Changes in the Italian wage distribution: the role of routine and social tasks

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Abstract

A broad economic literature has analyzed changes in the wage structure using a task-based framework. This paper complements this literature by providing evidence on the relationship between the task content of occupation (routine and social tasks) and wage inequality among Italian employees using unconditional quantile regressions (UQRs). This article also quantifies the contribution of changes in occupational task prices and other factors to changes in the distribution of wages over the 2009-2019 period using the RIF decomposition approach. Results show that behind the almost flat trend of wage inequality observed for the last decade operate divergent forces that counterbalance each other. In particular, changes in the reward for social tasks operate in an inequality-enhancing direction. However, changes in the wage structure linked to other factors, such as education and sector of economic activity, go in the opposite direction and offset the contribution of social task-intensive occupations.

Keywords: wage distribution, occupational tasks, unconditional quantile regression, RIF decomposition
JEL No. J21, J24, J31

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1. Introduction

An important economic literature has used the task-based approach developed by Autor, Levy, and Murnane (2003) to study changes in wage structure that occurred in many western countries starting from the second half of the eighties (Acemoglu & Autor, 2011; Firpo et al., 2014; Fortin & Lamieux, 2016). Generally, most of the studies investigating changes in the wage distribution over time focus on changes in the return to both observable (education and experience) and unobservable skills. More recently, attention has also been paid to the potential role of occupation in explaining changes in wage inequality. The role of occupation has become central in this analysis because, according to the "routinization theory", it represents a potential channel through which technological change can contribute to changes in wage inequality. The "routinization hypothesis" has been developed to explain the broad pattern of job polarization observed in the US and Europe that implies the faster growth of both high-skilled and low-skilled occupations with respect to mid-skilled jobs (Autor and Dorn, 2013, Goos et al., 2014).

Autor et al. (2003) explain this novel pattern by linking changes in the employment distribution to technological development that involves the substitution of computer capital for specific tasks previously performed by labor. More specifically, computers and machines tend to replace routine tasks, i.e., tasks that can be performed by following precise and codifiable rules. In contrast, they complement non-routine cognitive and interactive tasks that involve complex problem–solving and communication activities. Therefore, the substitution of new technologies for labor – pushed by the decline in the price of computer capital - alters the demand for professions according to the type of task required. In net, technological progress boosts demand for tasks complex to computerize that usually characterize professions located in the upper tier of the job quality distribution, such as managerial and professional occupations, and in the lower part of the distribution, such as low-paying service jobs. At the same time, the diffusion of new technologies decreased the demand for routine tasks performed by workers employed in occupations in the middle of the employment structure, mainly clerical and skilled manual jobs. Thus, demand shocks driven by the massive diffusion of computers and ICT may also have altered the returns of occupational tasks, carrying important implications for the wage structure. In particular, many scholars attribute the pattern of wage polarization observed in the US starting from the 1990s to the diffusion of routine-biased technologies that caused wages in the middle of the distribution to fall more than wages in the upper and lower quantiles of the distribution (Acemoglu & Autor, 2011; Firpo et al., 2014: Firpo et al., 2018).

Hence, the development of the task-based approach has placed occupation at the forefront of theoretical and empirical research on changes in wage distribution. This framework developed by Autor et al. (2003) and then refined by Acemoglu and Autor (2011) assesses the role of technology by looking at the occupation since the kind of tasks performed by workers is usually determined at the occupational level. An extensive literature investigating the main drivers behind polarization has focused on the degree of routinary tasks performed by workers and thus the extent to which tasks can be expressed in computer codes (Autor et al., 2003; Autor & Dorn, 2013; Goos et al., 2014, among others). More recently, some scholars have started to analyze also the interpersonal dimension of tasks (Borghans et al., 2014; Deming, 2017; Deming et al., 2018; Cortes et al., 2021). According to the literature on task-biased technological change, labor market returns to routine tasks are supposed to collapse, whereas returns to analytical and interpersonal tasks should rise since they cannot be substituted by technology. However, since the 1990s, technology may have expanded the range of tasks machines and robots can perform. According to some studies (Deming, 2017; Lu, 2015), the deceleration of high-skilled employment growth detected in the US in the post-2000 period is due to the possibility for technology to substitute also for an increasingly set of analytical tasks, especially those that can be expressed as a set of rules (Levy & Murnane, 2012). Since social tasks – i.e., those tasks that require social interactions – still cannot be substituted away by technology (Autor, 2015), intense social task occupations seem to have experienced substantial employment and wage growth in the last decade in the USA (Deming, 2017).

To understand the potential mechanisms that could link technological progress, tasks, and occupation, scholars have developed theoretical models that differ in how they account for skills and tasks. A first model explaining the effect of technological progress on the earning distribution - which Acemoglu and Autor (2011) refer to as the "canonical model" – assumes a "skill-biased" technological change. New technologies increase labor demand for skilled (high-educated) workers and thus their wages relative to those of the unskilled ones (low-educated) (Katz & Murphy, 1992; Autor, Katz, and Krueger, 1998). Hence, the main prediction of this model is a monotonic increasing relationship between wage growth and skills, often identified with education (Acemoglu, 2002). However, this model struggles to explain the pattern of wage polarization observed in the 1990s in the US. To overcome this shortcoming, Acemoglu and Autor (2011) developed a wage-setting model in which tasks, and thus occupations, are formally incorporated. In particular, they model a clear distinction between skills and tasks, where the former is used to produce the latter, and workers choose occupation according to comparative advantages in performing occupational tasks. According to this model, wage changes are not only linked to variation in the pricing of skills, as in the canonical model but to changes in the pricing of tasks determined by demand factors like technological change.

This paper aims to analyze changes in labor earning structure that occurred in Italy over the last decade in light of the task-based framework. More specifically, I investigate if occupation contributes to changes in the distribution of wages over the last 10 years in Italy, focusing on two key task dimensions: social and routine tasks. I do so using unconditional quantile regressions (UQRs) and the decomposition method both based on the recentered influence function regression (RIF) (Firpo et al., 2009; 2018). The RIF decomposition quantifies the contribution of changes in returns of occupational tasks – compared to other explanatory factors – to changes in wage structure over the period 2009 – 2019. The RIF regression approach is advantageous because it allows analyzing the relationship between tasks and wages in different parts of the distribution. Moreover, this methodology allows to decompose changes in inequality into a composition effect -i.e., changes in the characteristics of the workforce - and a wage structure effect – i.e., changes in rewards of these characteristics- and to evaluate the contribution of each single covariates. We apply the RIF decomposition to measure of top -end (90-50 inter – quantile range), low-end (50-10 inter – quantile range), and overall (90-10 inter – quantile range) wage inequality, as well as to the Gini Index and the variance of low wages. In our analysis, we take advantage of the 2009 and 2019 waves of the Italian Labor Force Survey matched with measures of task content of jobs computed from the Italian Sample Survey of Professions (ICP, hereafter) run by INAPP. The main advantage of using the ICP survey is that it provides highly detailed information on tasks and skills, allowing to adequately capture between-occupation heterogeneities.

First, I show no signs of wage polarization in Italy but rather a pattern of slightly decreasing inequality in the period considered. Results from the UQRs show that the increase in the fraction of people employed in jobs that require to perform social tasks is associated with an increase in inequality. Moreover, results from the RIF decomposition show that behind this slight decrease in wage dispersion operate two effects that push inequality in opposite directions: changes in the composition of the workforce go in an inequality enhancing direction, whereas changes in the wage structure entail a reducing impact on wage dispersion. The wage structure effect dominates the composition effect and drives the dynamics of wage changes. The wage structure effect related to social task-intensive occupations acts in an inequality-enhancing direction, but the wage structure effects associated with sectors of economic activity, education and firm size offsets it and have a relevant role in explaining the slight decrease registered in wage dispersion.

This article adds to the broad economic literature on the relationship between tasks and labor market outcomes by providing empirical evidence on the role of occupational tasks in shaping the earning distribution in Italy. Firpo et al. (2014), using a RIF regression approach, assess the contribution of occupational tasks to changes in the wage structure of the USA and found that technology plays a significant role in explaining changes in the wage distribution that occurred in the 1980s and 1990s in the USA but has a marginal role in the 2000s. Naticchioni et al. 2014 perform a similar analysis for Europe, founding slight signs of polarization of the wage structure and a weaker effect of technology with respect to the US. Recently other studies have used the RIF decomposition approach to explain the increase in wage inequality in Germany (Biewen & Seckler, 2019) and the divergence of wage inequality trends in many countries in Europe (Pereira & Galego, 2019). This last study considers Italy also, but the role of occupation has been analyzed at a 1-digit level of aggregation, and the task content of occupation is not taken into account. One of the main novelties of this paper is that we consider occupation at a highly detailed level, and measures of occupational task content are computed using the

Italian Sample Survey of Professions ICP INAPP – ISTAT 2012 survey, that provides, for every 5-digits Italian occupation, information on skills, abilities, and tasks. In an independent paper, Fana & Giangregorio (2021) analyzed changes in the Italian wage distribution in the 2007-2017 decade using the same RIF decomposition methodology proposed in the following. The two papers present different results due to the different data sources (they use the UE-SILC survey), the slightly different period under consideration and the different outcome variable (they use annual gross earnings whereas I use net hourly wages). The main difference is that Fana & Giangregorio (2021) focus on institutional factors, whereas, in this paper, the strong emphasis is on the role of occupational tasks. In particular, Fana & Giangregorio (2021) use 9 broad occupational categories and do not have information on tasks. On the opposite, exploiting the Italian Labor Force Survey matched with the ICP survey, I can assign task indexes to every 5-digit occupation. Only highly detailed information on tasks at the highest possible level of disaggregation, such as those in the ICP survey, allows for properly analyze between occupations heterogeneities.

The evidence provided in this paper also contributes to the growing literature that analyzes the role of social tasks. Borghans et al. (2014) find that, since women are more likely to be employed in occupations that require a high degree of social tasks, social task importance explains the trend in the gender wage gap. Deming (2017) assesses the impressive growth in the importance of social tasks in terms of employment and wage returns. This result is also confirmed by Cortes et al. (2021), that looking at within occupation changes in tasks over time, found that higher-paying occupations experienced a significant increase in the importance of social tasks over the last decades in the USA. As far as we know, this is the first paper that explicitly analyzes occupational tasks' role in explaining changes in wage distribution in Italy, investigating the role of social tasks.

The paper is organized as follows. Section 2 presents the decomposition methodology used. Section 3 describes the data and presents descriptive statistics. Section 4 presents and discusses the empirical findings. Section 5 concludes.

2. Methodology for Unconditional Quantile Regression and RIF decomposition

In order to study the relationship between occupational task content and wage structure I apply the RIF decomposition. A classic Oaxaca – Blinder decomposition can be applied to evaluate differences between two groups or time periods at the mean, but RIF regressions allows to extend the OB decomposition to any distributional statistics for which RIF can be defined. This methodology has been proposed by Firpo et al. (2009) that use recentered influence functions (RIFs) to perform unconditional quintile regressions (UQRs). The UQR allows to estimate the relationship between the explanatory variables with any unconditional quintile of the dependent variable. The RIF regression approach allows to estimate the effect of changes in covariates not on quantiles only, but on any distributional statistics besides the mean, for example Firpo et al. (2018) apply the RIF regression to inequality measures such as Gini Coefficient, variance of log wage and inter-quantile ranges.

Firpo et al. (2009) suggest replacing the dependent variable with the recentered version of its Influence function (IF) which is a statistical tool for testing the robustness of functionals and distributional statistics to outlier data (Hampel 1974). The recentered influence function is defined as:

$$RIF(w, v) = v(F_w) + IF(w, v)$$

Where w is the outcome variable, F_w its distribution function and $v(F_w)$ the statistic of interest, e.g. the qth quantile. One of the properties of the RIF is that integrates up to the statistics of interest:

$$v(F_w) = \int RIF(w, v)dF_w = E(RIF(w, v))$$

Firpo et al. (2009) assume that the conditional expectation of $RIF(w, v)$ can be modelled as a linear function of the explanatory variables, i.e.:

$$E(RIF(w, v)|X) = X\beta$$

where β can be estimated by OLS. Thus, using the law of iterative expectations the statistics of interest can be obtained as:

$$v(F_w) = E(E\ [RIF(w, v)|X]) = E(X)'\beta$$

Where β is the marginal effect of a "small location shift" (Firpo et al. 2009; p. 954) in the distribution of X.

Thus, as first step we compute the RIF for all the distributional parameters of interest and then we run OLS regressions of the RIFs over the explanatory variables.

Then, we apply a RIF regression decomposition to divide changes over time of the wage distribution between a composition effect – i.e. differences in characteristics - and a wage structure effect – i.e. differences in coefficients. Let v_0 be the RIF estimate of the distributional statistics at time 0 and v_1 at time 1, then the change of distributional parameter of interest is given by:

$$\Delta v = v(F_w^1) - v(F_w^0) = v_1 - v_0$$

where F_w is the distribution function of the dependent variable. To divide changes in the statistic of interest into a composition and a wage structure effect, it is necessary to estimate a counterfactual distribution obtained by combining the wage structure at time 0 with the characteristics at time 1. Then, the gap in the distributional statistics can be decomposed into two components:

$$\Delta v = \underbrace{v_1 - v_c}_{\Delta v_s} + \underbrace{v_c - v_0}_{\Delta v_x}$$

Where v_c is the RIF estimate of the distributional parameter of interest associated with the counterfactual distribution F_c , Δv_x represents differences in characteristics, i.e. the Xs, and Δv_s difference in the rewards of those characteristics, i.e. the coefficients. To identify the counterfactual statistics v_c , following Firpo et al. (2014, 2019) we use a reweighting strategy proposed by Di Nardo et al. (1996). The idea behind this strategy is to obtain an approximation of the counterfactual distribution by reweighting the distribution of Xs at time 0 to have the same distribution of time 1. The reweighting factor is given by:

$$\omega(X) = \frac{\Pr(t=1|X)\,/\Pr\,(t=1)}{\Pr(t=0|X)\,/\Pr\,(t=0)} = \frac{\Pr(t=1|X)\,/\Pr\,(t=1)}{[1-\Pr\,(t=1|X)/\Pr\,(t=0)}$$

Where $\Pr(t=1|X)$ is the conditional probability that an individual with characteristics X is in the sample t=1 and Pr $(t=1)$ and Pr $(t=0)$ are the sample proportions for the two time periods. A logit or probit model can be used to estimate the conditional probability (Firpo et al. 2018). Then, we estimate three separate RIF regressions:

$$v_0 = E\left[RIF\left(w, v(F_w^0)\right)\right] = \bar{X}^{0\prime}\hat{\beta}^0$$

$$v_1 = E\left[RIF\left(w, v(F_w^1)\right)\right] = \bar{X}^{1\prime}\hat{\beta}^1$$

$$v_c = E\left[RIF\left(w, v(F_w^c)\right)\right] = \bar{X}^{c\prime}\hat{\beta}^c$$

Where v_c is the distributional statistics computed on the reweighted sample. The estimates of the decomposition components can be defined as follows:

$$\Delta v = \underbrace{\bar{X}^{1\prime}(\hat{\beta}^1 - \hat{\beta}^c)}_{\Delta v_s^p} + \underbrace{(\bar{X}^1 - \bar{X}^c)\hat{\beta}^c}_{\Delta v_s^e} + \underbrace{(\bar{X}^c - \bar{X}^0)\hat{\beta}^0}_{\Delta v_x^p} + \underbrace{\bar{X}^{c\prime}(\hat{\beta}^c - \hat{\beta}^0)}_{\Delta v_x^e}$$

Where Δv_s^p and Δv_x^p are respectively the pure wage structure and the pure composition effect, Δv_s^e is the reweighting error that measure the quality of the reweighting strategy and Δv_x^e is the specification error that is used to assess the importance of departure from the linearity assumption.

Then, like in the traditional Oaxaca Blinder decomposition I further decompose the composition and wage structure effect into the contribution of each covariate. However, just as the standard OB decomposition, the contribution of each covariate to the wage structure effect is sensitive to the choice of the omitted base group (Firpo et al. 2011).

3. Data and descriptive statistics

The data source of this analysis is the 2009 and 2019 waves of the Italian Labor Force Survey (ILFS, hereafter). The ILFS provides a rich array of information on labor market status and socio-demographic characteristics. Usually, household income surveys are used to carry out analyses on income distribution. ILFS is not a household income survey, but since 2009 it has recorded net regular wages earned one month before the interview (additional month's remunerations excluded). The ILFS also collects information on the hours usually worked per week. Employees' monthly wages and weekly work hours are used to compute a proxy of hourly wages that is then deflated to 2015 real euros using the consumer price index. I select full-time and part-time employees aged 16 to 64 who spend at least 10 hours per week, thus excluding only workers with a marginal attachment to the labor market. However, I am forced to exclude self-employed since the ILFS records only employee earnings information. The lack of data on self-employed earnings represents an important caveat of using ILFS instead of a household survey (as SHIW or EU-SILC). In fact, self-employment is an important source of inequality in Italy (Iacono & Ranaldi, 2021), and excluding income from self-employment may result in underestimating earnings inequality. However, other studies that analyze which factors account for changes in distributions of wages focus on employees only since data on self-employed income often presents reliability issues (Pereira & Galego, 2019, among others). Moreover, this paper analyzes the relationship between earnings and the task content of occupations, which is likely to be the same across employees and self-employed. It is important to stress that the focus of this paper is only on workers in employment that earn positive earnings since the main aim is to study the relationship between changes in the return to task prices and the earning distribution. Therefore, using labor income as the only source of income is not a limitation in this contest. In fact, it is standard in the literature that studies changes in the wage distribution through a task framework to look at the distribution of wages only (Acemoglu & Autor, 2011; Firpo et al., 2013; Fortin & Lamieux, 2016; Firpo et al., 2018).

A limited number of works have used the ILFS to study inequality in Italy[2] (Carta, 2020; Carta & De Philippis, 2021). However, Firpo et al. (2014), in order to analyze the role of occupational tasks in shaping the income distribution in the US, exploit the same methodology proposed in this paper and use the Current Population Survey (CPS) which is a labor force survey conducted monthly by the U.S.

[2] Carta (2020) and Carta & De Philippis (2021) in their works rely on distributional indicators computed on ILFS data on earnings. Carta (2020) shows that indicators computed on the ILFS closely resemble those calculated using household income surveys.

Bureau of Labor Statistics[3]. A labor force survey is best suited to analyze changes in the labor market since it is specifically designed to describe and measure the labor force status, employment, and unemployment. Moreover, the ILFS contains information on occupations at a high level of disaggregation (5-digit occupational level) that allows assigning extremely detailed and granular information on tasks at each occupation.

I begin by providing descriptive statistics for the log of hourly wages. Table 1 displays percentiles of hourly wages (10th, 50th, and 90th) and measures of inequality: inter-quantile ranges (90-10, 90-50, and 50-10), the Gini index, and the variance of log wages. Log hourly wages experienced, on average, a slight increase of 1.5%. Looking at other parts of the distribution, the 10th and 5th percentiles have increased by 4.6% and 2.8%, respectively, whereas the 90th has decreased slightly by 1%. As a result, wage inequality in Italy, as measured by the 90-10 inter-quantile range, slightly decreased by almost 6%. A mild decrease in overall inequality is also confirmed by the Gini Index and the variance of log wages that has decreased over time by 1.9% and 1.5%, respectively.

The dynamic of both the 50th – 10th and 90th- 50th inter–quantile ranges shows that there is no evidence of wage polarization in Italy, with the indexes decreasing by 3.9% and 1.8%, respectively.

Table 1 Descriptive statistics on wage distribution

	Mean	p10	p50	p90	90-10	50-10	90-50	GINI	Variance
2009	2.086	1.678	2.063	2.533	0.856	0.470	0.386	0.129	0.198
2019	2.101	1.724	2.092	2.523	0.798	0.431	0.368	0.111	0.183
Time Change	0.015	0.046	0.028	-0.011	-0.057	-0.039	-0.018	-0.019	-0.015

Note. Authors' elaborations on ILFS data

From the ILFS, a set of explanatory variables is derived: geographical area (three categories: North; Centre; South), sex (female vs. male), education (three categories: primary; secondary, and at least tertiary), potential experience (3 categories: less than 10 years of experience; between 10 and 30 years; more than 30 years), type of employment contract (temporary vs. permanent; part-time vs. full-time), industry (5 categories: primary and utilities; manufacturing; construction; services; public administration, education, health, and social assistance) and firm size (less than 10 employees vs. more than 10 employees). I also include controls for marital status and citizenship. Table 2 presents descriptive statistics for the explanatory variables used in the analysis. Of particular interest is the growing share of workers with a tertiary degree. Moreover, it is possible to notice an increase in the share of workers employed with temporary and part-time arrangements. Looking at the sector of economic activity, we can see a loss of employment in the construction industry, which the 2008

[3] Firpo et al. (2018) also exploit the CPS to decompose changes in the wage distribution in US using RIF-regressions.

economic crisis severely hit. The share of employment in other sectors stayed pretty constant except for the service sector, which registers a noticeable increase in the share of workers employed.

Following the literature that studies the relationship between technological change and occupational tasks (Autor et al., 2003; Autor & Dorn, 2013; Firpo et al., 2014), I add to our set of covariates two measures of task content of jobs: the degree of routinization and the degree of social tasks required. These measures are computed from the Italian Sample Survey of Professions (ICP) survey provided by the Italian Institution of Public Policies Analysis (*Inapp*), which provides for every 5 digits of occupation information on working conditions, skills, abilities, and tasks. These measures are then merged to the LFS at a 5-digit occupation level. Hence, following Firpo et al. (2014) I first compute a "routinization" index averaging over four ICP items: i) time spent making repetitive motions; ii) degree of automation; iii) importance of repeating the same physical or mental activities over a relatively short period; iv) to what extent the worker is free to determine tasks, priority, and goals (which enters reversely). Then, following Deming (2017), I build the social task intensity index as the average of four ICP variables: i) coordination; ii) negotiation; iii) persuasion; iv) social perceptiveness. One of the main advantages of this paper is that we use the ICP to compute the task measures. Many papers that have analyzed the relationship between professions and changes in the employment structure in Europe (Goos et al., 2009; Goos et al., 2014; Naticchioni et al., 2014) have used the U.S. Occupational Information Network (O*Net), which provides a rich set of information on the characteristics of the U.S. occupations. However, a particular profession in Italy may have different characteristics with respect to the same profession carried out in the U.S. The ICP survey collects a rich set of information on all the Italian occupations at a 5 – digit. Therefore, using the ICP survey instead of the O*Net database may help avoid potential biases if we attribute to the Italian professions information that describes a different occupational structure.

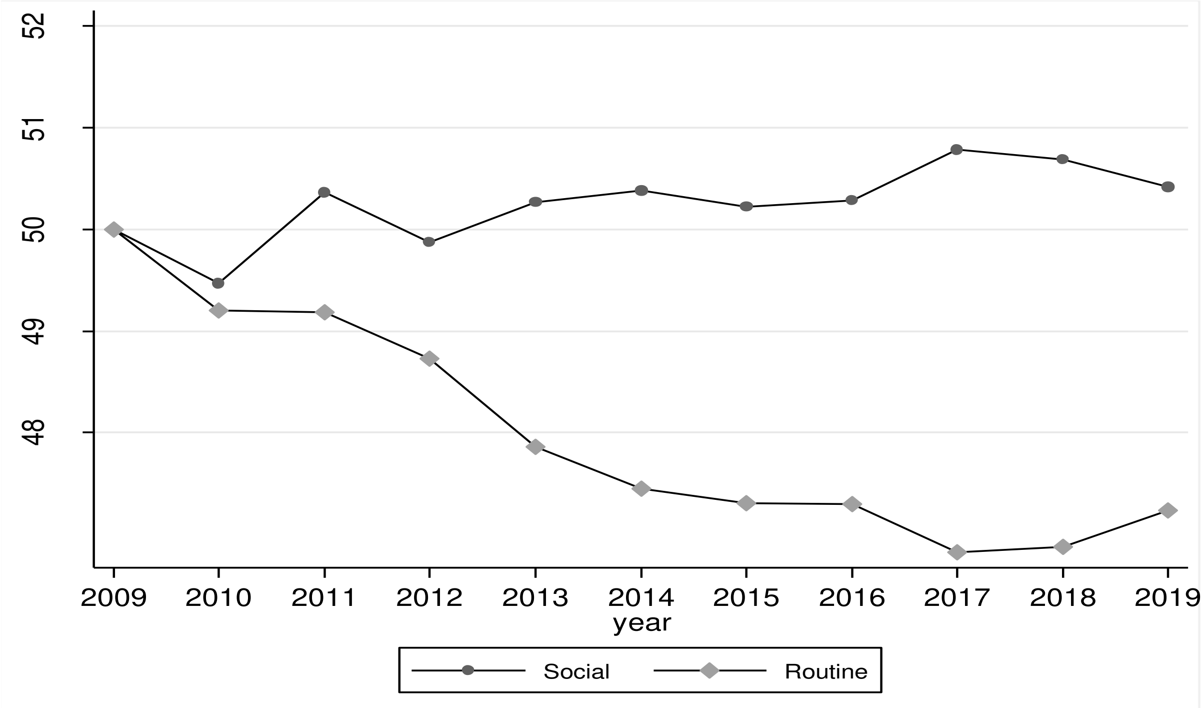
Table 2 Descriptive statistics on explanatory variables

	ILFS waves	
Variables	*2009*	*2019*
Not Married	0.32	0.09
No Citizenship	0.36	0.12
Female	0.44	0.45
North	0.53	0.54
Centre	0.21	0.21
South	0.26	0.25
Low education	0.36	0.30
medium education	0.48	0.48
High Education	0.16	0.22
Experience <10	0.17	0.15
10<Experience <30	0.54	0.46
Experience >30	0.29	0.38
Temporary Contract	0.12	0.17
Part-time	0.15	0.20
Primary and Utilities	0.04	0.05
Manufacturing	0.23	0.22
Construction	0.07	0.05
Service	0.42	0.45
PA, Health and Education	0.24	0.23
Seize <10	0.28	0.30

Note. Authors' elaborations on ILFS data

Now, I provide an overview of changes in the worker tasks performed in the Italian economy between 2009 and 2019. Figure 1 is constructed following Deming (2017) and Autor et al. (2003), imposing each task measure to have a mean of 50 centiles in 2009. Thus, succeeding points depict changes in the employment-weighted mean of each task's measures relative to its relevance in 2009. Since both task variables are time-invariant, changes in the tasks performed by the Italian workers are driven solely by changes in the occupational distribution. Figure 1 shows that the two measures took a clearly divergent path from 2012. From 2012 onwards, the share of workers employed in routine occupations started to decrease, whereas the share of workers employed in socially intense occupations started to increase, albeit at a more contained pace. The period under investigation may be too short to appreciate significant changes in work tasks but still can give an idea about relevant trends.

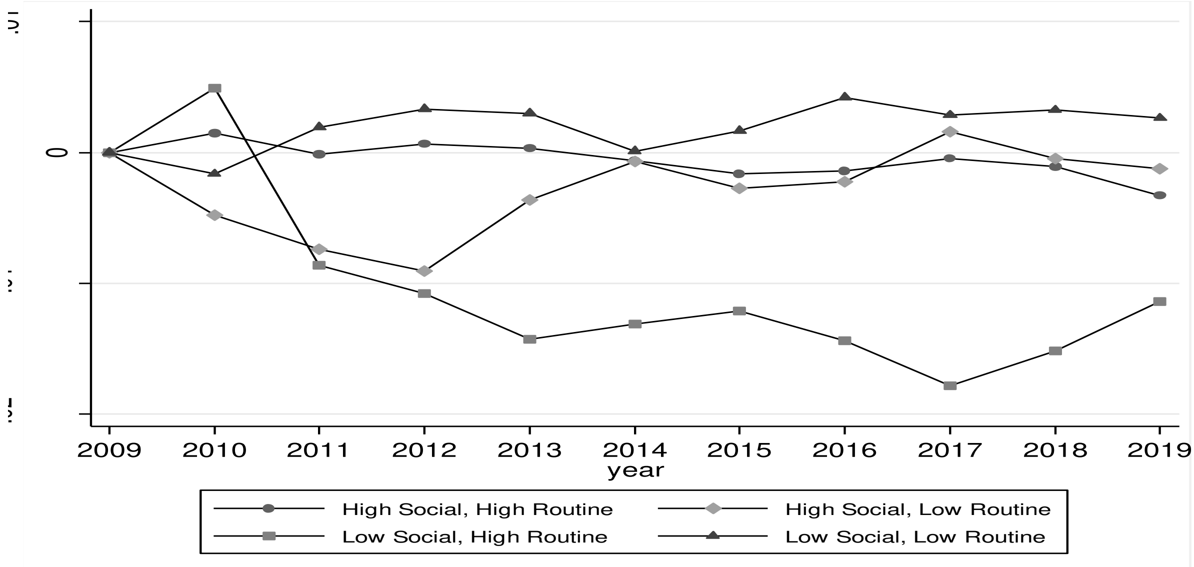
Figure 1 Workers Tasks, 2009-2019



Note. Authors' elaborations on ILFS and ICP data

Next, I present the evolution of employment share by their routine and social task intensity degree. A strong negative correlation exists between the two task measures (-0.6). Thus, I build 4 mutually exclusive occupational groups: the job is above the median percentile in both the routine and social index; the job is below the median percentile in both the routine and social index; the job is above the 50th percentile in social intensity but below in routine intensity; the job is above the 50th percentile in routine intensity but below in social intensity. Figure 2 displays employment share changes for each occupational group, taking 2009 as the base year. Patterns of labor force changes employed in the high-routine/low-social group and in the low-routine/high-social group resemble the trends observed in Figure 1, thus confirming the negative correlation between the two task indexes. Moreover, it is clear that changes in the employment distribution occurred in these two groups of jobs, whereas for the other two groups (intensive in both the measures or not intensive in both the measures), the share of labor input employed stayed relatively constant. These 4 occupational dummies are added to the model along with the other explanatory variables.

Figure 2 Relative changes in employment share by task intensity



Note. Authors' elaborations on ILFS and ICP data

4. Empirical results

4.1 Results from unconditional quantile regressions

In this section, I explore the determinants of labor earnings at different parts of the wage distribution using the unconditional quantile regression proposed by Firpo et al. (2009). Unconditional quantile regression allows estimating the association between changes in the workforce characteristics and changes in the quantiles of the marginal distribution of earnings. In particular, I want to assess if the workforce's occupational/task intensity composition influences wage distribution. I start estimating a model that relates hourly wages to the complete set of explanatory variables described in section 3, including the 4 occupational-task intensity dummies.

Table 3 provides the results of the RIF regressions using the 10th, 50th, and 90th percentiles, and Figure 1 reports estimates of coefficients for main regressors from the 5th to the 95th percentile for the years 2009 and 2019. Table 4 shows the results of the RIF regressions using the Gini Index and the variance of log wages. Standard errors are obtained using a bootstrap procedure with 100 replications and are reported in parenthesis under the estimated parameters. The coefficients from the unconditional quantile regression give the association between a change in a specific wage quantile (or distributive statistics) and a slight increase in the share of workers with a certain characteristic. First, from Table 3 and Figure 3, it is possible to notice that the penalty for being a female worker is pretty homogeneous across the different quantiles of the earning distribution. Table 3 also shows that an increase in the share of workers with a tertiary degree ("high education" dummy) is associated with a rise in inequality since the estimated coefficients for tertiary education increase along with the wage distribution. This result is confirmed by Figure 3 which shows increasing convex returns to tertiary education across wage percentiles for 2009 and 2019. Thus, the upward sloping curves reported in Figure 3 highlight the inequality boosting power of tertiary education (the base group is middle education). However, it is possible to notice that from 2009 to 2019, the positive association between a change in the share of tertiary-educated workers and quantiles has decreased more for the upper part of the distribution. These changes across time in the marginal returns of tertiary education act in an inequality reduction direction, as confirmed by the RIF regression coefficients for the Gini index and the variance of log wages (Table 4): an increase in the share of tertiary graduates increases both the variance of log wages and the Gini index but with less intensity in 2019 than in 2009.

Moreover, the penalty for working in a temporary arrangement (the base group is "permanent contract") is highest for workers at the lower end of the earnings distribution and turns into a reward after the 90th quantile. This could be because among workers in the upper part of the wage distribution, those in high-paying occupations, e.g., managers and consultants, are often employed temporarily. These results suggest that the increase in the number of workers employed with temporary arrangements registered between 2009 and 2019 (see table 2) is likely to hurt more lower-earning workers and exacerbate inequality. Looking at the coefficient estimates for part-time workers, returns to part-time are positive but higher for central quintiles. Table 4 shows that an increase in part-time workers does not have a significantly different from zero association with the variance of log wages, but an increase in the share of part-time workers lowers the Gini Index.

Table 3. Unconditional Quantile Regression Coefficients on Log Hourly Wages

ILFS wave		2009			2019	
Quantiles:	10	50	90	10	50	90
Explanatory variables:						
Not married	-0.130***	-0.093***	-0.080***	-0.071***	-0.068***	-0.072***
	[0.006]	[0.003]	[0.007]	[0.004]	[0.003]	[0.005]
Not Italian citizenship	-0.263***	-0.145***	-0.075***	-0.202***	-0.117***	-0.065***
	[0.014]	[0.004]	[0.006]	[0.008]	[0.003]	[0.004]
Female	-0.141***	-0.109***	-0.090***	-0.085***	-0.090***	-0.086***
	[0.007]	[0.003]	[0.006]	[0.004]	[0.003]	[0.006]
North	0.067***	0.034***	0.017***	0.041***	0.038***	0.034***
	[0.007]	[0.003]	[0.006]	[0.004]	[0.002]	[0.005]
South	-0.201***	-0.036***	0.009	-0.126***	-0.039***	0
	[0.009]	[0.003]	[0.007]	[0.005]	[0.003]	[0.007]
Low education	-0.128***	-0.110***	-0.153***	-0.067***	-0.094***	-0.108***
	[0.007]	[0.002]	[0.008]	[0.005]	[0.003]	[0.004]
High Education	0.106***	0.145***	0.497***	0.084***	0.134***	0.376***
	[0.008]	[0.003]	[0.013]	[0.004]	[0.003]	[0.008]
Experience <10	-0.162***	-0.103***	-0.233***	-0.102***	-0.094***	-0.181***
	[0.010]	[0.003]	[0.008]	[0.007]	[0.003]	[0.007]
experience>30	0.022***	0.047***	0.100***	0	0.044***	0.085***
	[0.005]	[0.003]	[0.005]	[0.004]	[0.002]	[0.005]
Temporary contract	-0.288***	-0.102***	0.015***	-0.222***	-0.108***	0.021***
	[0.012]	[0.003]	[0.005]	[0.007]	[0.003]	[0.005]
Part-time	0.022**	0.055***	0.032***	0.052***	0.070***	0.032***
	[0.010]	[0.003]	[0.007]	[0.004]	[0.003]	[0.006]
High Social, High Routine	0.090***	0.125***	0.111***	0.023***	0.096***	0.108***
	[0.008]	[0.005]	[0.013]	[0.005]	[0.004]	[0.009]
High Social, Low Routine	0.043***	0.134***	0.220***	-0.036***	0.096***	0.226***
	[0.006]	[0.003]	[0.014]	[0.005]	[0.003]	[0.006]
Low Social, Low Routine	-0.127***	-0.006*	-0.013***	-0.102***	-0.044***	-0.010**
	[0.011]	[0.003]	[0.004]	[0.007]	[0.003]	[0.004]
PA, Health and Education	0.022*	0.090***	0.155***	-0.012	0.060***	0.131***
	[0.012]	[0.005]	[0.011]	[0.008]	[0.007]	[0.010]
Primary & Utilities	-0.213***	0.010*	-0.042***	-0.155***	0.008	-0.027**
	[0.017]	[0.006]	[0.009]	[0.012]	[0.006]	[0.011]
Services	-0.101***	-0.012***	-0.008	-0.109***	-0.032***	-0.022***
	[0.011]	[0.004]	[0.007]	[0.008]	[0.005]	[0.007]
Manufacturing	-0.106***	-0.038***	-0.031***	-0.046***	-0.010**	-0.032***
	[0.011]	[0.004]	[0.006]	[0.007]	[0.005]	[0.008]
Firm with <10 employees	-0.224***	-0.090***	-0.050***	-0.158***	-0.103***	-0.065***
	[0.009]	[0.002]	[0.005]	[0.005]	[0.003]	[0.004]
No. Of observations	162323	162323	162323	143306	143306	143306
R squared	0.119	0.271	0.195	0.15	0.257	0.145

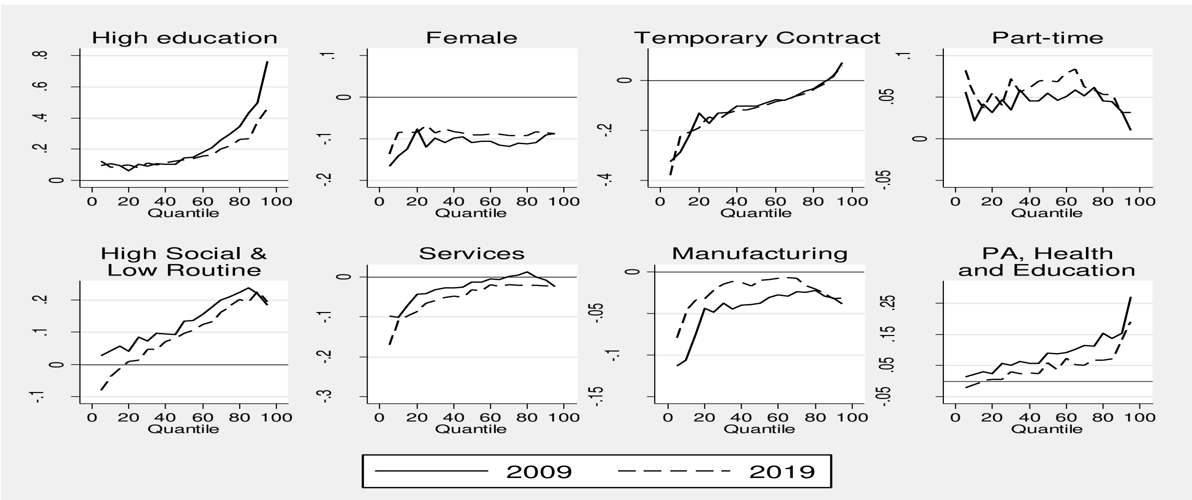
Bootstrapped standard errors (100 repetitions) in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Next, I look at the link between occupational task content and wage inequality. In order to do that, I build 4 dummy variables from the 4 mutually exclusive occupational groups presented in the previous section:

1. "High Social, High Routine", a dummy equal to 1 if the worker is employed in a job above the median in both the routine and the social index.
2. "High Social, Low Routine", equal to 1 if the worker is employed in a job above the 50th percentile in social intensity but below in routine intensity.
3. "Low Social, High Routine" is a dummy that takes the value of 1 if the worker is employed in a job above the 50th percentile in routine intensity but below in social intensity.
4. "Low Social, Low Routine", a dummy coded 1 if the worker is employed in a job below the median percentile in both the routine and social index.

I am particularly interested in the impact of the increase in the fraction of workers employed in "High Social, Low Routine Occupations" on earning dispersion (I choose "Low Social, High Routine" as the reference group). The RIF estimates (Table 3 and Figure 3) show that the returns for being employed in a "High social but low routine" occupation increase along with the wage distribution, meaning that the wage dispersion would increase as more individuals get employed in this kind of jobs. These results are confirmed by looking at Table 4, where the estimated coefficients show that an increase in the share of "High Social, Low Routine" worker are related to an increase in inequality as measured by both the Gini Index and the variance of log wages. It is also possible to notice that the magnitude of this association has increased between 2009 and 2019.

Figure 3. Unconditional Quantile Regression Coefficients



Note. Authors' elaborations on ILFS and ICP data

Looking at the contribution of the sector of economic activity (construction sector is the base category), an increase in the share of workers employed in the service sector and the "PA, Health and Education" sector leads to an increase in the earning dispersion since the rate of returns to both sectors rises along with the wage distribution.

Table 4 RIF regression on inequality measures

ILFS wave	**2009**		**2019**	
	GINI	**Variance of log wages**	**GINI**	**Variance of log wages**
Explanatory variables				
Not married	0.008***	-0.450***	0.004***	-0.515***
	[0.001]	[0.143]	[0.001]	[0.128]
Not Italian citizenship	0.025***	0.384***	0.031***	1.082***
	[0.002]	[0.148]	[0.001]	[0.128]
Female	0.006***	-1.163***	0.002**	-1.310***
	[0.001]	[0.156]	[0.001]	[0.138]
North	-0.005***	0.078	-0.004***	0.204
	[0.001]	[0.184]	[0.001]	[0.169]
South	0.031***	2.511***	0.026***	1.563***
	[0.002]	[0.200]	[0.001]	[0.177]
Low education	-0.006***	-2.381***	-0.001	-1.260***
	[0.001]	[0.105]	[0.001]	[0.088]
High Education	0.102***	17.510***	0.058***	9.703***
	[0.002]	[0.281]	[0.002]	[0.208]
Experience <10	-0.027***	-6.287***	-0.012***	-3.414***
	[0.002]	[0.196]	[0.002]	[0.210]
experience>30	0.014***	2.416***	0.013***	1.909***
	[0.001]	[0.154]	[0.001]	[0.143]
Temporary contract	0.047***	3.268***	0.053***	3.451***
	[0.002]	[0.183]	[0.001]	[0.153]
Part-time	-0.004***	0.152	-0.006***	0.178
	[0.002]	[0.185]	[0.001]	[0.160]
High Social, High Routine	-0.005***	-0.489**	0.003*	0.302*
	[0.002]	[0.220]	[0.002]	[0.179]
High Social, Low Routine	0.027***	4.355***	0.041***	4.890***
	[0.001]	[0.142]	[0.001]	[0.118]
Low Social, Low Routine	0.010***	0.210*	0.018***	0.794***
	[0.001]	[0.125]	[0.001]	[0.123]
PA, Health and Education	0.035***	6.177***	0.027***	3.918***
	[0.002]	[0.270]	[0.002]	[0.267]
Primary & Utilities	0.017***	0.161	0.021***	0.679**
	[0.003]	[0.260]	[0.003]	[0.283]
Services	0.011***	0.468***	0.017***	0.631***
	[0.002]	[0.163]	[0.002]	[0.194]
Manufacturing	0.008***	-0.011	0.002	-0.342*
	[0.001]	[0.155]	[0.002]	[0.205]
Firm with <10 employees	0.022***	0.651***	0.022***	0.317***
	[0.001]	[0.126]	[0.001]	[0.108]
No. Of observations	162323	162323	143306	143306
R squared	0.101	0.145	0.086	0.097

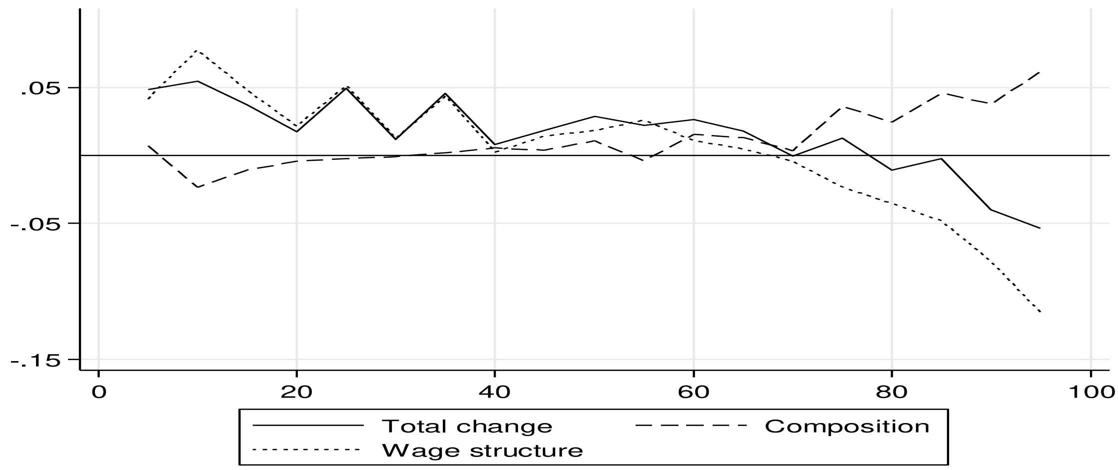
Bootstrapped standard errors (100 repetitions) in parentheses.
* p < 0.10, ** p < 0.05, *** p < 0.01

4.2 Decomposition results

In this section, I decompose changes that occurred between 2009 and 2019 in the wage distribution using the RIF decomposition discussed in section 2. In particular, I perform the decomposition on several inequality statistics such as inter-quantile ranges (90-10, 50-10, 90-50), Gini index, and variance of log wages.

Figure 4 displays the results for the aggregated decomposition. Changes in log wages at each percentile are decomposed into a composition and wage structure effect using the reweighting procedure described in section 2. The overall change curve's negative slope describes a decreasing inequality pattern more pronounced for the upper part of the distribution. Table 5a shows that overall wage inequality – as measured by the 90-10 log wage gap, the Gini, and the variance of log wages – lightly decreased between 2009 and 2019. Wage dispersion declined in both the top-end and the low-end of the distribution, as measured by the 90-50 and 50-10 log wage gap, respectively. Hence, we do not find a pattern of wage polarization for Italy like the one detected for the US in the 90s, where overall changes were described by a U-shaped curve (Firpo et al. 2014; 2018). Figure 4 shows that behind the decreasing trend for wage dispersion are operating countervailing forces: the composition effect goes in an increasing inequality direction, whereas the wage structure effect in the opposite direction. Looking at both figure 4 and table 5a is possible to see that the latter effect offsets the former and prevails over it. The magnitude of the change is entirely attributable to the wage structure effect that in all the considered inequality measured explains all the decrease in inequality (Table 5a). On the other hand, the composition effect has an inequality-enhancing impact but has a smaller magnitude with respect to the coefficients' component effect.

Figure 4 Overall change, Composition and Wage Structure Effect

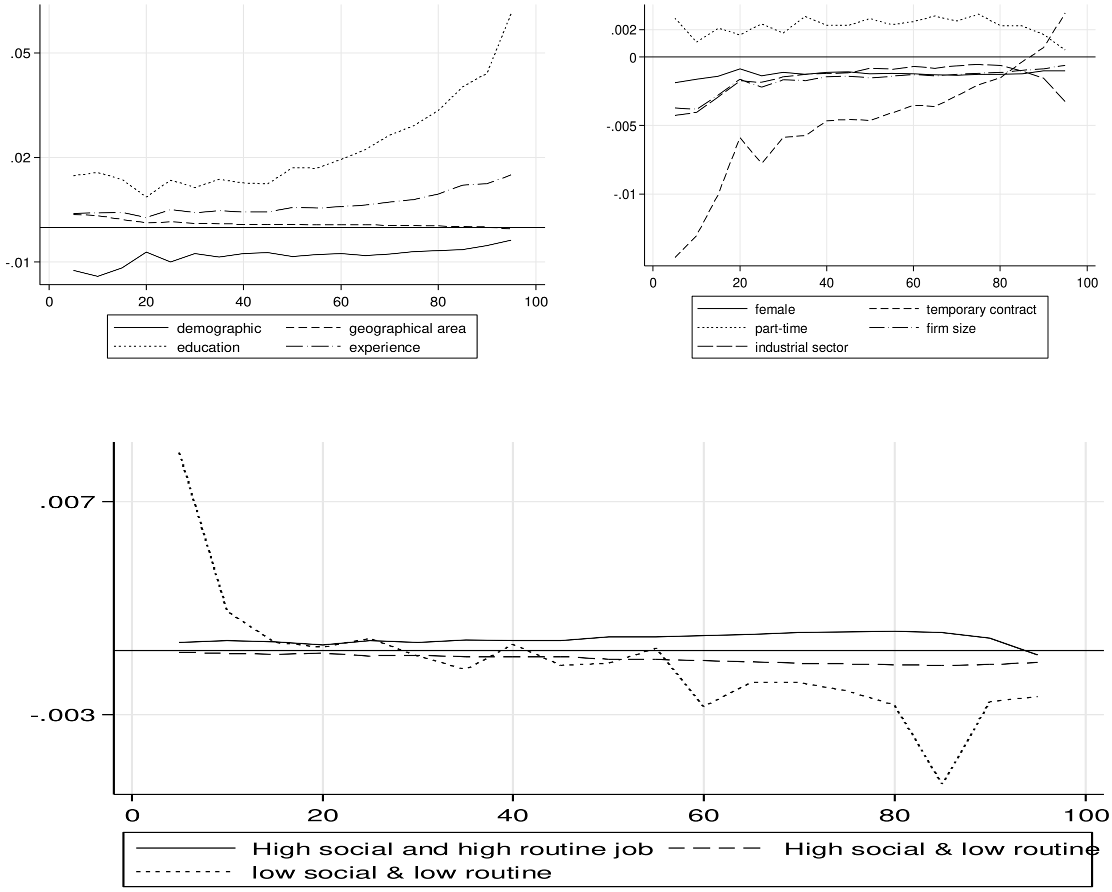


Note. Authors' elaborations on ILFS and ICP data

Figure 5 and figure 6 show the contribution of each set of explanatory variables to composition and wage structure effect, respectively. Figure 5a shows that the composition effect linked to education goes in an increasing wage dispersion direction. In particular, the composition effect related to education increases inequality in the upper end but has a less critical role in the lower - end of the distribution, where the curve is relatively flat. Thus, the increase in the share of high-educated workers reported in table 2, having a larges effect on higher percentiles, tends to increase wage dispersion. This means that if only the educational composition of the workforce had changed over time, there would have been an increase in wage dispersion. This result is confirmed by estimates reported in table 5a where it is possible to notice that the contribution of education to the composition effect is more important than composition effects related to other explanatory variables. This result holds for all the inequality measures except for the 50-10 log wage differential, where education accounts for a smaller part of the composition effect with respect to other indexes.

Moreover, the increase in the diffusion of temporary arrangements is another factor that acts in an inequality-increasing direction. On the other hand, Figure 5 shows that changes in the number of workers employed in occupations requiring high social interactions and low routine tasks do not contribute to inequality reduction. This result also holds for the other two categories of occupational task content. Composition effects related to other explanatory factors such as experience and demographic have a way smaller explanatory power since their contribution appears to be relatively flat across percentiles.

Figure 5. Detailed composition effect

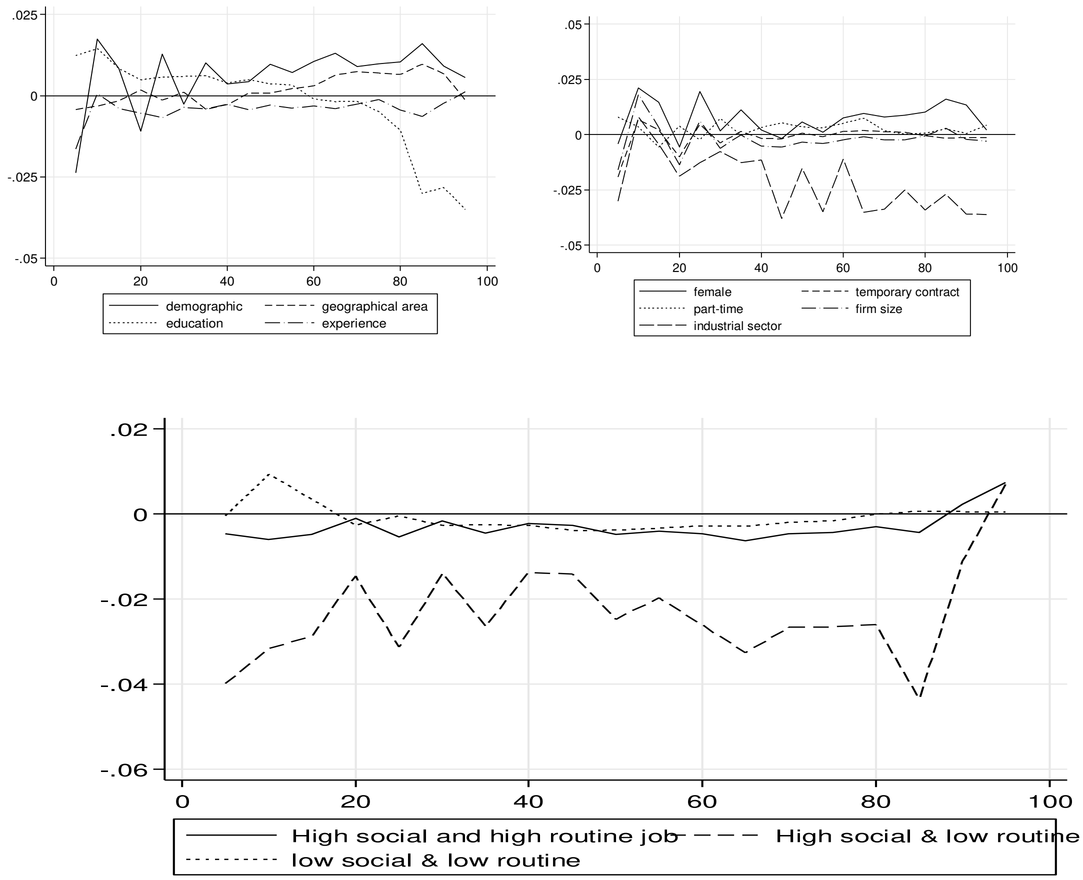


Note. Authors' elaborations on ILFS and ICP data

Considering changes in coefficients, changes in rewards for temporary contracts act in an inequality reduction direction for the 90-10 and 50-10 interquantile ranges, but slightly increase wage dispersion for the Gini Index and variance of log wages (Figure 6 and Table 5b). Figure 6 shows that coefficients for experience are relatively flat and close to zero, and thus the contribution of this component to the wage dynamics is very modest and not statistically significant. On the other end, education is a factor that pushes wage dispersion down (tertiary education returns for workers in the upper part of the wage distribution have decreased over time). Looking at the task content measures, changes in the wage structure linked to being employed in a "High social, low routine" occupation go in an inequality-increasing direction when we consider all our inequality measures. Engaging in a "High social, high routine" occupation goes in the same inequality-increasing direction, whereas the wage structure effect linked to "Low social, low routine" professions accounts for inequality reduction.

Looking at other components that entail a reducing impact on wage dispersion, we can observe a highly non-monotonic decreasing curve across the distribution for the sector of economic activity. More specifically, table 5b shows that the wage structure effect linked to the sector of economic activity accounts for a significant part of the decline of the wage dispersion for the 90-10 and 90-50 interquantile ranges. The changing wage structure effect linked to workers employed in micro-sized firms (less than 10 employees) also accounts for a significant reduction in the 90-10 and 50-10 interquintile ranges.

Figure 5. Detailed wage structure effect



Note. Authors' elaborations on ILFS and ICP data

Table 5a. Overall Change and Composition effect

Inequality measures:	90-10	50-10	90-50	Gini	Variance
Total Change	-0.094***	-0.025***	-0.069***	-0.015***	-0.019***
	[0.012]	[0.003]	[0.013]	[0.001]	[0.001]
Composition	0.059***	0.034***	0.024*	0.011***	0.013***
	[0.014]	[0.004]	[0.014]	[0.000]	[0.001]
Wage Structure	-0.153***	-0.060***	-0.093***	-0.027***	-0.032***
	[0.006]	[0.004]	[0.005]	[0.001]	[0.001]
		Composition effect			
Demographics	0.009***	0.006***	0.003***	0.001***	0.001***
	[0.001]	[0.001]	[0.000]	[0.000]	[0.000]
Macro area	-0.004***	-0.003***	-0.001***	-0.000***	-0.001***
	[0.001]	[0.000]	[0.000]	[0.000]	[0.000]
Education	0.029***	0.002**	0.028***	0.008***	0.008***
	[0.002]	[0.001]	[0.002]	[0.000]	[0.000]
Experience	0.008***	0.002***	0.007***	0.002***	0.002***
	[0.001]	[0.001]	[0.001]	[0.000]	[0.000]
Temporary Contract	0.014***	0.008***	0.005***	0.002***	0.003***
	[0.001]	[0.001]	[0.000]	[0.000]	[0.000]
Female	0.001***	0.000***	0.000**	0.000***	0.000***
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Firm with <1o employees	0.003***	0.002***	0.001***	0.000***	0.000***
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
High Social, High Routine	0	0.000**	0	-0.000**	0
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
High Social, Low Routine	-0.001	0	0	0	0
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Low Social, Low Routine	0.000*	0.000*	0	0.000*	0.000*
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Part-time	0.001	0.002***	-0.001***	-0.000***	-0.000**
	[0.001]	[0.001]	[0.000]	[0.000]	[0.000]
Industrial Sectors	0.002***	0.003***	-0.001***	0.000*	0.000***
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Specification error	-0.004	0.012***	-0.016	-0.001***	-0.001***
	[0.015]	[0.004]	[0.014]	[0.000]	[0.000]

Note. Authors' elaborations on ILFS and ICP data

Table 5b. Wage structure effect

Inequality measures:	90-10	50-10	90-50	Gini	Variance
		Wage Structure Effect			
Demographics	-0.007	-0.007	0	0.002**	0.002**
	[0.006]	[0.004]	[0.004]	[0.001]	[0.001]
Macro area	0.01	0.004	0.006	0.002	0.002
	[0.008]	[0.007]	[0.008]	[0.002]	[0.002]
Education	-0.042***	-0.011***	-0.032***	-0.006***	-0.008***
	[0.005]	[0.004]	[0.004]	[0.001]	[0.001]
Experience	-0.003	-0.003	0.001	0.001	0.001
	[0.006]	[0.004]	[0.004]	[0.001]	[0.001]
Temporary Contract	-0.007**	-0.005**	-0.002	0.002***	0.001***
	[0.003]	[0.002]	[0.002]	[0.000]	[0.001]
Female	-0.007	-0.014***	0.008*	0	0
	[0.006]	[0.004]	[0.005]	[0.001]	[0.001]
Firm with <10 employees	-0.019***	-0.020***	0.002	0.001	0
	[0.004]	[0.003]	[0.002]	[0.000]	[0.001]
High Social, High Routine	0.008***	0.001	0.007***	0.001***	0.001***
	[0.002]	[0.001]	[0.001]	[0.000]	[0.000]
High Social, Low Routine	0.020***	0.007**	0.013***	0.004***	0.002*
	[0.005]	[0.004]	[0.004]	[0.001]	[0.001]
Low Social, Low Routine	-0.008***	-0.013***	0.004***	0	-0.001**
	[0.002]	[0.002]	[0.001]	[0.000]	[0.000]
Part-time	-0.003	0	-0.003	0	0
	[0.004]	[0.003]	[0.002]	[0.000]	[0.001]
Industrial Sectors	-0.042**	-0.021	-0.021*	-0.002	-0.002
	[0.018]	[0.014]	[0.012]	[0.002]	[0.003]
Constant	-0.046*	0.025	-0.071***	-0.030***	-0.030***
	[0.024]	[0.020]	[0.017]	[0.003]	[0.004]
Reweight Error	-0.008***	-0.002***	-0.005***	-0.001***	-0.002***
	[0.001]	[0.000]	[0.000]	[0.000]	[0.000]
N	305629	305629	305629	305629	305629

Note. Authors' elaborations on ILFS and ICP data

5. Conclusions

This article presents evidence on the relationship between occupational tasks (social and routine) and changes in the Italian employees' wage distribution. Taking advantage of the rich information contained in the ICP survey, I was able to assign to each Italian occupation extremely granular information on professional task content. First, I show evidence of the decline of relative employment for routine-intensive jobs and the relative employment growth – even if quite content - in occupations requiring a high degree of social interactions. UQRs estimates show that a rise in the share of workers employed in "High social, low routine" occupations is associated with an increase in earnings inequality. This association's magnitude has increased from 2009 to 2019. Then, by using the RIF – decomposition approach proposed by Fortin et al. (2011), I analyze changes in the Italian wage distribution in the last decade. I do not find signs of wage polarization but rather a stable trend of wage inequality that presents only a slight fall attributable to wage structure effects, which account for the entire change in distributional indexes. When I evaluate the contribution of task content to change in inequality indexes, I find that changes in task prices (mainly changes in the rewards of being employed in social intensive occupations, either "High social and low routine" or "High social and high routine") operate in an inequality enhancing direction. However, this positive impact on inequality is offset by opposing forces. In particular, the inequality-enhancing impact of "social" occupations is offset by the wage structure effect linked to the sector of economic activity, firm size and education. However, these results should be interpreted with caution since the 2008 economic crisis may have left the most vulnerable workers out of the labor market, thus leading to an only apparent and paradoxical decline in wage inequality.

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