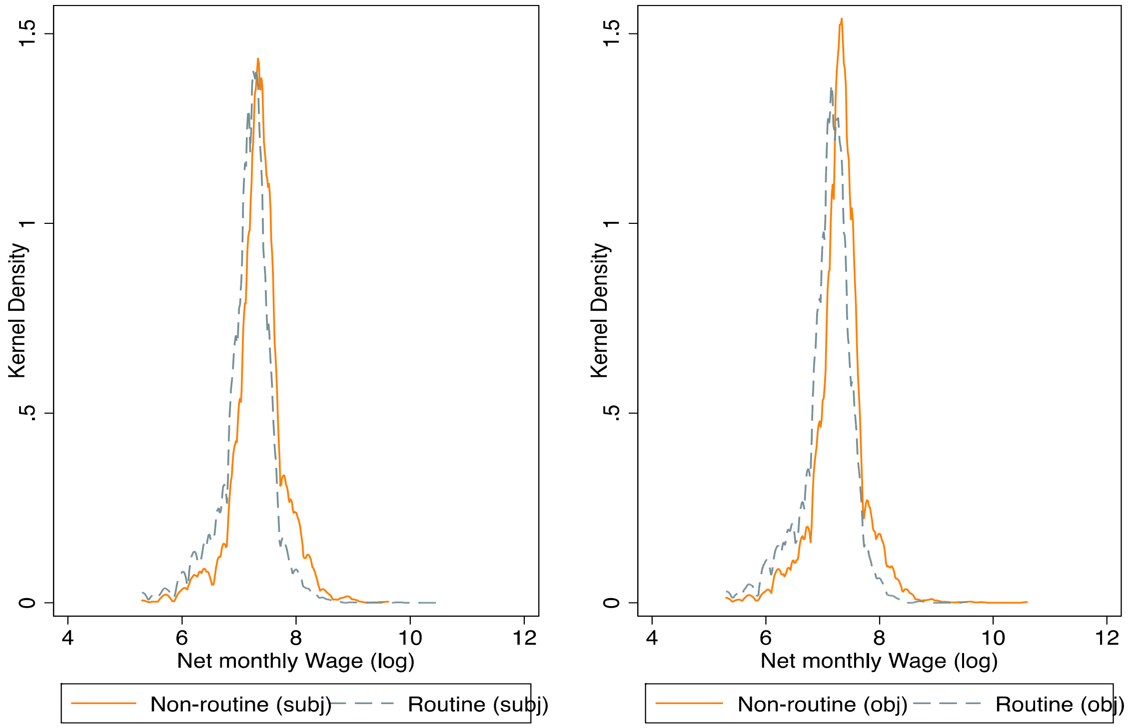
Table 2. Summary Statistics for the whole sample and by subjective and objective routine

	Whole Sample	Mean Routine (Subj)	Mean No Routine (Subj)	Difference	Mean Routine (Obj)	Mean No Routine (Obj)	Difference
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**
obj_routine	0.43	0.49	0.29				
lognmw	7.21	7.15	7.35	0.20***	7.09	7.30	0.21***
Age	45.58	45.45	45.89	0.44	44.18	46.64	2.46***
dmale	0.53	0.52	0.56	0.05***	0.64	0.45	-0.19***
make_ends_meet	1.12	1.05	1.30	0.24***	0.99	1.23	0.24***
edu_fath	1.84	1.76	2.03	0.26***	1.60	2.02	0.42***
work_exp	23.43	23.58	23.03	-0.55	23.50	23.37	-0.12
pasted	3.91	3.68	4.51	0.84***	2.97	4.63	1.66***
dfull	0.82	0.79	0.87	0.08***	0.80	0.83	0.04***
permanent contract	0.89	0.88	0.91	0.03***	0.86	0.91	0.05***
mobility	1.13	1.14	1.11	-0.04	1.29	1.01	-0.28***
stability	0.96	0.93	1.04	0.10***	0.91	1.00	0.09***
dtraining	0.55	0.52	0.64	0.12***	0.43	0.65	0.22***
supervisor	0.36	0.33	0.45	0.12***	0.32	0.39	0.07***
telework	0.15	0.11	0.24	0.12***	0.05	0.22	0.17***
contr	0.96	0.96	0.98	0.02***	0.95	0.97	0.02***
mismatch	0.21	0.22	0.18	-0.04***	0.23	0.19	-0.04***
stress	1.13	1.14	1.13	-0.01	1.07	1.18	0.10***
firmsize	240.46	229.96	267.27	37.31	206.49	266.34	59.85***
mezz	0.24	0.26	0.20	-0.06***	0.23	0.25	0.02*
routine					0.81	0.65	-0.17***
Observations	8655	6220	2435	8655	3743	4912	8655

Note: * $p < .1$, ** $p < .05$, *** $p < .01$.
Source: elaborations on data Inapp QoW 2015 and ICP 2012

Figure 2 plots the kernel estimates of the wage density for both groups, according to both definitions of routine. It can be noted that the top of the monthly net wage density for non-routine workers is reached at a higher wage than that for routine workers. Furthermore, the wage distribution for non-routine worker is clearly shifted to the right with respect to the routine workers.

Figure 2. Observed differences in non-routine/routine workers wage distribution



Source: elaborations on data Inapp QoW 2015 and ICP 2012

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 3 confirm that the net monthly wages of non-routine workers stochastically dominate, at the 1 percent significance level, those of routine workers.

Table 3. Kolmogorov-Smirnov test for comparison between routine and non-routine workers, for both definitions

	Combined	Subj. Yes	Subj. No	Combined	Obj. Yes	Obj. No
KS_2	0,207 (0.000)			0,2563 (0.000)		
KS_1		-0,207 (0.000)	0,000 (1.000)		-0,2313 (0.000)	0,000 (1.000)

Note: *p*- values in parentheses.
Source: elaborations on data Inapp QoW 2015 and ICP 2012

5. Results

5.1 *Ordinary least squares and quantile regression*

As a first step, we estimate classic Mincerian wage equations, separately for non-routine and routine workers, according to their subjective and objective measure. The estimation results are depicted in figure 3a-3b and then presented in tables 4a-4b and 5a-5b. In particular we show, for the two groups, respectively, the OLS coefficients as well as the conditional coefficients at representative quantiles: θ10, θ25, θ50, θ75, θ90.

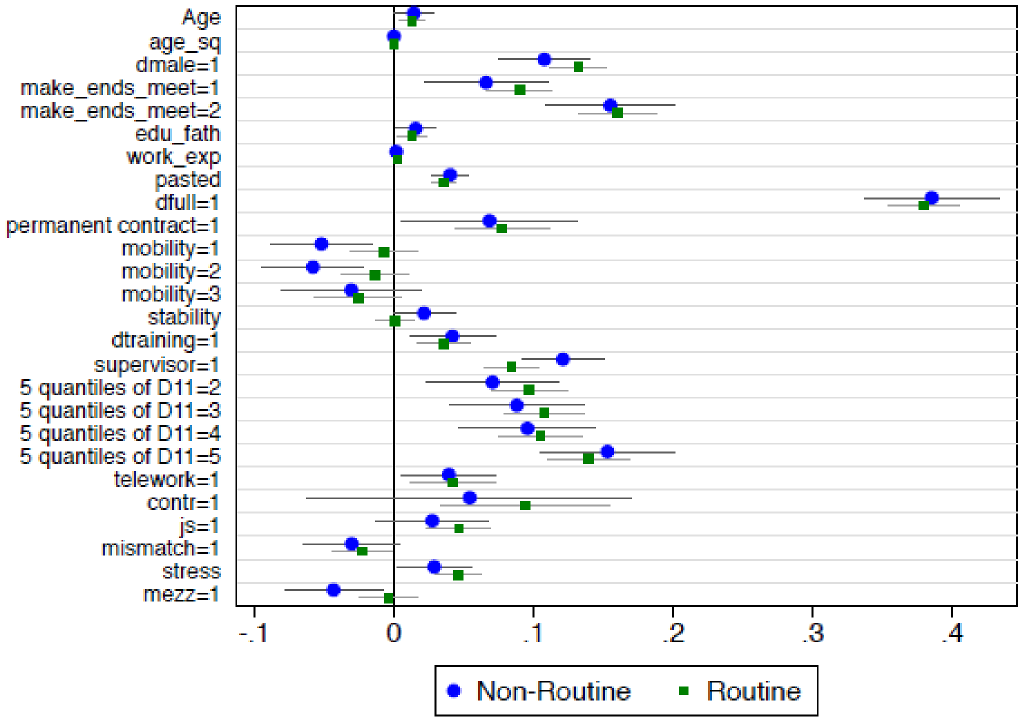
5.1.1 Subjective Routine

Regarding subjective routine, both the OLS and the quantile regressions show that for routine workers, wage grows with age at a somewhat slower pace along the whole wage distribution except for the highest (90th percentiles). Males have higher wages no matter the quantile is. Of course making ends meet more easily is associated with a higher salary: likewise work experience, the level of education obtained, having a full contract, being in a permanent or a secure position, job training. On the other hand, the father's education level is significant except for the lowest quantiles. Too much job mobility (more than 5 changes) seems associated to lower wages. A higher degree of job stability is associated with a reduction of wages at lower quantiles but to higher wages at the 90th percentile. Enteprise size matters positively no matter the quantile (or the mean) considered. Telework determines higher wages as well in the QR but not if the analysis is conducted at the conditional mean through OLS. Paid retirement contributions are associated to higher wages at the mean, the median and the 10th quantile. Skill mismatch is negatively associated at the conditional mean and the 90th percentile. Stress is associated to higher wages except at the 75th percentile, while being in the South is found to be statistically insignificant.

For non-routine workers the positive effects on the wage of age, gender gap favoring males, greater easiness of making ends meet, having a full time or permanent contract, educational level achieved, job training, larger enterprise size, stress[6], are confirmed. What is striking is that now working experience is statistically significant only at the 10th percentile and the median, while having a permanent contract has a smaller stastitical significance at the quantiles examined w.r.t the routine workers. The effect of fathers' education is significant only at the mean and the 75th quantile. Mobility seems to have a stronger negative effect on non-routine wages, even when it is mild. Stability is found to have an opposite positive sign in the case of non-routine workers again with a stronger significance at least up to the median. In this second equation, telework is significant and positive at the mean and the lower quantiles up to the median. Job security is not found to be significant regardless of the percentiles, while paid retirement contributions are statistically significant only at the lower percentiles. This time being in Italy's Southern Regions negatively affects non-routine wages at the conditional mean and the lower quantiles, again up to the median.

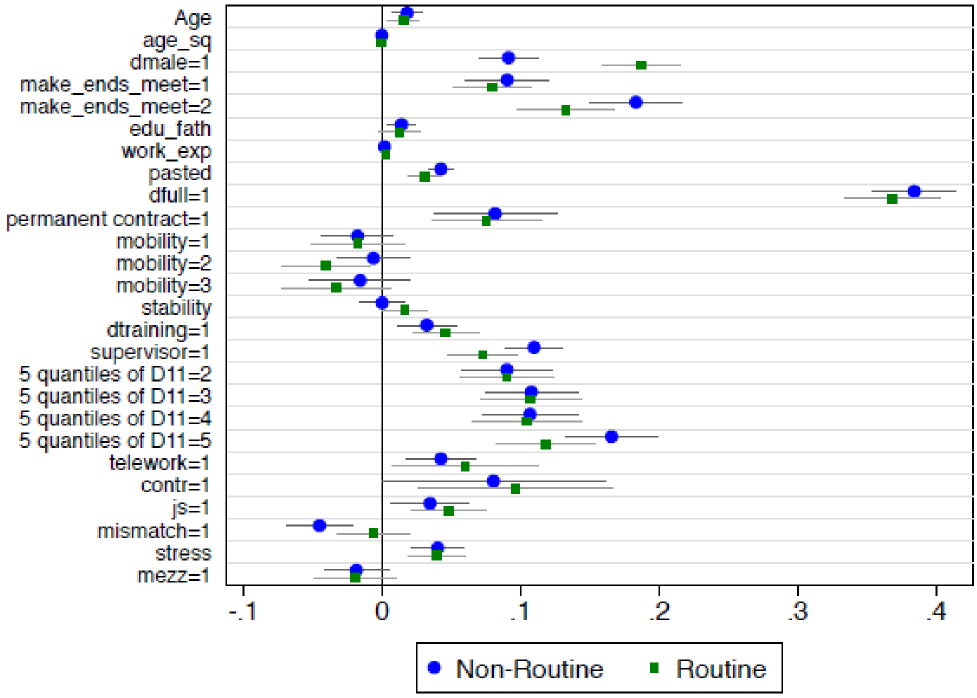
[6] Stress is not significant at the 90th quantile.

Figure 3a. Mincerian Wage Regressions, OLS estimates - Subjective Routine



Source: elaborations on data Inapp QoW 2015 and ICP 2012

Figure 3b. Mincerian Wage Regressions, OLS estimates - Objective Routine



Source: elaborations on data Inapp QoW 2015 and ICP 2012

Table 4a. Mincerian wage regression, Subjective Routine = No

	(1)	(2)	(3)	(4)	(5)	(6)
	OLS	Q10	Q25	Q50	Q75	Q90
Age	0.014*	0.018**	0.015**	0.020***	0.023***	0.022*
	[0.007]	[0.008]	[0.006]	[0.005]	[0.007]	[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]
dmale==1	0.108***	0.079***	0.090***	0.103***	0.099***	0.087***
	[0.016]	[0.013]	[0.012]	[0.014]	[0.013]	[0.026]
make_ends_meet==1	0.066***	0.044**	0.024	0.061***	0.089***	0.121***
	[0.022]	[0.018]	[0.019]	[0.013]	[0.014]	[0.031]
make_ends_meet==2	0.155***	0.123***	0.096***	0.124***	0.138***	0.199***
	[0.024]	[0.019]	[0.019]	[0.015]	[0.016]	[0.039]
edu_fath	0.016**	0.000	0.008	0.009	0.013**	0.007
	[0.007]	[0.006]	[0.005]	[0.006]	[0.006]	[0.012]
work_exp	0.002	0.003***	0.001	0.002***	0.000	0.002
	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]	[0.002]
pasted	0.040***	0.040***	0.035***	0.032***	0.029***	0.040***
	[0.007]	[0.005]	[0.005]	[0.006]	[0.006]	[0.010]
dfull==1	0.385***	0.549***	0.378***	0.348***	0.323***	0.276***
	[0.025]	[0.082]	[0.029]	[0.026]	[0.018]	[0.039]
dperm==1	0.068**	0.060*	0.109***	0.075***	0.080***	0.074
	[0.032]	[0.035]	[0.021]	[0.027]	[0.022]	[0.060]
mobility==1	-0.052***	-0.050***	-0.066***	-0.059***	-0.026*	-0.029
	[0.019]	[0.014]	[0.014]	[0.017]	[0.014]	[0.030]
mobility==2	-0.058***	-0.059***	-0.051***	-0.043***	-0.034**	-0.057*
	[0.019]	[0.017]	[0.015]	[0.015]	[0.014]	[0.031]
mobility==3	-0.031	-0.104***	-0.065**	-0.037*	0.001	0.021
	[0.026]	[0.026]	[0.031]	[0.022]	[0.029]	[0.039]
stability	0.022*	0.034***	0.020**	0.018**	0.012	0.015
	[0.011]	[0.013]	[0.009]	[0.009]	[0.010]	[0.018]
dtraining==1	0.042***	0.033**	0.041***	0.022	0.029***	0.044*
	[0.015]	[0.013]	[0.013]	[0.014]	[0.011]	[0.023]
supervisor==1	0.121***	0.091***	0.081***	0.090***	0.140***	0.191***
	[0.015]	[0.012]	[0.011]	[0.012]	[0.015]	[0.027]
firmsize1==2	0.071***	0.008	0.055**	0.092***	0.066***	0.096***
	[0.024]	[0.028]	[0.023]	[0.022]	[0.019]	[0.037]
firmsize1==3	0.088***	0.084***	0.086***	0.105***	0.099***	0.099***
	[0.024]	[0.024]	[0.017]	[0.022]	[0.019]	[0.036]
firmsize1==4	0.096***	0.087***	0.099***	0.112***	0.093***	0.103***
	[0.025]	[0.024]	[0.017]	[0.021]	[0.021]	[0.034]
firmsize1==5	0.153***	0.098***	0.155***	0.165***	0.164***	0.199***
	[0.024]	[0.022]	[0.018]	[0.023]	[0.020]	[0.040]
telework==1	0.039**	0.008	0.029**	0.030**	0.014	0.043
	[0.017]	[0.017]	[0.014]	[0.013]	[0.014]	[0.028]
contr==1	0.054	0.394***	0.069***	0.07	-0.033	0.011
	[0.059]	[0.033]	[0.023]	[0.100]	[0.075]	[0.060]
js==1	0.027	0.021	0.025	0.025	0.022	-0.003
	[0.020]	[0.015]	[0.016]	[0.016]	[0.014]	[0.035]
mismatch==1	-0.030*	-0.074***	-0.028*	-0.011	-0.011	-0.026
	[0.017]	[0.012]	[0.016]	[0.016]	[0.014]	[0.029]
stress	0.029**	0.049***	0.030***	0.031***	0.018*	0.015
	[0.014]	[0.011]	[0.010]	[0.011]	[0.010]	[0.020]
mezz==1	-0.043**	-0.040***	-0.050***	-0.029*	-0.013	-0.039
	[0.018]	[0.014]	[0.015]	[0.016]	[0.014]	[0.025]
Observations	1555	1555	1555	1555	1555	1555

Note: standard errors in brackets. * $p < .1$, ** $p < .05$, *** $p < .01$.
Source: elaborations on data Inapp QoW 2015 and ICP 2012

Table 4b. Mincerian wage regression, Subjective Routine = Yes

	(1)	(2)	(3)	(4)	(5)	(6)
	OLS	Q10	Q25	Q50	Q75	Q90
Age	0.013**	0.029***	0.014***	0.015***	0.015***	0.007
	[0.006]	[0.003]	[0.005]	[0.004]	[0.004]	[0.005]
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]
dmale==1	0.132***	0.119***	0.109***	0.108***	0.120***	0.162***
	[0.020]	[0.008]	[0.008]	[0.008]	[0.009]	[0.013]
make_ends_meet==1	0.090***	0.119***	0.082***	0.067***	0.051***	0.026*
	[0.010]	[0.016]	[0.012]	[0.010]	[0.010]	[0.015]
make_ends_meet==2	0.160***	0.178***	0.146***	0.120***	0.113***	0.111***
	[0.015]	[0.019]	[0.012]	[0.010]	[0.014]	[0.017]
edu_fath	0.013***	-0.006	0.008**	0.017***	0.017***	0.016**
	[0.004]	[0.004]	[0.004]	[0.004]	[0.005]	[0.006]
work_exp	0.003***	0.003***	0.004***	0.003***	0.002**	0.002*
	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]
pasted	0.036***	0.028***	0.028***	0.027***	0.033***	0.041***
	[0.007]	[0.003]	[0.003]	[0.004]	[0.004]	[0.006]
dfull==1	0.380***	0.552***	0.461***	0.357***	0.266***	0.232***
	[0.016]	[0.016]	[0.023]	[0.017]	[0.019]	[0.020]
dperm==1	0.078***	0.137***	0.098***	0.076***	0.054**	-0.005
	[0.017]	[0.035]	[0.017]	[0.012]	[0.021]	[0.024]
mobility==1	-0.007	-0.012	-0.018*	-0.003	-0.005	-0.021
	[0.008]	[0.010]	[0.010]	[0.010]	[0.011]	[0.015]
mobility==2	-0.013	-0.019*	-0.021**	-0.015	-0.010	-0.003
	[0.009]	[0.010]	[0.010]	[0.010]	[0.009]	[0.017]
mobility==3	-0.026*	-0.011	-0.036***	-0.035***	-0.024*	-0.043***
	[0.014]	[0.013]	[0.013]	[0.010]	[0.014]	[0.015]
stability	0.001	-0.016***	-0.010*	-0.002	0.007	0.018**
	[0.009]	[0.005]	[0.005]	[0.005]	[0.006]	[0.009]
dtraining==1	0.036***	0.049***	0.026***	0.020***	0.011	0.020*
	[0.010]	[0.007]	[0.008]	[0.007]	[0.008]	[0.011]
supervisor==1	0.084***	0.060***	0.060***	0.073***	0.100***	0.142***
	[0.005]	[0.008]	[0.008]	[0.007]	[0.010]	[0.016]
firmsize1==2	0.097***	0.141***	0.092***	0.067***	0.074***	0.055***
	[0.018]	[0.020]	[0.013]	[0.012]	[0.010]	[0.020]
firmsize1==3	0.108***	0.138***	0.090***	0.087***	0.099***	0.073***
	[0.013]	[0.019]	[0.015]	[0.011]	[0.015]	[0.019]
firmsize1==4	0.105***	0.157***	0.117***	0.094***	0.095***	0.045**
	[0.018]	[0.019]	[0.013]	[0.013]	[0.012]	[0.019]
firmsize1==5	0.139***	0.139***	0.127***	0.118***	0.139***	0.092***
	[0.017]	[0.022]	[0.015]	[0.013]	[0.012]	[0.021]
telework==1	0.042	0.031***	0.027***	0.031***	0.030**	0.034**
	[0.030]	[0.010]	[0.010]	[0.011]	[0.013]	[0.016]
contr==1	0.094*	0.153*	0.042	0.063*	0.026	0.010
	[0.051]	[0.088]	[0.038]	[0.034]	[0.036]	[0.027]
js==1	0.047***	0.072***	0.050***	0.042***	0.039***	0.029*
	[0.012]	[0.012]	[0.010]	[0.008]	[0.009]	[0.015]
mismatch==1	-0.022**	-0.009	-0.013	-0.011	-0.009	-0.026*
	[0.009]	[0.010]	[0.008]	[0.007]	[0.009]	[0.014]
stress	0.046***	0.039***	0.035***	0.024***	0.009	0.031***
	[0.012]	[0.006]	[0.007]	[0.007]	[0.008]	[0.011]
mezz==1	-0.004	-0.008	-0.005	0.003	0.001	0.015
	[0.020]	[0.009]	[0.009]	[0.009]	[0.011]	[0.013]
Observations	3831	3831	3831	3831	3831	3831

Note: standard errors in brackets. * $p < .1$, ** $p < .05$, *** $p < .01$.
Source: elaborations on data Inapp QoW 2015 and ICP 2012

5.1.2 Objective Routine

We repeat the same regressions also for the alternative (objective) definition of routine. The estimation results are presented in figure 3b (OLS) tables 5a and 5b (QR).

Table 5a. Mincerian wage regression, Objective Routine = No

	(1)	(2)	(3)	(4)	(5)	(6)
	OLS	Q10	Q25	Q50	Q75	Q90
Age	0.018***	0.028***	0.018***	0.018***	0.020***	0.018***
	[0.005]	[0.005]	[0.005]	[0.004]	[0.004]	[0.006]
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]
dmale==1	0.091***	0.067***	0.073***	0.083***	0.085***	0.097***
	[0.011]	[0.013]	[0.010]	[0.008]	[0.009]	[0.013]
make_ends_meet==1	0.090***	0.103***	0.080***	0.055***	0.057***	0.054***
	[0.015]	[0.017]	[0.017]	[0.011]	[0.013]	[0.020]
make_ends_meet==2	0.183***	0.168***	0.149***	0.121***	0.131***	0.170***
	[0.017]	[0.019]	[0.017]	[0.013]	[0.015]	[0.024]
edu_fath	0.014***	0.002	0.007	0.015***	0.017***	0.013**
	[0.005]	[0.006]	[0.005]	[0.004]	[0.004]	[0.006]
work_exp	0.002*	0.002**	0.001*	0.003***	0.001	0.002
	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]
pasted	0.043***	0.034***	0.035***	0.033***	0.036***	0.039***
	[0.005]	[0.005]	[0.004]	[0.003]	[0.004]	[0.005]
dfull==1	0.384***	0.564***	0.432***	0.344***	0.284***	0.261***
	[0.015]	[0.031]	[0.024]	[0.019]	[0.016]	[0.014]
dperm==1	0.082***	0.136***	0.106***	0.074***	0.064**	0.063***
	[0.023]	[0.044]	[0.015]	[0.023]	[0.028]	[0.020]
mobility==1	-0.018	-0.031**	-0.026***	-0.027***	-0.018	-0.024*
	[0.013]	[0.016]	[0.010]	[0.010]	[0.012]	[0.014]
mobility==2	-0.006	-0.037**	-0.033**	-0.012	-0.014	0.006
	[0.013]	[0.015]	[0.015]	[0.011]	[0.011]	[0.019]
mobility==3	-0.016	-0.057***	-0.041***	-0.041***	-0.018	0.012
	[0.018]	[0.018]	[0.015]	[0.014]	[0.015]	[0.016]
stability	0.000	0.008	-0.004	-0.001	0.001	0.019**
	[0.008]	[0.009]	[0.007]	[0.006]	[0.007]	[0.008]
dtraining==1	0.032***	0.023	0.027***	0.016**	0.005	0.002
	[0.011]	[0.016]	[0.010]	[0.008]	[0.010]	[0.012]
supervisor==1	0.110***	0.069***	0.071***	0.088***	0.123***	0.173***
	[0.011]	[0.012]	[0.010]	[0.008]	[0.010]	[0.014]
firmsize1==2	0.090***	0.097***	0.072***	0.070***	0.076***	0.094***
	[0.017]	[0.018]	[0.016]	[0.015]	[0.016]	[0.020]
firmsize1==3	0.108***	0.115***	0.102***	0.091***	0.093***	0.081***
	[0.017]	[0.022]	[0.016]	[0.014]	[0.013]	[0.018]
firmsize1==4	0.107***	0.113***	0.105***	0.096***	0.105***	0.067***
	[0.017]	[0.021]	[0.015]	[0.014]	[0.013]	[0.018]
firmsize1==5	0.166***	0.159***	0.136***	0.143***	0.165***	0.153***
	[0.017]	[0.021]	[0.017]	[0.014]	[0.014]	[0.020]
telework==1	0.043***	0.044***	0.026***	0.026***	0.036***	0.022
	[0.013]	[0.014]	[0.010]	[0.009]	[0.010]	[0.018]
contr==1	0.081*	0.121***	0.063*	0.086*	0.052	0.081
	[0.041]	[0.035]	[0.038]	[0.053]	[0.036]	[0.078]
js==1	0.035**	0.038***	0.036**	0.047***	0.024*	0.000
	[0.015]	[0.015]	[0.015]	[0.009]	[0.013]	[0.013]
mismatch==1	-0.045***	-0.032**	-0.038***	-0.015*	-0.026***	-0.041***
	[0.012]	[0.016]	[0.012]	[0.009]	[0.010]	[0.012]
stress	0.040***	0.025**	0.020***	0.018**	0.024***	0.035***
	[0.010]	[0.011]	[0.008]	[0.007]	[0.008]	[0.012]
mezz==1	-0.018	-0.011	-0.027***	-0.009	0.008	-0.008
	[0.012]	[0.013]	[0.008]	[0.009]	[0.011]	[0.013]
Observations	3198	3198	3198	3198	3198	3198

Note: standard errors in brackets. * $p < .1$, ** $p < .05$, *** $p < .01$.
Source: elaborations on data Inapp QoW 2015 and ICP 2012

Table 5b. Mincerian wage regression, Objective Routine = Yes

	(1)	(2)	(3)	(4)	(5)	(6)
	OLS	Q10	Q25	Q50	Q75	Q90
Age	0.015**	0.032***	0.022***	0.021***	0.020***	0.015*
	[0.007]	[0.007]	[0.005]	[0.005]	[0.005]	[0.008]
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]
dmale==1	0.187***	0.186***	0.160***	0.171***	0.179***	0.221***
	[0.011]	[0.017]	[0.013]	[0.010]	[0.010]	[0.017]
make_ends_meet==1	0.079***	0.107***	0.088***	0.064***	0.060***	0.044**
	[0.018]	[0.017]	[0.014]	[0.010]	[0.012]	[0.019]
make_ends_meet==2	0.133***	0.165***	0.149***	0.109***	0.109***	0.080***
	[0.013]	[0.021]	[0.014]	[0.011]	[0.015]	[0.021]
edu_fath	0.012	-0.011	0.011*	0.020***	0.018***	0.034***
	[0.009]	[0.012]	[0.006]	[0.006]	[0.006]	[0.010]
work_exp	0.003***	0.005***	0.003***	0.002***	0.001	0.001
	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]
pasted	0.031***	0.028***	0.025***	0.021***	0.024***	0.040***
	[0.007]	[0.007]	[0.005]	[0.005]	[0.005]	[0.008]
dfull==1	0.368***	0.580***	0.470***	0.345***	0.272***	0.224***
	[0.018]	[0.032]	[0.025]	[0.021]	[0.021]	[0.025]
dperm==1	0.075***	0.112***	0.097***	0.054***	0.044***	0.006
	[0.023]	[0.030]	[0.016]	[0.021]	[0.016]	[0.038]
mobility==1	-0.018	-0.016	-0.017	-0.001	-0.004	-0.046**
	[0.012]	[0.015]	[0.017]	[0.013]	[0.014]	[0.021]
mobility==2	-0.041***	-0.049**	-0.015	-0.017	-0.013	-0.045**
	[0.013]	[0.021]	[0.014]	[0.012]	[0.014]	[0.019]
mobility==3	-0.033	-0.025	-0.020	-0.035**	-0.014	-0.053*
	[0.021]	[0.027]	[0.016]	[0.016]	[0.014]	[0.031]
stability	0.016*	-0.006	-0.003	0.012*	0.028***	0.025**
	[0.009]	[0.009]	[0.007]	[0.006]	[0.007]	[0.011]
dtraining==1	0.046***	0.054***	0.029***	0.031***	0.031***	0.059***
	[0.012]	[0.012]	[0.010]	[0.009]	[0.010]	[0.017]
supervisor==1	0.073***	0.045***	0.055***	0.069***	0.082***	0.113***
	[0.010]	[0.012]	[0.011]	[0.009]	[0.013]	[0.017]
firmsize1==2	0.090***	0.125***	0.102***	0.064***	0.048***	0.040*
	[0.028]	[0.020]	[0.016]	[0.013]	[0.011]	[0.022]
firmsize1==3	0.107***	0.104***	0.093***	0.088***	0.087***	0.076***
	[0.018]	[0.020]	[0.019]	[0.013]	[0.017]	[0.021]
firmsize1==4	0.104***	0.143***	0.115***	0.097***	0.077***	0.047*
	[0.023]	[0.022]	[0.019]	[0.014]	[0.016]	[0.024]
firmsize1==5	0.118***	0.100***	0.119***	0.119***	0.104***	0.081***
	[0.030]	[0.022]	[0.018]	[0.014]	[0.015]	[0.023]
telework==1	0.060	-0.018	0.033	0.084***	0.063***	0.111
	[0.038]	[0.038]	[0.032]	[0.026]	[0.024]	[0.084]
contr==1	0.096*	0.241***	0.032	0.046	0.012	0.002
	[0.052]	[0.080]	[0.100]	[0.039]	[0.026]	[0.042]
js==1	0.048**	0.071***	0.058***	0.033***	0.032***	0.036**
	[0.018]	[0.018]	[0.012]	[0.010]	[0.010]	[0.015]
mismatch==1	-0.006	0.000	-0.007	-0.014	0.004	0.014
	[0.010]	[0.015]	[0.011]	[0.011]	[0.010]	[0.015]
stress	0.039***	0.036***	0.040***	0.024***	0.006	0.026**
	[0.012]	[0.012]	[0.009]	[0.008]	[0.008]	[0.013]
mezz==1	-0.019	-0.007	-0.010	-0.013	-0.015	-0.021
	[0.016]	[0.015]	[0.013]	[0.011]	[0.011]	[0.023]
Observations	2188	2188	2188	2188	2188	2188

Note: standard errors in brackets. * $p < .1$, ** $p < .05$, *** $p < .01$.
Source: elaborations on data Inapp QoW 2015 and ICP 2012

For routine workers, both the OLS and the quantile regressions show results that are essentially analogous to the previous ones. The male-wage premium seems to be slighly stronger now, consistent with a larger share of men classified as objectively routine workers. On the other hand, the father's education level looses its significance in the OLS, while is still significant and larger in magnitudes at and above the median. Interestingly, work experience looses significance at the top of the distribution. On the other side, the possibility of having access to training is larger in magnitude, for both the OLS and the whole distribution. A higher degree of job stability is associated with a reduction of wages at lower quantiles but to significantly higher wages at and above the median. Skill mismatch is not anymore significant, neither at the conditional mean nor at any quintiles.

Patterns are consistent across the two types of definitions also for non-routine workers. A relevant difference to stress is for the effect of working experience: while it was statistically significant only at the 10th percentile and the median for subjective non-routine workers, it is now stable and positively significant for the whole bottom half of the distribution and also for the conditonal mean. On the other side, stability is not anymore significant at the conditional mean and at all quantiles, expect for the very top of the distribution. Most strikingly, job security, mismatch and stress all acquire significance relative to the other definition. Job security and stress are now always a positive and significant, except for the 90th percentile; mismatch instead has always a significant negative impact. Finally, being in Italy's Southern Regions looses its significance, except for the first quartile.

5.2 Counterfactual decomposition

5.2.1 Subjective Routine

Table 6 reports decomposition results for the mean and for several quantiles of the wage distribution according to the subjective definition of routine. The observed wage gaps between non-routine and routine 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 showed in section 3.2. Figure 4 plots the decomposition results at each of the 99 different quantiles, with a 95 per cent bootstrap confidence interval. All estimates are significantly different from 0 at the 1% significance level.

Table 6. Counterfactual Decomposition, Subjective Routine

	Raw	Semi-parametric estimate					Non-parametric estimate				
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**	**(10)**	**(11)**
		Tot. Diff..	Char.	*%*	Coeff.	*%*	Tot. Diff..	Char.	*%*	Coeff.	*%*
Mean	0.200	0.200	0.153	*77%*	0.047	*23%*	0.168	0.170	*101%*	0,068	*-1%*
θ=.10	0.357	.244	.209	*86%*	.035	*14%*	0.177	0.228	*128%*	-0.001	*-28%*
θ=.20	0.182	.187	.165	*88%*	.022	*12%*	0.155	0.175	*113%*	-0.050	*-13%*
θ=.30	0.122	.166	.139	*84%*	.026	*16%*	0.147	0.155	*106%*	-0.012	*-6%*
θ=.40	0.223	.158	.126	*80%*	.032	*20%*	0.144	0.145	*101%*	-0.001	*-1%*
θ=.50	0.163	.156	.116	*74%*	.04	*26%*	0.144	0.140	*97%*	0.004	*3%*
θ=.60	0.125	.163	.112	*69%*	.051	*31%*	0.148	0.138	*93%*	0.010	*7%*
θ=.70	0.151	.173	.110	*64%*	.063	*36%*	0.156	0.140	*90%*	0.016	*10%*
θ=.80	0.163	.198	.116	*59%*	.082	*41%*	0.173	0.150	*86%*	0.023	*14%*
θ=.90	0.223	.248	.139	*56%*	.110	*44%*	0.212	0.174	*82%*	0.039	*18%*

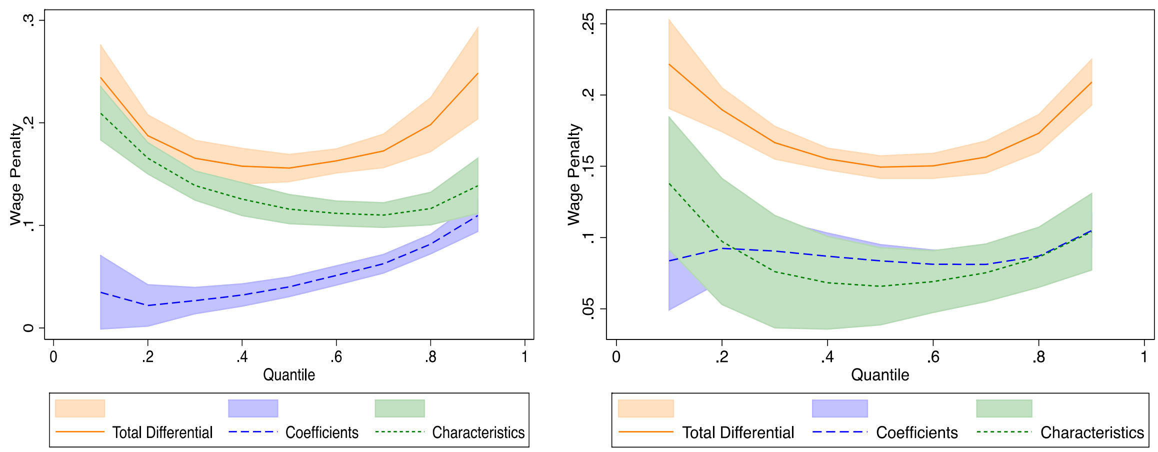
Note: bootstrap standard errors for semi-parametric estimates are obtained with 200 replications. Mean values for the semi-parametric estimation are obtained with the B-O decomposition. All coefficients are significant at 1%.
Source: elaborations on data Inapp QoW 2015 and ICP 2012

The standard B-O decomposition shows a difference between mean wages of the two groups of 301 euros (1659 vs. 1358 euros). Thus, the non-routine group earns 18 pp more than the routine workers. The difference in endowments account for 77% of this gap (0.153 out of 0.200 when computed in natural logs). The difference in coefficients accounts for the remaining 23%.

However, OLS coefficients do not consider that the distribution of wages around the mean can be different for the two groups. This seems indeed to be the case, if we look at the conditional quantile estimates. In fact, the estimated non-routine wage premium varies strongly over quantiles. Furthermore, 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. Figure 4 indicates that the routine group of workers suffer 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 follows a U-shaped pattern. Thus, we find indications of both significant sticky floor's effects – computed as the difference between the 10^{th} and the 50^{th} quantiles – and glass ceiling's effects, defined as the difference between the 90^{th} and the 50^{th} quantiles. Indeed, as figure 4 clearly shows, the 10^{th} percentile and the 90^{th} are not contained within the 95% confidence bands constructed for the 50^{th} percentile (the median), which also presents the lowest overall value in the wage gap between the two groups. However, we see that the difference in the distribution of characteristics explains essentially the entire gap at the bottom, while the relative incidence of the coefficient component (wage structure), ranging from 12% to 44% of the total difference, becomes relevant mostly at the top of the wage distribution, thus showing a greater effect of routine for high wages.

The pattern at the bottom leads to reject the sticky floor hypothesis: the gap is not due to discriminatory practices against routine workers, but rather to difference in characteristics of routine workers in low-paid jobs, relative to non-routine workers (probably, mostly experience and age). On the other side, the top part of the distribution suggests that workers in routine jobs are compensated less than workers in non-routine jobs with analogous characteristics – evidence for some glass ceiling.

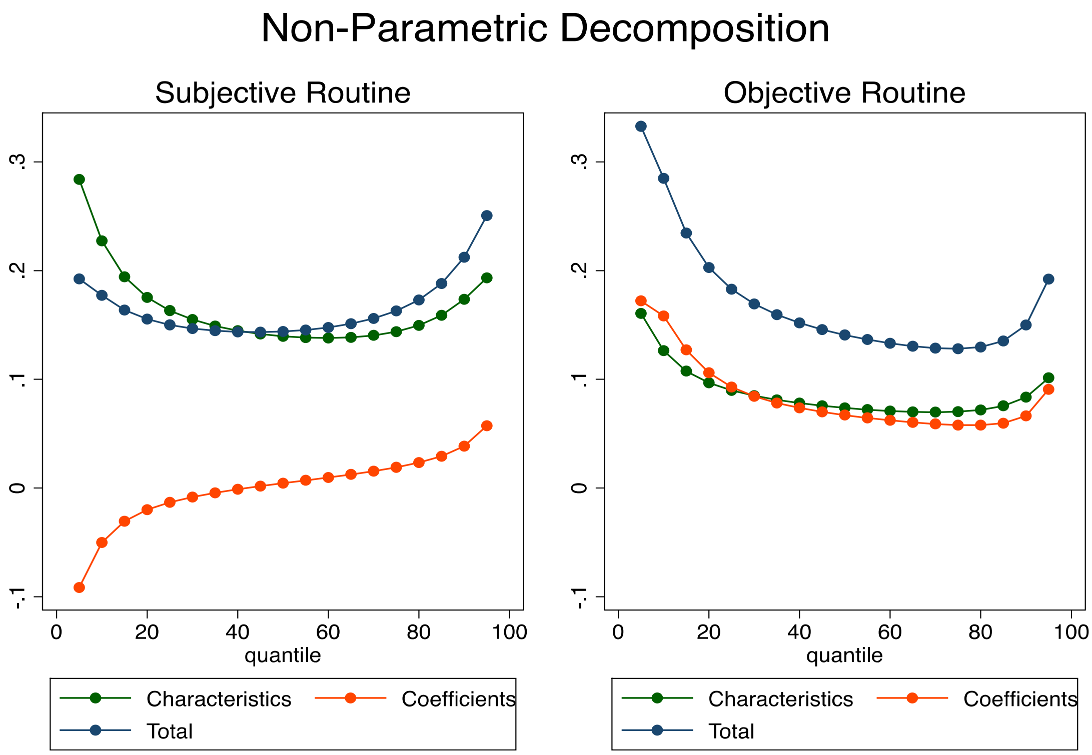
Figure 4. Decomposition of differences in distribution using quantile regression (Semi-Parametric). Subjective routine (left panel), objective routine (right panel)



Source: elaborations on data Inapp QoW 2015 and ICP 2012

Up to now, results can be interpreted as "causal" only if we assume that the routine status is exogenous. But given that workers choose their jobs, and that the first definition of routine is based on their self-perception, selection patterns are likely to be in place. We thus performed a non-parametric approach as a robustness check. Results are shown in the left panel of figure 5. Overall, results from the non-parametric model confirm those from the semi-parametric estimation: the total pay gap follows a U-shaped pattern and the contribution of coefficients is increasing along the the wage distribution. However, we observe a reduction of both the predictors/characteristcs (explained) and coefficients (unexplained) contributions, thus showing that semi-parametric results may have been biased upwards by endogenous selection patterns. At the median, higher wages gained in non-routine tasks are almost completely accounted for (96.9%) by the group differences in characteristics (i.e. the quantity effect or the explained part). In other words, differences in the distribution of characteristics are the almost unique driver of the observed wage gap between routine and non-routine workers. At the mean, the unexplained part is even slightly negative (-0.74%). The negative effect of coefficients can be seen at the lower quantiles, up to the 40th. In other words, there is a sort of negative discrimination on the non-routine workers in the real world (Jann 2008): were everybody employed in non-routine tasks, the wage at the lower quantiles would be even higher, which is not absolutely bad if it is determined by characteristics to be paid more. In a real world, it is a fair competition based on personal characteristics which seems to be relevant in the wage determination.

Figure 5. Decomposition of differences in distribution using fully non-parametric estimation. Subjective routine (left panel), objective routine (right panel)



Source: elaborations on data Inapp QoW 2015 and ICP 2012

5.2.2 Objective Routine

When we turn to analyze the same decomposition but dividing workers according to their objective routine levels, we obtain very different results, in both the semi-parametric and the non-parametric case, as can be seen from the right panels of figure 4 and 5. Numerical results are also reported in table 7. The standard B-O decomposition shows a raw difference between mean wages of the two groups of 265 euros (1552 vs. 1287 euros), over 10% less than the difference calculated according to the subjective distinction. Now, the non-routine group earns 17 pp more than the routine workers. The difference in endowments now account for 57% of the gap, while before it was accounting for almost 77%. The difference in coefficients accounts for the remaining 43%.

Going beyond the mean, now in both semi-parametric and the non-parametric analysis the effects of characteristics and components explain essentially half of the differential along the entire distribution of wages, with characteristics being slightly more important at the bottom, although the difference is not statistically significant. Indeed, the U-shaped pattern persists, and now the more substantial role of coefficients in the bottom part of the distribution suggests the presence of some sticky floor effect for workers employed in objectively high-routine jobs. Another relevant difference to note is in the size of the gap: while in the case of subjective routine the non-parametrically was smaller than the one estimated using semi-parametric methods, in the case of objective routine the opposite is true. The average wage gap for objectively routine workers estimated via non-parametric estimation is now of 0.179 (in logarithm terms), while it was of 0.168 for the other definition. More strikingly, the difference in the size of the gap is much wider at the bottom of the distributions. This seems to suggest the presence of a positive selection pattern, with «better» workers self-selecting into routine jobs, especially at the bottom of the wage distribution.

Table 7. Counterfactual Decomposition, Objective Routine

	Raw	Semi-parametric estimate					Non-parametric estimate				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
		Tot. Diff..	Char.	*%*	Coeff.	*%*	Tot. Diff..	Char.	*%*	Coeff.	*%*
Mean	0.211	0.187	0.106	*57%*	0.046	*43%*	0.179	0.090	*51%*	0.088	*49%*
θ=.10	0.325	.222	.138	*62%*	0.107	*38%*	0.285	0.126	*44%*	0.158	*56%*
θ=.20	0.234	.190	.097	*51%*	0.071	*49%*	0.203	0.097	*48%*	0.106	*52%*
θ=.30	0.167	.167	.076	*45%*	0.052	*55%*	0.169	0.085	*50%*	0.084	*50%*
θ=.40	0.154	.155	.068	*44%*	0.044	*56%*	0.152	0.078	*51%*	0.074	*49%*
θ=.50	0.143	.149	.066	*44%*	0.038	*56%*	0.141	0.074	*52%*	0.067	*48%*
θ=.60	0.134	.150	.069	*46%*	0.037	*54%*	0.133	0.071	*53%*	0.062	*47%*
θ=.70	0.194	156	.075	*48%*	0.038	*52%*	0.129	0.70	*54%*	0.059	*46%*
θ=.80	0.172	.173	.086	*50%*	0,038	*50%*	0.130	0.072	*55%*	0.058	*45%*
θ=.90	0.233	.209	.104	*50%*	0.045	*50%*	0.150	0.084	*56%*	0.066	*44%*

Note: 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%.
Source: elaborations on data Inapp QoW 2015 and ICP 2012

Overall, both the semi-parramtric and the non-parametric technique confirm that the perceived definition of routine (with respect to the actual one) is able to explain a higher portion of wage inequality between routine and non-routine workers. In other words, regardless of the econometric method used, the self-assessed approach, by considering workers' perceptions, is able to reduce the set of omitted variables, thus improving the estimate of the RBTC effect on wage.

6. Discussion and conclusions

This paper introduces perceptions into the RBTC literature. We estimate and compare wage inequality along the whole wage distribution between routine and non-routine workers, where workers are classified according to both the actual and perceived level of routinarity.

The comparison between semi-parametric and non-parametric estimates delivers some relevant insights on potential selection patterns. First, the non-parametric estimates confirm the absence of a sticky floor effect: if anything, wage structure is slightly over-compensating routine workers in low-paid jobs. This is probably due to the diffused presence of unionization among employees in Italy, compressing wages across the two groups especially in the bottom of the distribution.

Furthermore, the difference in the behavior of the bottom part of the distribution suggests some important considerations regarding subjective routine. In particular, results seem to highlight the fact that some self-selection pattern is in place, with workers with different (lower) distribution of characteristics concentrated into low-paid jobs that they perceived as being highly routinary. In other words: a worker doing a perceived routinary low-paid job would not suffer a wage gap relative to an identical worker who does a job that he perceives as non-routinary; on the other side, a worker in a low-paid objectively routinary job with identical characteristics to another one doing an objectively non-routine job would still suffer a pay gap.

Overall, the difference between subjective and objective routine in terms of salary is not so high: this is because, especially in Italy, the salary is determined at the professional level and hardly takes into account unobservable skills. That is why we can use the subjective routine as well as the objective routine to evaluate the RBTC in terms of wage distribution. The difference is widened when the weight of the characteristics is evaluated because the subjective definition of routine also takes into account the worker's perception and therefore reduces the set of omitted variables that could explain the observed wage gap. Overall, we provide evidence of the stable presence of a U-shaped wage gap between non-routine and routine workers, which is robust to different estimation tecniques and different definitions of routine. This confirms that Routine-Biased-Technical-Change is still producing significant social changes: after leading to job polarization, it induced a similar polarizing effects on wages in Italy. To the best of our knowledge, this is the first paper to empirically establish the presence of this phenomenon in Italy.

Technological change has always had a decisive impact on the labour market. The current Covid-19 pandemic is seen as an automation-forcing event, whose effects on technology and work are destined to last over time (Autor *et al.* 2020; Autor and Reynolds 2020): further researches may test this hypothesis and investigate whether Covid-19 will have a persistent effect on technological change and further consequences on the income inequality.

References

Acemoglu D. (2002a), Directed technical change, *Review of Economic Studies*, 69, n.4, pp.781-809

Acemoglu D. (2002b), Technical change, inequality, and the labor market, *Journal of Economic Literature*, 40, n.1, pp.7-72

Acemoglu D. (1998), Why do new technologies complement skills? Directed technical change and wage inequality, *Quarterly Journal of Economics*, 113, n.4, pp.1055-1089

Acemoglu D., Autor D. (2011), Skills, tasks and technologies. Implications for employment and earnings, in Card D., Ashenfelter O. (eds.), *Handbook of labor economics Vol. 4B*, New York, Elsevier, pp.1043-1171

Agasisti T., Johnes G., Paccagnella M. (2020), Tasks, occupations and wages in OECD countries, *International Labour Review*, 8 May, article in press

Autor D.H. (2013), The “task approach” to labor markets. An overview, *Journal of Labour Market Research*, 46, n.3, pp.185-199

Autor D.H., Dorn D. (2013), The Growth of Low-Skill Service Jobs and the Polarization of the US Labor Market, *American Economic Review*, 103, n.5, pp.1553-1597

Autor D.H., Handel M.J. (2013), Putting Tasks to the Test. Human Capital, Job Tasks, and Wages, *Journal of Labor Economics*, 31, n.2, pp.S59-S96

Autor D.H., Katz L.F., Kearney M.S. (2008), Trends in U.S. Wage Inequality. Revising the Revisionists, *Review of Economics and Statistics*, 90, n.2, pp.300-323

Autor D.H., Katz L.F., Kearney M.S. (2006), The Polarization of the U.S. Labor Market, *American Economic Review*, 96, n.2, pp.189-194

Autor D.H., Katz L.F., Krueger A.B. (1998), Computing Inequality. Have Computers Changed the Labor Market?, *Quarterly Journal of Economics*, 113, n.4, pp.1169-1213

Autor D.H., Levy F., Murnane R.J. (2003), The Skill Content of Recent Technological Change. An Empirical Exploration, *Quarterly Journal of Economics*, 118, n.4, pp.1279-1333

Autor D.H., Mindell D., Reynolds E. (2020), *The Work of the Future. Building Better Jobs in an Age of Intelligent Machines*, Cambridge MA, MIT Task Force on the Work of the Future

Autor D.H., Reynolds E. (2020), *The Nature of Work after the COVID Crisis. Too Few Low-Wage Jobs*, Washington DC, The Hamilton Project

Barbieri T., Basso G., Scicchitano S. (2020), *Italian workers at risk during the Covid-19 epidemic*, GLO Discussion Paper n.513, Essen, Global Labor Organization

Basso G. (2020), The Evolution of the Occupational Structure in Italy. 2007-2017, *Social Indicators Research*, 152, n.2, pp.673-704

Boll C., Leppin J., Rossen A., Wolf A. (2016), *Overeducation - New evidence for 25 European countries*, HWWI Research Paper n.173, Hamburg, Hamburg Institute of International Economics

Bonacini L., Gallo G., Scicchitano S. (2021), Working from home and income inequality. Risks of a 'new normal' with COVID-19, *Journal of Population Economics*, 34, n.1, pp.303-360

Card D., DiNardo J. (2002), Skill-biased technological change and rising wage inequality. Some problems and puzzles, *Journal of Labor Economics*, 20, n.4, pp.733-783

Caselli M., Fracasso A., Scicchitano S. (2020), *From the lockdown to the new normal. An analysis of the limitations to individual mobility in Italy following the Covid-19 crisis*, GLO Discussion Paper n.683, Essen, Global Labor Organization

Cirillo V., Evangelista R., Guarascio D., Sostero M. (2020), Digitalization, routineness and employment. An exploration on Italian task-based data, *Research Policy*, article 104079, in press

Coupe T. (2019), Automation, job characteristics and job insecurity, *International Journal of Manpower*, 40, n.7, pp.1288-1304

De la Rica S., Gortazar L., Lewandowski P. (2020), Job Tasks and Wages in Developed Countries. Evidence from PIAAC, *Labour Economics*, 65, article 101845

Dengler K., Matthes B. (2018), The impacts of digital transformation on the labour market. Substitution potentials of occupations in Germany, *Technological Forecasting and Social Change*, 137, issue C, pp.304-316

Di Nardo J., Fortin N., Lemieux T. (1996), Labour market institutions and the distribution of wages 1973-1992. A semiparametric approach, *Econometrica*, 64, n.5, pp.1001-1044

Dolton P., Vignoles A. (2000), The incidence and effects of over-education in the UK graduate labour market, *Economics of Education Review*, 19, n.2, pp.179-198

Dustmann C., Ludsteck J., Schönberg U. (2009), Revisiting the German Wage Structure, *Quarterly Journal of Economics*, 124, n.2, pp.843-881

Esposito P., Scicchitano S. (2020), *Educational Mismatches, Routine Biased Technological Change and Unemployment. Evidence from Italy*, available at SSRN <https://bit.ly/37Cqnpp>

Firpo S., Fortin N.M., Lemieux T. (2011), Occupational Tasks and Changes in the Wage Structure, IZA Discussion Paper n.5542, Bonn, IZA

Gashi A.N., Pugh G., Adnett N. (2010), Technological change and employer-provided training: evidence from UK workplaces, *International Journal of Manpower*, 31, n.4, pp.426-448

Goos M., Manning A. (2007), Lousy and Lovely Jobs. The Rising Polarization of Work in Britain, *Review of Economics and Statistics*, 89, n.1, pp.118-133

Goos M., Manning A., Salomons A. (2014), Explaining Job Polarization. Routine-Biased Technological Change and Offshoring, *American Economic Review*, 104, n.8, pp.2509-2526

Green F., Zhu Y. (2010), Over qualification, job dissatisfaction, and increasing dispersion in the returns to graduate education, *Oxford Economic Papers*, 62, n.4, pp.740-763

Hantrais L., Allin P., Kritikos M., Sogomonjan M., Prathivadi B.A., Livingstone S., Williams M., Innes M. (2020), Covid-19 and the digital revolution, *Contemporary Social Science*, pp.1-15 <https://bit.ly/3s9m3G2>

Hirano K., Imbens G.W., Ridder G. (2003), Efficient estimation of average treatment effects using the estimated propensity score, *Econometrica*, 71, n.4, pp.1161-1189

Jann B. (2008), The Blinder-Oaxaca Decomposition for linear regression models, *The Stata Journal*, 8, n.4, pp.453-479

Jung J.H., Lim D.G. (2020), Industrial robots, employment growth, and labor cost. A simultaneous equation analysis, *Technological Forecasting and Social Change*, 159, article 120202

Katz L.F., Murphy K.M. (1992), Changes in Relative Wages, 1963-1987. Supply and Demand Factors, *The Quarterly Journal of Economics*, 107, n.1, pp.35-78

Li Y., Zhao Y., Liu Y. (2006), The relationship between HRM, technology innovation and performance in China, *International Journal of Manpower*, 27, n.7, pp.679-697

Loader C.R. (1999), Bandwidth selection. Classical or plugin?, *The Annals of Statistics*, 27, n.2, pp.415-438

Melly B. (2005), Decomposition of differences in distribution using quantile regression, *Labour Economics*, 12, n.4, pp.577-590

McGuinness S., Pouliakas K., Redmond P. (2018), Skill mismatch. Concepts, measurement, and policy approaches, *Journal of Economic Surveys*, 32, n.4, pp.985-1015

Muñoz de Bustillo Llorente R., Sarkar S., Sebastian R., Antón J.I. (2018), Educational mismatch in Europe at the turn of the century. Measurement, intensity and evolution, *International Journal of Manpower*, 39, n.8, pp.977-995

Naticchioni P., Ragusa G., Massari R. (2014), *Unconditional and Conditional Wage Polarization in Europe*, IZA Discussion Paper n.8465, Bonn, IZA <https://bit.ly/2NtGizw>

Neves P.C., Afonso O, Sequeira T.N. (2018), Population growth and the wage skill premium, *Economic Modelling*, 68, issue C, pp.435-449

Paunov C., Planes-Satorra S. (2020), Science, technology and innovation in times of Covid-19 and policy responses. Preliminary overview in June 2020, in *Science, technology and innovation in times of Covid-19 and policy responses*, OECD, virtual workshop 17 and 24 June

Scicchitano S., Biagetti M., Chirumbolo A. (2020), More insecure and less paid? The effect of perceived job insecurity on wage distribution, *Applied Economics*, 52, n.18, pp.1998-2013

Sheather S.J. (2004), Density Estimation, *Statistical Science*, 19, n.4, pp.588-597

Spitz-Oener A. (2006), Technical Change, Job Tasks, and Rising Educational Demands. Looking Outside the Wage Structure, *Journal of Labor Economics*, 24, n.2, pp.235-270

Weiss M., Garloff A. (2009), Skill-biased technological change and endogenous benefits. The dynamics of unemployment and wage inequality, *Applied Economics*, 43, n.7, pp.811-821