Estimating the Wage Gap between Routine and Non-Routine Workers: the role of Perceptions

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# Abstract

In this paper, we introduce the role of perceptions into the Routine Bias Technical Change (RBTC) literature, in order to investigate 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 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. We adopt a counterfactual semi-parametric decomposition technique to quantify the importance of characteristics of workers in explaining the gaps. Results show that workers' characteristics fully explain the gap in the case of perceived routine for workers with earnings up to the 4th decile the wage distribution, while they account for no more than 50% of the gap across the distribution in the case of actual routine. Overall, results highlight i) the presence of a significant pattern of wage polarization ii) the importance of taking into account workers' perceptions to explain observed wage inequality, as they significantly reduce the set of omitted variables

Keywords: *routine, Counterfactual distribution, Semi-parametric methodology, Wage gap, Blinder/Oaxaca, Quantile regression, Italy.*

JEL classification: *J21, J23, J24, J31, R23.*

1 Introduction

In recent years, the US and many European countries experienced increasing job polarization and a surge in wage inequality. A number of papers have provided a novel technology-based explanation of these dynamics, a theory widely known as Routine- Biased Technological Change (RBTC) (Autor, Levy and Murnane 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 com- puterization leads to the replacement of occupations intense in routine tasks, which are usually the occupations in the middle of the wage distribution. Some papers have also documented how RBTC-induced job polarization may translate into wage polarization (Autor et al. 2006, Autor and Handel 2013, Firpo, Fortin, and Lemieux, 2013). All the previous papers, however, look at the actual definition of routine and focus mainly on the average wage level, by occupation. 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' gap is due to workers' characteristics?

Thanks to the availability of unique survey data, we are able to classify workers according to both the actual and their perceived level of routinarity of jobs (AR and PR). We apply a semi-parametric Counterfactual Decomposition Analysis (CDA) using Quantile Regression (QR) to quantify the relative importance of labor market characteristics of workers vs. returns in explaining the observed wage gaps. Beyond the mean, we find evidence of a 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]. Non-routine workers are paid significantly more than routine workers at any percentile of the wage distribution, but routine individuals with median levels of wage suffers from a relatively lower pay gap with respect to the two tails of the wage distribution. When we perform CDA we

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

see that workers' characteristics almost fully explain the observed wage 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 seem 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.

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 distribution.

The rest of the paper is organized as follows: section two reviews previous related literature. Section three describes the semi-parametric CDA and the data used. Empirical results are discussed in section four, while section five concludes.

2 Related Literature

Starting with the seminal work of Katz and Murphy (1992), a large literature has dis- cussed the impacts of technological change on employment and wages (Autor, Katz, and Krueger (1998); Autor, Levy, and Murnane (2003); Autor, Katz, Kearney (2006); Acemoglu and Autor (2011)). The majority of works focus on 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 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 rises 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 (1999)).

Autor, Levy and Murnane (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 labor 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 RBTC, rather than uniformly favoring skilled workers, technology has a polarizing effect on the labor 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, Spitz-Oener 2006, Dustmann et al. 2009, Goos et al. 2012, Acemoglu and Autor 2011, Autor and Dorn 2013).

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). Firpo, Fortin, and Lemieux (2013) 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.

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 (Italian National Institute for the Analysis of Public Policies). They show 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%). However, there is no immediate evidence on the extent to which these trends were reflected in the wage distribution. To the best of our knowledge, this is the first study to analyze the routine-non-routine wage distributions in Italy and evaluate differences between perceived and actual definitions of routine jobs.

3 Data and Empirical Strategy

3.1 Data

To conduct the analysis, we use unique survey data from the Fourth INAPP

Survey on Quality of Work (InappQoW), 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. To conduct our analysis, 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 8655 workers, representative of the Italian employed population, among which we observe 6,232 non-routine and 2,439 routine workers. To measure subjective (perceived) level of jobs' routinarity, we refer to the following question Do routine tasks prevail in your current work?, and the possible answers were simply Yes or No. On the other side, the survey also contains information on the occupation of each employed individual, at the 4-digit ISCO occupation-level. This allows us to construct the Routine Task Index (RTI) proposed by Autor and Dorn (2013), which we use as a measure of the actual level of routinarity. To construct the RTI, we exploit detailed information on the task-content of occupation titles, using data from the Italian Survey of Professions (ICP), which represents a European examples of Dictionary of Occupations comparable to the US O*NET database. 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. To account for the effect of observable characteristics, 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, equaled 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, skill mismatch, 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 1 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 perceived definition of routine, while columns (5) - (7) refer to the actual 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. 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.

As a first test for the difference between the two distributions we perform the non- parametric Kolmogorov-Smirnov test, based on the concept of first-order stochastic dominance. The results of the test, shown in Table 2, confirm what can be seen in Figure 2, namely that the net monthly wages of non-routine workers stochastically dominate, at the 1 percent significance level, those of routine workers, for both actual and perceived measures of routine.

3.2 Blinder-Oaxaca decomposition and Semi-Parametric Counterfactual Decomposition Analysis

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 R and NR are the two groups of routine and non-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 by R and NR, respectively:

$$\Delta\bar{y} = \bar{y}_n - \bar{y}_r \qquad (1)$$

In the context of a linear regression, the above expression can be rewritten as:

$$\Delta\bar{y} = \bar{X}'_{\mathrm{n}}\hat{\beta}_{\mathrm{n}} - \bar{X}'_{\mathrm{r}}\hat{\beta}_{\mathrm{r}} \qquad (2)$$

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

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

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

The majority of empirical articles evaluating the effect of being engaged in routine tasks on wage have focused on its average level, applying the method of B-O decomposition on the mean. Distributional effects have been largely neglected, and yet they are of significant policy relevance. 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, as it allows each quantile of a variable conditional on some covariates to be accounted for and the effect of those covariates at selected quantiles of the distribution to be estimated.

Let y_i be the dependent variable and the vector of the chosen explanatory variables. The relation is given by:

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

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

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

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), the assumptions behind the standard Blinder-Oaxaca (B-O) mean decomposition procedure[2] are not going to hold at quintiles. For this reason, we 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 quantiles; secondly it is integrated over the range of covariates.

Representing with $\hat{\beta}$ the vector of estimated quantile regression parameters and integrating over all of the quantiles and observations, an estimator of the τ^{th} unconditional quantile of the wage is given by:

[2]I.e. the mean wage conditional on the average values of explanatory variables equal to the unconditional mean wage

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

Where 1(.) is the indicator function. Then, the counterfactual distribution can be estimated by replacing either the estimated parameters of the distribution of characteristics for routine (r) or not routine (nr) workers. The difference at each quantile of the unconditional distribution can be decomposed into the two above mentioned components as follows:

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

The first right-hand term 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. The QR framework does not need any distributional assumptions and allows the covariates to influence the whole conditional distribution. To estimate standard errors and confidence intervals, we applied a bootstrapping technique with 200 replications.

4 Results

4.1 Ordinary least squares and semi-parametric quantile regression

4.1.1 Perceived Routine

As a first step, we estimate classic Mincerian wage equations, separately for routine and non-routine workers, according to their perceived elicitation. The estimation results are depicted in Figure 3 and then presented in tables 3 and 4. In particular we show, for the two groups, respectively, the OLS coefficients as well as the conditional coefficients at representative quantiles: $\theta_{10}, \theta_{25}, \theta_{50}$, θ_{75}, θ_{90}. Both the OLS and the quantile regressions show that for routine workers, wage grows with age, while 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. Enterprise's 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 are con- firmed. 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 statistical significance at the quantiles examined w.r.t the routine workers. The effect of fathers' education is significant only at the mean and the 75*th* 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.

4.1.2 Actual Routine

We repeat the same regressions also for the alternative (actual) definition of routine. The estimation results are depicted in Figure 4 and then presented in tables 5 and 6. 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 slightly stronger now, consistent with a larger share of men classified as actually routine workers. On the other hand, the father's education level loses its significance in the OLS, while is still significant and larger in magnitudes at and above the median. Interestingly, work experience loses 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 any more 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 perceived non-routine workers, it is now stable and positively significant for the whole bottom half of the distribution and also for the conditional 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 loses its significance, except for the first quartile.

4.2 Counterfactual Decomposition Analysis

Table 7 reports decomposition results for the mean and several quantiles of the wage distribution. Columns (2) - (6) and (7) - (11) refer to models using perceived and objective level the routine respectively. Figure 5 plots the decomposition results at each of the 99 different quantiles, with a 95% bootstrapped confidence interval, for both PR (top panel) and AR (bottom panel) respectively. All estimates are significantly different from 0 at the 1% significance level. Independently of the definition used, routine workers suffers from a significant pay gap all along the wage distribution, even after controlling for the predictors. For perceived routine, 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 22 pp more than the routine workers. The difference in endowments account for 69% of this gap (0.137 out of 0.200 when computed in natural logs). The difference in coefficients accounts for the remaining 31%. For objective routine, the raw difference between mean wages of the two groups is 10% less than the difference calculated according to the perceived distinction, amounting to 265 euros (1552 vs. 1287 euros). The non-routine group earns 20 pp more than the routine workers. The difference in endowments now account for 57% of the gap, while before it was accounting for almost 70%. The difference in coefficients accounts for the remaining 43%. However, OLS coefficients at the mean 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, when looking at the whole distribution, the pay gap is U-shaped, with the presence of both significant sticky floor (i.e. a situation in which the 10th percentile wage gap is higher than the estimated wage gap at the 50th percentile) and glass ceiling (i.e. a situation in which the 90th percentile wage gap is higher than the estimated wage gap at the 50th percentile).

CDA results show that differences in returns explain significantly less than that differences in covariates at each of the estimated quantiles when using perceived routine, while the opposite is true when using actual routine, with the exception of the first 2 deciles. In particular, with perceived routine the relative incidence of the coefficient component accounts roughly for 12 up to 44% of the total difference, while with actual routine such an incidence accounts for 38% up to 56%. More specifically, characteristics component is much more relevant in the PR with respect to the AR: this evidence suggests that perceptions represent a crucial component in determining consequences of RBTC as they significantly reduce the set of omitted variables.

The difference in the behavior of the bottom part of the distribution lead us to make some important considerations regarding perceived routine. In particular, results lead to essentially reject the sticky floor hypothesis for perceived routine workers: the gap is not due to discriminatory practices against them, but rather to difference in characteristics of routine workers in low-paid jobs, relative to non-routine workers (mostly experience and age). This also seems to highlight the presence of negative self-selection patterns, with workers with relatively worse characteristics concentrated into low-paid jobs that they perceived as being highly routine.

On the other side, the top part of the distribution suggests that workers in perceived routine jobs are compensated less than workers in non-routine jobs with analogous characteristics, suggesting the presence of some glass ceiling effect.

Turning to actual routine, it is notable that both 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 actually high-routine jobs. More generally, the fact that the explanatory power of characteristics is stable along the whole distribution provides evidence of the fact that the RBTC-induced job polarization patterns also translate into negative effects on the wage: the labor market returns for routine workers with identical characteristics to non-routine workers are significantly lower, along the entire wage distribution. This article is the first to provide evidence of this topic for Italy.

5 Discussion and Conclusion

This papers introduces perceptions into the RBTC literature. To the best of our knowledge, this article is the first attempt to estimate and compare the gap in earnings 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.

We document the presence of significant wage inequality between non-routine and routine workers, robust to different definitions of routine, in the form of a U-shaped wage gap. This suggests that, alongside with job polarization, RBTC is also increasing wage polarization in Italy. We also document a significant difference in the behavior of the bottom part of the distribution across definitions, suggesting the presence of negative self-selection patterns of low-skilled workers in perceived routine jobs. Most importantly, results from our CDA demonstrate that the perceived definition of routine is able to reduce the unexplained component of the wage gap, because it also takes into account the worker's perception and therefore reduces the set of omitted variables that could explain the observed wage inequality. Thus, our results highlight the importance of taking into account individuals' perceptions when looking at the impact of RBTC on the wage distribution, other than simply looking at objective observable characteristics. Overall, the difference between perceived and actual routine in terms of salary is small: 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 perceived routine as well as the actual routine to evaluate the RBTC in terms of wage distribution.

Some policy indications for the Italian welfare state emerge from the article. Indeed, to fill the wage gap and to reduce wage inequality, there is a need for social policies tailored to deal with income support measures. As to income support scheme, some authors noted that, although improved compared to the past, thanks to the creation of a form of Guaranteed Minimum Income starting in 2018, the Italian Welfare State needs further improvements to deal with challenges derived by current technological changes (Sacchi, 2018). In this context, the paper shows that endowments of the routine group of workers (i.e. their predictor levels in the regressions performed) should be strengthened. For this to happen, well-functioning and well-intertwined labour market and industrial institutions are needed in order to improve the quality of job contracts (full-time and permanent being of course strongly correlated with the high level of the wage), increase employees' educational attainment, promote job training, reduce job insecurity and mismatch during the job. This challenge appears all the more important as high wage gaps between skills increase inequality while at the same time threatening Italian social fabric.

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Table 1
Summary Statistics for the whole sample and by perceived and actual routine.

		Perceived:			Actual:		
	Whole	Routine	No-Routine	Diff	Routine	No-Routine	Diff
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Actual 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*
Perceived Routine					0.81	0.65	-0.17***
Observations	8655	6220	2435	8655	3743	4912	8655

Table 2
Kolmogorov-Smirnov test for comparison between routine and non-routine workers

	Combined	Perc. Yes	Perc. No	Combined	Act. Yes	Act. No
KS_2	0.207			0.231		
	[0.000]			[0.000]		
KS_1		0.207	0		-0.231	0
		[0.000]	[-1.000]		[0.000]	[-1.000]

Note: *p*- values in parentheses

Table 3
Mincerian wage regressions, Perceived Routine = Yes

	(1) OLS	(2) q10	(3) q25	(4) q50	(5) q75	(6) q90
Age	0.0130**	0.0293***	0.0143***	0.0154***	0.0149***	0.00727
	[0.006]	[0.003]	[0.005]	[0.004]	[0.004]	[0.005]
age_sq	-0.000106	0.000301***	0.000145***	0.000138***	-0.000113**	0.0000293
	[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	0.0897***	0.119***	0.0824***	0.0668***	0.0510***	0.0257*
	[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	0.0130***	-0.00559	0.00848**	0.0172***	0.0175***	0.0158**
	[0.004]	[0.004]	[0.004]	[0.004]	[0.005]	[0.006]
work_exp	0.00260***	0.00315***	0.00371***	0.00267***	0.00159**	0.00172*
	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]
pasted	0.0359***	0.0275***	0.0284***	0.0269***	0.0330***	0.0414***
	[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	0.0775***	0.137***	0.0978***	0.0759***	0.0539**	-0.00498
	[0.017]	[0.035]	[0.017]	[0.012]	[0.021]	[0.024]
mobility==1	-0.00736	-0.0121	-0.0179*	-0.00335	-0.00480	-0.0210
	[0.008]	[0.010]	[0.010]	[0.010]	[0.011]	[0.015]
mobility==2	-0.0134	-0.0187*	-0.0208**	-0.0153	-0.00966	-0.00318
	[0.009]	[0.010]	[0.010]	[0.010]	[0.009]	[0.017]
mobility==3	-0.0257*	-0.0113	-0.0356***	-0.0351***	-0.0240*	0.0429***
	[0.014]	[0.013]	[0.013]	[0.010]	[0.014]	[0.015]
stability	0.000736	-0.0163***	-0.0103*	-0.00225	0.00713	0.0179**
	[0.009]	[0.005]	[0.005]	[0.005]	[0.006]	[0.009]
dtraining==1	0.0359***	0.0486***	0.0265***	0.0203***	0.0114	0.0204*
	[0.010]	[0.007]	[0.008]	[0.007]	[0.008]	[0.011]
supervisor==1	0.0841***	0.0601***	0.0603***	0.0730***	0.100***	0.142***
	[0.005]	[0.008]	[0.008]	[0.007]	[0.010]	[0.016]
firmsize1==2	0.0969***	0.141***	0.0917***	0.0666***	0.0738***	0.0548***
	[0.018]	[0.020]	[0.013]	[0.012]	[0.010]	[0.020]
firmsize1==3	0.108***	0.138***	0.0904***	0.0869***	0.0992***	0.0730***
	[0.013]	[0.019]	[0.015]	[0.011]	[0.015]	[0.019]
firmsize1==4	0.105***	0.157***	0.117***	0.0941***	0.0948***	0.0449**
	[0.018]	[0.019]	[0.013]	[0.013]	[0.012]	[0.019]
firmsize1==5	0.139***	0.139***	0.127***	0.118***	0.139***	0.0917***
	[0.017]	[0.022]	[0.015]	[0.013]	[0.012]	[0.021]
telework==1	0.0417	0.0311***	0.0266***	0.0312***	0.0299**	0.0336**
	[0.030]	[0.010]	[0.010]	[0.011]	[0.013]	[0.016]
contr==1	0.0941*	0.153*	0.0423	0.0634*	0.0260	0.00957
	[0.051]	[0.088]	[0.038]	[0.034]	[0.036]	[0.027]
js==1	0.0465***	0.0719***	0.0496***	0.0419***	0.0392***	0.0286*
	[0.012]	[0.012]	[0.010]	[0.008]	[0.009]	[0.015]
mismatch==1	-0.0225**	-0.00905	-0.0129	-0.0110	-0.00890	-0.0257*
	[0.009]	[0.010]	[0.008]	[0.007]	[0.009]	[0.014]
stress	0.0457***	0.0393***	0.0355***	0.0240***	0.00882	0.0312***
	[0.012]	[0.006]	[0.007]	[0.007]	[0.008]	[0.011]
mezz==1	-0.00380	-0.00756	-0.00519	0.00341	0.000755	0.0153
	[0.020]	[0.009]	[0.009]	[0.009]	[0.011]	[0.013]
Observations	3831	3831	3831	3831	3831	3831

Notes: Robust standard errors in parenthesis. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table 4
Mincerian wage regressions, Perceived Routine = No

	(1) OLS	(2) q10	(3) q25	(4) q50	(5) q75	(6) q90
Age	0.0142*	0.0180**	0.0153**	0.0204***	0.0226***	0.0215*
	[0.007]	[0.008]	[0.006]	[0.005]	[0.007]	[0.012]
age_sq	-0.0000863	-0.000142*	0.0000989	0.000166***	0.000175**	-0.000168
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
dmale==1	0.108***	0.0786***	0.0902***	0.103***	0.0995***	0.0873***
	[0.016]	[0.013]	[0.012]	[0.014]	[0.013]	[0.026]
make_ends_meet==1	0.0659***	0.0440**	0.0243	0.0609***	0.0888***	0.121***
	[0.022]	[0.018]	[0.019]	[0.013]	[0.014]	[0.031]
make_ends_meet==2	0.155***	0.123***	0.0961***	0.124***	0.138***	0.199***
	[0.024]	[0.019]	[0.019]	[0.015]	[0.016]	[0.039]
edu_fath	0.0155**	0.000456	0.00760	0.00895	0.0126**	0.00724
	[0.007]	[0.006]	[0.005]	[0.006]	[0.006]	[0.012]
work_exp	0.00162	0.00345**	0.000887	0.00245***	0.000214	0.00250
	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]	[0.002]
pasted	0.0403***	0.0397***	0.0353***	0.0322***	0.0290***	0.0397***
	[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	0.0684**	0.0600*	0.109***	0.0753***	0.0802***	0.0736
	[0.032]	[0.035]	[0.021]	[0.027]	[0.022]	[0.060]
mobility==1	-0.0520***	-0.0499***	0.0656***	-0.0593***	-0.0263*	-0.0288
	[0.019]	[0.014]	[0.014]	[0.017]	[0.014]	[0.030]
mobility==2	-0.0580***	-0.0591***	0.0509***	-0.0432***	-0.0336**	-0.0566*
	[0.019]	[0.017]	[0.015]	[0.015]	[0.014]	[0.031]
mobility==3	-0.0306	-0.104***	-0.0650**	-0.0366*	0.000755	0.0210
	[0.026]	[0.026]	[0.031]	[0.022]	[0.029]	[0.039]
stability	0.0215*	0.0342***	0.0196**	0.0183**	0.0124	0.0148
	[0.011]	[0.013]	[0.009]	[0.009]	[0.010]	[0.018]
dtraining==1	0.0419***	0.0327**	0.0413***	0.0218	0.0286***	0.0443*
	[0.015]	[0.013]	[0.013]	[0.014]	[0.011]	[0.023]
supervisor==1	0.121***	0.0911***	0.0809***	0.0905***	0.140***	0.191***
	[0.015]	[0.012]	[0.011]	[0.012]	[0.015]	[0.027]
firmsize1==2	0.0706***	0.00812	0.0545**	0.0925***	0.0658***	0.0960***
	[0.024]	[0.028]	[0.023]	[0.022]	[0.019]	[0.037]
firmsize1==3	0.0880***	0.0843***	0.0855***	0.105***	0.0987***	0.0995***
	[0.024]	[0.024]	[0.017]	[0.022]	[0.019]	[0.036]
firmsize1==4	0.0956***	0.0871***	0.0991***	0.112***	0.0926***	0.103***
	[0.025]	[0.024]	[0.017]	[0.021]	[0.021]	[0.034]
firmsize1==5	0.153***	0.0979***	0.155***	0.165***	0.164***	0.199***
	[0.024]	[0.022]	[0.018]	[0.023]	[0.020]	[0.040]
telework==1	0.0393**	0.00822	0.0287**	0.0298**	0.0144	0.0428
	[0.017]	[0.017]	[0.014]	[0.013]	[0.014]	[0.028]
contr==1	0.0542	0.394***	0.0687***	0.0697	-0.0329	0.0115
	[0.059]	[0.033]	[0.023]	[0.100]	[0.075]	[0.060]
js==1	0.0274	0.0207	0.0255	0.0249	0.0219	-0.00343
	[0.020]	[0.015]	[0.016]	[0.016]	[0.014]	[0.035]
mismatch==1	-0.0302*	-0.0740***	-0.0283*	-0.0113	-0.0113	-0.0258
	[0.017]	[0.012]	[0.016]	[0.016]	[0.014]	[0.029]
stress	0.0288**	0.0491***	0.0304***	0.0313***	0.0181*	0.0148
	[0.014]	[0.011]	[0.010]	[0.011]	[0.010]	[0.020]
mezz==1	-0.0433**	-0.0401***	0.0501***	-0.0295*	-0.0134	-0.0393
	[0.018]	[0.014]	[0.015]	[0.016]	[0.014]	[0.025]
Observations	1555	1555	1555	1555	1555	1555

Notes: Robust standard errors in parenthesis. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table 5
Minceriam wage regressions, Actual Routine = Yes

	(1) OLS	(2) q10	(3) q25	(4) q50	(5) q75	(6) q90
Age	0.0154**	0.0318***	0.0223***	0.0208***	0.0201***	0.0149*
	[0.007]	[0.007]	[0.005]	[0.005]	[0.005]	[0.008]
age_sq	-0.000149*	0.000364***	0.000235***	0.000212***	0.000183***	-0.000117
	[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	0.0794***	0.107***	0.0877***	0.0643***	0.0597***	0.0442**
	[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***	0.0795***
	[0.013]	[0.021]	[0.014]	[0.011]	[0.015]	[0.021]
edu_fath	0.0125	-0.0106	0.0111*	0.0201***	0.0185***	0.0341***
	[0.009]	[0.012]	[0.006]	[0.006]	[0.006]	[0.010]
work_exp	0.00274***	0.00529***	0.00292***	0.00239***	0.000725	0.000950
	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]
pasted	0.0308***	0.0281***	0.0251***	0.0206***	0.0240***	0.0399***
	[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	0.0753***	0.112***	0.0972***	0.0538***	0.0438***	0.00645
	[0.023]	[0.030]	[0.016]	[0.021]	[0.016]	[0.038]
mobility==1	-0.0175	-0.0164	-0.0170	-0.000963	-0.00408	-0.0457**
	[0.012]	[0.015]	[0.017]	[0.013]	[0.014]	[0.021]
mobility==2	-0.0410***	-0.0487**	-0.0145	-0.0173	-0.0133	-0.0454**
	[0.013]	[0.021]	[0.014]	[0.012]	[0.014]	[0.019]
mobility==3	-0.0328	-0.0250	-0.0203	-0.0345**	-0.0137	-0.0532*
	[0.021]	[0.027]	[0.016]	[0.016]	[0.014]	[0.031]
stability	0.0165*	-0.00607	-0.00274	0.0116*	0.0283***	0.0252**
	[0.009]	[0.009]	[0.007]	[0.006]	[0.007]	[0.011]
dtraining==1	0.0460***	0.0539***	0.0295***	0.0306***	0.0311***	0.0588***
	[0.012]	[0.012]	[0.010]	[0.009]	[0.010]	[0.017]
supervisor==1	0.0727***	0.0447***	0.0545***	0.0691***	0.0825***	0.113***
	[0.010]	[0.012]	[0.011]	[0.009]	[0.013]	[0.017]
firmsize1==2	0.0903***	0.125***	0.102***	0.0635***	0.0477***	0.0395*
	[0.028]	[0.020]	[0.016]	[0.013]	[0.011]	[0.022]
firmsize1==3	0.107***	0.104***	0.0928***	0.0876***	0.0872***	0.0764***
	[0.018]	[0.020]	[0.019]	[0.013]	[0.017]	[0.021]
firmsize1==4	0.104***	0.143***	0.115***	0.0973***	0.0766***	0.0467*
	[0.023]	[0.022]	[0.019]	[0.014]	[0.016]	[0.024]
firmsize1==5	0.118***	0.100***	0.119***	0.119***	0.104***	0.0810***
	[0.030]	[0.022]	[0.018]	[0.014]	[0.015]	[0.023]
telework==1	0.0602	-0.0175	0.0331	0.0840***	0.0635***	0.111
	[0.038]	[0.038]	[0.032]	[0.026]	[0.024]	[0.084]
contr==1	0.0964*	0.241***	0.0320	0.0457	0.0123	0.00226
	[0.052]	[0.080]	[0.100]	[0.039]	[0.026]	[0.042]
js==1	0.0480**	0.0713***	0.0577***	0.0334***	0.0317***	0.0363**
	[0.018]	[0.018]	[0.012]	[0.010]	[0.010]	[0.015]
mismatch==1	-0.00616	0.000104	-0.00654	-0.0137	0.00408	0.0137
	[0.010]	[0.015]	[0.011]	[0.011]	[0.010]	[0.015]
stress	0.0394***	0.0358***	0.0398***	0.0237***	0.00553	0.0262**
	[0.012]	[0.012]	[0.009]	[0.008]	[0.008]	[0.013]
mezz==1	-0.0194	-0.00712	-0.0105	-0.0132	-0.0150	-0.0214
	[0.016]	[0.015]	[0.013]	[0.011]	[0.011]	[0.023]
Observations	2188	2188	2188	2188	2188	2188

Notes: All regressions include Year and Region FE. Robust standard errors in parenthesis.
$^{*}p < 0.1, ^{**}p < 0.05, ^{***}p < 0.01$.

Table 6
Mincerian wage regressions, Actual Routine = No

	(1) OLS	(2) q10	(3) q25	(4) q50	(5) q75	(6) q90
Age	0.0181***	0.0278***	0.0185***	0.0183***	0.0197***	0.0179***
	[0.005]	[0.005]	[0.005]	[0.004]	[0.004]	[0.006]
age_sq	0.000128**	0.000250***	-0.000136**	-0.000147***	0.000141***	-0.000117*
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
dmale==1	0.0914***	0.0665***	0.0727***	0.0829***	0.0846***	0.0966***
	[0.011]	[0.013]	[0.010]	[0.008]	[0.009]	[0.013]
make_ends_meet==1	0.0904***	0.103***	0.0798***	0.0552***	0.0568***	0.0543***
	[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	0.0141***	0.00224	0.00743	0.0150***	0.0168***	0.0132**
	[0.005]	[0.006]	[0.005]	[0.004]	[0.004]	[0.006]
work_exp	0.00178*	0.00241**	0.00140*	0.00271***	0.00125	0.00172
	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]
pasted	0.0425***	0.0345***	0.0346***	0.0334***	0.0358***	0.0395***
	[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	0.0817***	0.136***	0.106***	0.0744***	0.0643**	0.0631***
	[0.023]	[0.044]	[0.015]	[0.023]	[0.028]	[0.020]
mobility==1	-0.0177	-0.0309**	-0.0261***	-0.0272***	-0.0179	-0.0245*
	[0.013]	[0.016]	[0.010]	[0.010]	[0.012]	[0.014]
mobility==2	-0.00621	-0.0373**	-0.0332**	-0.0122	-0.0142	0.00589
	[0.013]	[0.015]	[0.015]	[0.011]	[0.011]	[0.019]
mobility==3	-0.0157	-0.0566***	-0.0414***	-0.0413***	-0.0182	0.0121
	[0.018]	[0.018]	[0.015]	[0.014]	[0.015]	[0.016]
stability	0.000163	0.00797	-0.00431	-0.000680	0.00146	0.0190**
	[0.008]	[0.009]	[0.007]	[0.006]	[0.007]	[0.008]
dtraining==1	0.0323***	0.0226	0.0271***	0.0158**	0.00488	0.00168
	[0.011]	[0.016]	[0.010]	[0.008]	[0.010]	[0.012]
supervisor==1	0.110***	0.0695***	0.0713***	0.0879***	0.123***	0.173***
	[0.011]	[0.012]	[0.010]	[0.008]	[0.010]	[0.014]
firmsize1==2	0.0902***	0.0969***	0.0715***	0.0699***	0.0757***	0.0938***
	[0.017]	[0.018]	[0.016]	[0.015]	[0.016]	[0.020]
firmsize1==3	0.108***	0.115***	0.102***	0.0914***	0.0927***	0.0811***
	[0.017]	[0.022]	[0.016]	[0.014]	[0.013]	[0.018]
firmsize1==4	0.107***	0.113***	0.105***	0.0962***	0.105***	0.0667***
	[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	0.0425***	0.0437***	0.0257***	0.0258***	0.0364***	0.0217
	[0.013]	[0.014]	[0.010]	[0.009]	[0.010]	[0.018]
contr==1	0.0805*	0.121***	0.0626*	0.0865*	0.0519	0.0812
	[0.041]	[0.035]	[0.038]	[0.053]	[0.036]	[0.078]
js==1	0.0347**	0.0376***	0.0358**	0.0467***	0.0240*	0.000392
	[0.015]	[0.015]	[0.015]	[0.009]	[0.013]	[0.013]
mismatch==1	-0.0451***	-0.0322**	-0.0383***	-0.0151*	-0.0255***	-0.0411***
	[0.012]	[0.016]	[0.012]	[0.009]	[0.010]	[0.012]
stress	0.0402***	0.0254**	0.0201***	0.0180**	0.0242***	0.0354***
	[0.010]	[0.011]	[0.008]	[0.007]	[0.008]	[0.012]
mezz==1	-0.0185	-0.0111	-0.0274***	-0.00933	0.00805	-0.00831
	[0.012]	[0.013]	[0.008]	[0.009]	[0.011]	[0.013]
Observations	3198	3198	3198	3198	3198	3198

Notes: Robust standard errors in parenthesis. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

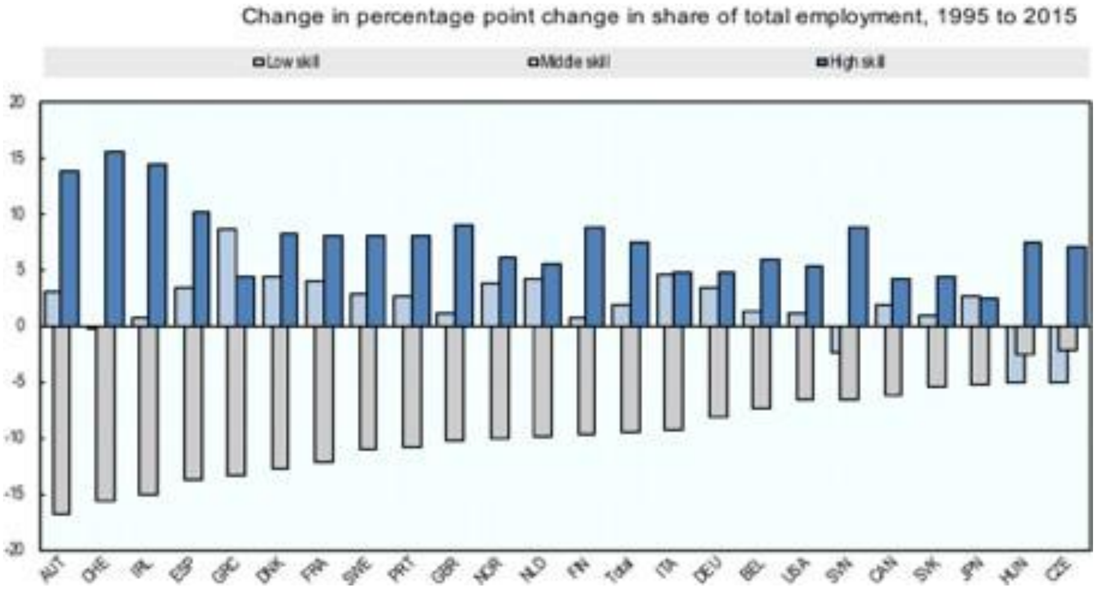
Table 7

Decompositions of the wage gap between routine/non-routine workers according to both definitions, using semi-parametric counterfactual distribution

	Perceived Routine						Actual Routine					
	Raw	Counterfactual Decomposition					Raw	Counterfactual Decomposition				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
		Tot. Diff.	Char.	%	Coeff.	%		Tot. Diff.	Char.	%	Coeff.	%
Mean	0.198	0.200	0.153	*77%*	0.044	*33%*	0.209	0.187	0.106	*57%*	0.046	*43%*
θ=.10	0.357	0.244	0.209	*86%*	0.035	*14%*	0.325	0.222	0.138	*62%*	0.084	*38%*
θ=.20	0.182	0.187	0.165	*88%*	0.022	*12%*	0.234	0.190	0.097	*51%*	0.092	*49%*
θ=.30	0.122	0.166	0.139	*84%*	0.026	*16%*	0.167	0.167	0.076	*45%*	0.091	*55%*
θ=.40	0.223	0.158	0.126	*80%*	0.032	*20%*	0.154	0.155	0.068	*44%*	0.087	*56%*
θ=.50	0.163	0.156	0.116	*74%*	0.040	*26%*	0.143	0.149	0.066	*44%*	0.084	*56%*
θ=.60	0.125	0.163	0.112	*69%*	0.051	*31%*	0.134	0.150	0.069	*46%*	0.081	*54%*
θ=.70	0.151	0.173	0.110	*64%*	0.063	*36%*	0.194	0.156	0.075	*48%*	0.081	*52%*
θ=.80	0.163	0.198	0.116	*59%*	0.082	*41%*	0.172	0.173	0.086	*50%*	0.087	*50%*
θ=.90	0.223	0.248	0.139	*56%*	0.110	*44%*	0.233	0.209	0.104	*50%*	0.105	*50%*

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%

Figure 1
Job Polarization in Europe.



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

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

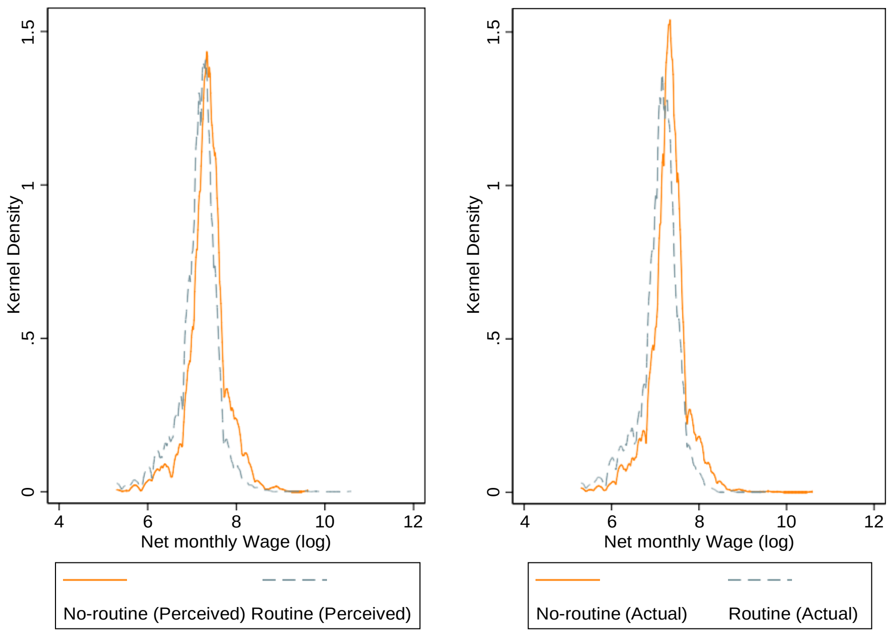


Figure 3
Mincerian Wage Regressions, OLS estimates - Perceived Routine

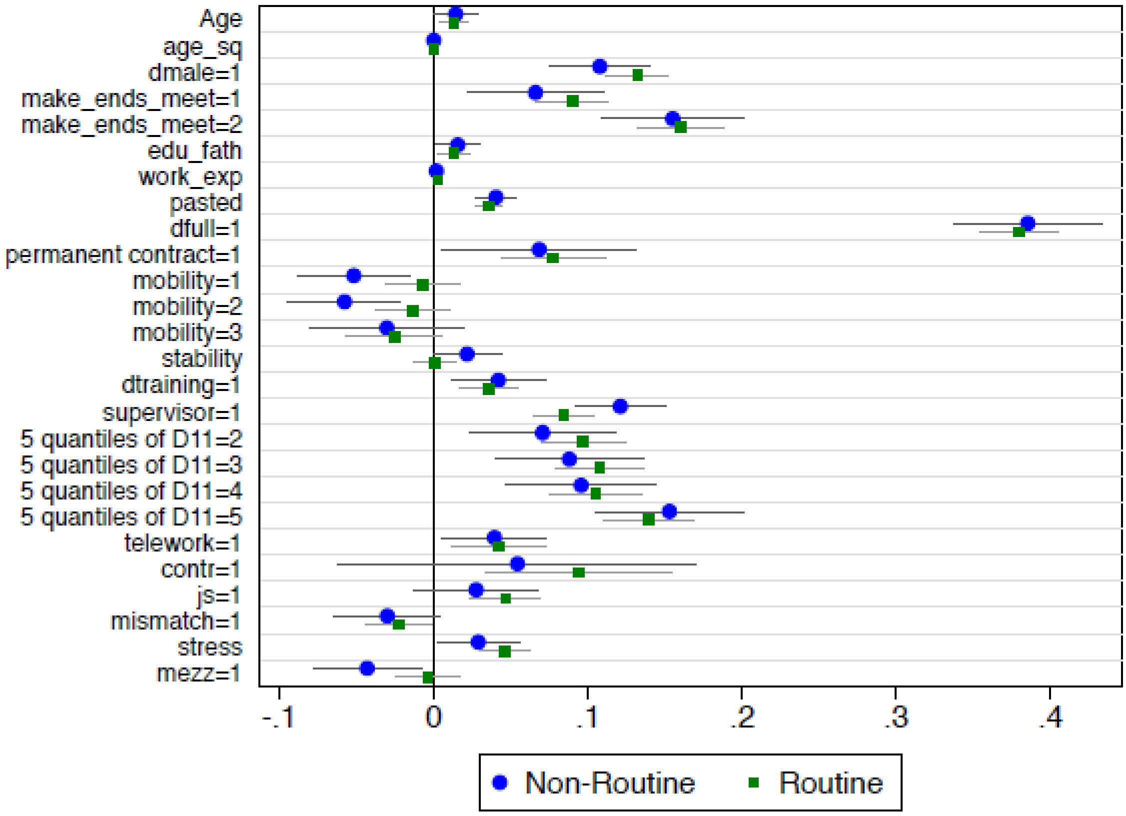


Figure 4
Minceriam Wage Regressions, OLS estimates - Actual Routine

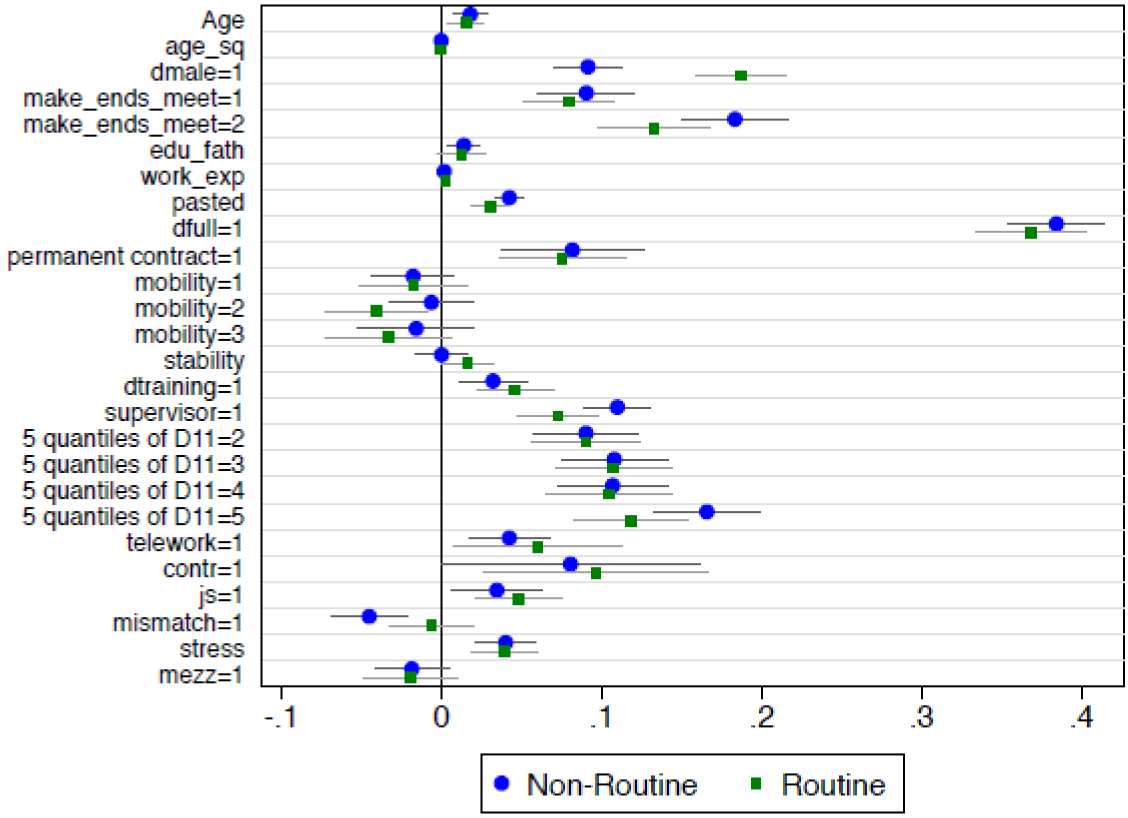


Figure 5
Counterfactual Decomposition using quantile regression (Semi-Parametric), for Perceived (Top) and Actual (Bottom)