A RIF REGRESSION APPROACH TO EVALUATE WAGE CHANGES: A FOCUS ON ITALY

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1. Introduction

The recent structural changes in the European labour markets and in their income distribution are being encouraged by the ongoing economic crisis (see Acemoglu 1999; Autor 2003; Goos et al. 2009 among others). In Italy, the effects of the crisis have been made more serious because of the political instability and geographical disparities (Ballarino et al. 2014). Moreover, its impact on politics and society has been as relevant as its impact on the economy (Di Quirico, 2010).

In this context, our paper aims at investigating the dynamics and the strength of changes in wage and wage inequality in Italy in the years of the Great Recession by analysing the role of individuals' skills and of countries' labour markets in rewarding employees. In line with the aim of identifying the driving forces of income changes over time and their intensity, we perform the *Recentered Influence Function* (hereafter, RIF) regression (Firpo et al., 2007; 2009; 2011) of Gini, variance, median and the two extreme deciles (q10 and q90) on log-wage. The RIF methodology is an extension of the Oaxaca-Blinder decomposition (Blinder, 1973; Oaxaca, 1973). However, unlike the latter can be applied only to the mean, the RIF decomposition is suitable to different distributional statistics. This allows us to explore the primary factors of wage levels and wage inequality and to decompose their changes over time into the composition and wage structure effects and, finally, to evaluate the contribution each factor gives to the overall changes. While the first component refers to the effect attributable to workers' characteristics, the second captures the effect due to the capability of the country's labour market to valorise individual skills and endowments.

We use the Italian section of the EU-SILC data (European Union Statistics on Income and Living Conditions) with regard to two different years (2005 and 2013), which enables capturing the potential impact of the economic and financial crises on wage distribution and inequality. The paper is structured as follows. Section 2 offers a methodological overview and discusses some descriptive statistics of the crucial variables. Section 3 argues the results of the RIF regressions and decompositions. Section 4 concludes.

2. Methodology and Technical Choices

We perform RIF regression (Firpo et al., 2007; 2009; 2011) of several distributional statistics on the logarithm of individual gross wage. Yearly gross wage has been computed starting from the monthly gross wage and considering the months during which the employee has experienced a paid employment[1]. This methodology replaces the dependent variable (Y_i) with the RIF of the generic distributional statistic to study, which is denoted by $v(F_y)$. Y_i denotes the observed wage, which is supposed to be a function of some observed and unobserved components, X_i and ε_i, respectively:

$$Y_{ti} = f_t(X_{i,}\varepsilon_i), \qquad for \quad t = 0, 1 \tag{1}$$

with $t = 0$ if individual i was an employee in 2005 and $t = 1$ if he/she was an employee in 2013. Mathematically, the influence function $IF(Y,v)$ is the first-order directional derivative and measures the relative effect of a small perturbation in the underlying outcome distribution on the statistic of interest (Hampel, 1974).

The RIF regression is defined as follows:

$$RIF(Y; v) = IF(Y; v) + v(F) \tag{2}$$

and assuming having mean zero by construction (Firpo et al. 2011).

The RIF regression can be written for some distribution statistics (Firpo et al., 2007) and consequently for all the quantiles (Firpo et al., 2011). Here we adopt a mix approach; that is, we introduce the RIF regression for Gini, Variance and Median (as in Firpo et al., 2007) and also for two quantiles of the distribution to understand what it the behaviour in the extreme of the distribution, namely q10 and q90.

Consequently, for the Gini index, the RIF regression can be written as follows:

$$RIF(y; v^{GC}) = 1 + 2\mu^{-2}R(F_y) - 2\mu^{-1}\left[y[1 - p(y)] + GL(p(y); F_y)\right] \tag{3}$$

and for the variance $RIF(y; v^{\sigma^2})$ and quantiles $RIF(y; Q_p)$we have:

[1] The incidence of the missing data on the gross monthly wage is little more than 7%. We consider this value reasonable given the high sample sizes for Italy (14,996 employees in 2005 and 11,670 in 2013). Notwithstanding the deletion of missing data, the sample sizes of Italy are still higher than in some of the major European countries (e.g., France: 9,077 and 8,935 in 2005 and 2013, respectively; Germany: 11,047 and 10476; the United Kingdom: 7,418 and 8,130). We also controlled for missing values on covariates whose proportions are rather negligible and, in any case, lower than 1%. However, given the low presence of missing data and based on other simulations, we can consider the relative generating process as missing at random and the potential bias due to their deletion negligible.

$$RIF(y; v^{\sigma^2}) = (y - \int z dF_y(y))^2 = (y - \mu)^2 \quad (4)$$

$$RIF(y; Q_p) = Q_p + [p - \mathbb{I}(y \leq Q_p)]/f_y(Q_p) \quad (5)$$

where $f_y(Q_p)$ is the marginal density, Q_p is the sample quantile and $\mathbb{I}(y \leq Q_p)$ is an indicator function that allows one to include employees in a specific quantile where the outcome variable is smaller or equal to Q_p (Firpo et al., 2011).

As anticipated, we estimate the RIF regression for Gini index, variance, median, q10 and q90. Once the estimates have been obtained for each measure, the changes in these distributional statistics between 2005 and 2013 are decomposed into the composition effect and wage structure. Then, we compute the two components by covariate to quantify their contribution to gaps over time.

Let us denote the gap between period $t = 0$ and $t = 1$ of the five distributional statistics – $v(F)$ – with $\Delta_t^{v(F)}$. The next step consists in decomposing $\Delta_t^{v(F)}$ into the two terms of the wage structure ($\Delta_s^{v(F)}$) and composition effect ($\Delta_x^{v(F)}$). In general, for a given measure, we have:

$$\widehat{\Delta_O^v} = \bar{X}_1(\hat{\gamma}_{1,v} - \hat{\gamma}_{0,v}) + (\bar{X}_1 - \bar{X}_0)\hat{\gamma}_{0,v} = \hat{\Delta}_S^v + \hat{\Delta}_X^v \quad (6)$$

Assuming that for $t = 1$ the distribution of $(\mathrm{X}, \varepsilon)$ is constant, we get the wage structure, that is, the effect on v of a change from $f_1(\cdot,\cdot)$ to $f_0(\cdot,\cdot)$. Instead, assuming the return effect $f_0(\cdot,\cdot)$ fixed, the effect of changes from $(\mathrm{X}, \varepsilon)|_{t=0}$ to $(\mathrm{X}, \varepsilon)|_{t=1}$ represents the composition effect.

In this work, we focus on adult employees between 16 and 64 years old. Previously, we classified them into the three groups of high-, middle- and low-skilled according to their average level of education. In fact, since it is well known the strong correlation between the average educational levels and the skills required to a given job (Eurostat, 2010), we use education as a proxy of the level of skills required.

Since in EU-SILC interviews, individuals can report more than one labour activity, we consider the main employment, which is the activity with the largest number of hours usually worked. We consider the employees' wage in the gross form (composed of cash, near cash and non-cash wages) before any deductions for tax or social transfers. The explanatory variables of the RIF regression are classified into the three groups of individual characteristics (gender, couple, health), human capital (work experience, educational attainment), and job characteristics (type of contract, economic status, type of occupation). Table A1 in the Appendix shows the complete list with a detailed description of these variables.

3. Main Results

As argued by Castellano et al. (2017) and by Punzo and Ciommi (2017), while the most European labour markets are characterised by upgrading of occupations[2] or job polarisation[3], Italy sketched a *hybrid pattern* of structural changes over the years 2005-2013. In other words, it is not possible to define which employment structure prevails in Italy because the share of employees decreased for each of the three groups even though the decline in high-skill jobs was less marked than in low- and middle-skill counterparts (Garofalo et al., 2017).

Table 1 – *Sample measures on wages.*

	Gini	Variance	Median	q10	q90
2005	0.27488	1.77e+08	18,722	9,943	32,256
2013	0.31290	5.77e+08	26,742	10,225	48,478

*Wages are adjusted for inflation to guarantee their comparability over time in real terms.

Table 2 – *Occupation level by education, percentage, 2005.*

Education\Occupation	Low	Middle	High	Total
Low	17.40	19.82	2.65	39.87
Medium	7.64	26.39	10.49	44.53
High	0.54	4.65	10.41	15.60
Total	25.58	50.87	23.55	100.00

Table 3 – *Occupation level by education, percentage, 2013.*

Education\Occupation	Low	Middle	High	Total
Low	11.02	15.85	2.68	29.55
Medium	8.65	25.00	16.04	49.68
High	0.78	4.91	15.07	20.76
Total	20.45	45.76	33.79	100.00

Table 1 collects summary statistics on the measures involved in our analysis. In particular, we estimate the Gini index, the variance, the median and two quantiles of the wage distribution (q10 and q90) for both 2005 and 2013 with the aim of evaluating their evolution over time.

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[2] Upgrading of occupations occurs when there is a growth in the demand of high skills that is accompanied by a reduction of low- and middle-skill activities.

[3] Job polarisation occurs if there is a contraction of middle-skill activities in favour of high- and low skills jobs.

Table 4 – *RIF regression estimates. Year 2005.*

	Gini	Variance	Median	10^{th} perc	90^{th} perc
Male	-0.0015**	0.0359***	0.1641***	0.1462**	0.2750***
	(0.0005)	(0.0109)	(0.0090)	(0.0299)	(0.)
Never married	0.0008	0.0061	-0.1019***	-0.1288***	-0.1121***
	(.0005)	(0.0122)	(0.0106)	(0.0313)	(0.0230)
Other married	-0.0013	-0.0453**	-0.0458***	-0.0566	-0.0620*
	(0.0009)	(0.0195)	(0.0160)	(0.0509)	(0.0355)
Good health	0.0013**	0.0082	0.0236**	-0.0124	0.0806***
	(0.0005)	(0.0119)	(0.0099)	(0.0276)	(0.0234)
Experience	-0.0001	0.0006	0.0209***	0.0254***	0.0263***
	(0.0001)	(0.0019)	(0.0017)	(0.0052)	(0.0038)
Experience squared	3.62e-06*	0.00002	-0.0003***	-0.0004***	-0.0003***
	(2.10e-06)	(0.00005)	(0.00003)	(0.0001)	(0.0001)
Medium education	-0.0076***	-0.1633***	-0.1285***	-0.1468***	-0.4565***
	(0.0008)	(0.0169)	(0.0139)	(0.0317)	(0.0477)
Low education	0.0070***	-0.1506***	-0.2747***	-0.3410***	-0.6834***
	(0.0008)	(0.0184)	(0.0157)	(0.0407)	(0.0493)
Permanent job	-0.0148***	-0.2856***	0.1514***	0.7048***	0.1258***
	(0.0007)	(0.0153)	(0.0128)	(0.0618)	(0.0195)
Full time	-0.0261***	-0.4184***	0.2586***	1.5253***	0.1292***
	(0.0007)	(0.0167)	(0.0111)	(0.0732)	(0.0180)
Senior Official	0.0191***	0.4426***	0.3857***	0.5064***	1.2189***
	(0.0015)	(0.0344)	(0.0207)	(0.0751)	(0.1003)
Managers small	-0.0088***	-0.1547***	0.1695***	0.4627***	0.1423
	(0.0027)	(0.0594)	(0.0467)	(0.1213)	(0.1798)
Professionals	0.0033**	0.0728**	0.3103***	0.6099***	0.8638***
	(0.0013)	(0.0295)	(0.0238)	(0.0789)	(0.0808)
Teaching	-0.0162***	-0.2795***	0.3075***	0.5216***	-0.2563***
Professional	(0.0015)	(0.0332)	(0.0255)	(0.0862)	(0.0667)
Technicians	-0.0109***	-0.1639***	0.2763***	0.6339***	0.1028***
	(0.0010)	(0.0224)	(0.0194)	(0.0740)	(0.0363)
Clerks	-0.0101***	-0.1575***	0.1754***	0.6028***	0.1070***
	(0.0008)	(0.0180)	(0.0162)	(0.0711)	(0.0215)
Service workers	-0.0054***	-0.0803***	0.1268***	0.4213***	0.1206***
	(0.0010)	(0.0219)	(0.0183)	(0.0840)	(0.0284)
Skilled agricultural	-0.0040*	-0.0828*	0.0275	0.1715	-0.0321
	(0.0021)	(0.0466)	(0.0490)	(0.2070)	(0.0550)
Machine operator	-0.0118***	-0.1895***	0.1445***	0.5794506***	0.0011
	(0.0009)	(0.0207)	(0.0186)	(0.0740)	(0.0259)

In brackets, Standard Errors estimates. (***), (**) and (*) denote significance at 0.01, 0.05 and 0.1, respectively

Between the eight-year period, Italy showed a large increase in wage inequality. The Gini index, for instance, grew from 0.27 to 0.31, whereas the variance of wages in 2013 was more than three time greater than the value achieved in 2005. Looking at the main percentiles of wage distribution, we find that the wage levels had widened rapidly along the entire distribution. In particular, Italian high-paid employees (q90) experienced the greatest wage growth (almost 50%). The median wage also substantially increased (42.83%), whereas low-paid employees (q10) showed a more modest increase (2.83%).

Table 2 and Table 3 report the percent changes in 2005-2013 according to both the levels of education (low, medium, high), which is based on the ISCED-97 classification, and the categories of low-, middle- and high-skilled employees, which is based on the ISCO-08 classification. Between 2005 and 2013 there was a decrease in the share of low- and middle-skill occupations in favour of the high ones. If we look at the conditional distributions, there was an increase in the share of employees with a high level of education that perform low-skilled jobs. The greater negative percent variation was recorded for employees with a low level in both education and occupation (-6.38%), whereas the greater positive percent variation corresponds to medium level of education with a high level in occupation (5.55%).

Results from the RIF-regressions of the five statistics on log-wage are displayed in Tables 4 and 5. It is worth to note that for each statistic considered, gender, education and work experience play a crucial role in determining wage levels and inequality. More specifically, the evidence shows how better education and more experience in the labour market can reduce wage inequality.

Wage differentials are also associated with job characteristics, such as the economic status, the type of contracts and, above all, the different typologies of occupation. The most professions improve wage levels and reduce wage inequality compared to the more elementary jobs. Having a permanent contract and being a full-time employee are crucial to personal earnings. Their effect is negatively sloped – it is smaller at the 90^{th} than at the 10^{th} percentile – and well-structured workers tend to increase wages for the low quantiles. Being a service worker or machine operator has a stronger effect on the wage-generating process than being an elementary worker at the lower quantiles. The magnitude of the effect decreases at the right side of the wage distribution. This means that the advantage of being a service worker or machine operator rather than an elementary worker becomes irrelevant as they move up the pay distribution.

The differences in 2005-2013 of the five statistics are decomposed into the composition effect (endowment) and the wage structure (return effect). Table 6 summarizes the results. As stressed above, in 2013, all the statistics are increased. On the one hand, the five statistics confirm that for Italy the greater weight is associated with the return effect. The latter contributes from 86.68% for q90 and 98.62% for the variance to the total gaps. This implies that the total differentials in wage and wage inequality depend on the capacity of the Italian labour market to transform inputs into job opportunities and earnings

Table 5 – *RIF regression estimates. Year 2013.*

	Gini	Variance	Median	10th perc	90th perc
Male	-0.0030***	0.0985***	0.1765***	0.0300	0.2234***
	(0,0007)	(0.0215)	(0.0127)	(0.0338)	(0.0240)
Never married	-0.0003	-0.0021	-0.0046	-0.0307	-0.0798***
	(0.0008)	(0.0238)	(0.149)	(0.0358)	(0.0257)
Other married	0.0038***	0.1143**	0.0038	-0.1463***	0.0193
	(0.0012)	(0.0357)	(0.0195)	(0.0538)	(0.0395)
Good health	0.0009	0.0065	0.0290*	0.0069	0.1077***
	(0.0008)	(0.0246)	(0.0151)	(0.0389)	(0.0238)
Experience	-0.0010***	-0.0247***	0.0290***	0.0497***	0.0270***
	(0.0001)	(0.0038)	(0.0023)	(0.0074)	(0.0036)
Experience squared	0.00002***	0.0005***	-0.0004***	-0.0009***	-0.0004***
	(2.85e-06)	(0.0001)	(0.0001)	(0.0002)	(0.0001)
Medium education	-0.0032***	-0.0882**	-0.1657***	-0.1087**	-0.3146***
	(0.0009)	(0.0282)	(0.0171)	(0.0371)	(0.0406)
Low education	0.0025**	-0.0949**	-0.3138***	-0.2432***	-0.5020***
	(0.0011)	(0.0341)	(0.0217)	(0.0523)	(0.0431)
Permanent job	-0.0262***	-0.6185***	0.2510***	0.9511***	0.0544***
	(0.0010)	(0.0311)	(0.0167)	(0.0783)	(0.0203)
Full time	-0.0230***	-0.4127***	0.3392***	0.9090***	0.1114***
	(0.0009)	(0.0288)	(0.0144)	(0.0690)	(0.0184)
Senior Official	0.0160***	0.4328***	0.3071***	0.4215**	1.1933***
	(0.0035)	(0.1061)	(0.0628)	(0.1807)	(0.1929)
Managers small	0.0374***	-1.0107***	0.4765***	0.6554***	2.1695***
	(0.0044)	(0.1325)	(0.0493)	(0.0985)	(0.2006)
Professionals	-0.0037**	-0.0571	0.4296***	0.6559***	0.8588***
	(0.0016)	(0.0497)	(0.0287)	(0.0916)	(0.0695)
Teaching Professional	-0.0158***	-0.3155***	0.2721***	0.6027***	-0.0716
	(0.0016)	(0.0493)	(0.0293)	(0.0947)	(0.0471)
Technicians	-0.0115***	-0.2022***	0.4186***	0.6900***	0.3008***
	0.0013	(0.0403)	(0.0241)	(0.0869)	(0.0396)
Clerks	-0.0150***	-0.2938***	0.2199***	0.70467***	0.0540**
	(0.0012)	(0.0354)	(0.0214)	(0.0833)	(0.0237)
Service workers	-0.0100***	-0.2099***	0.10134***	0.5194***	0.0514**
	(0.0013)	(0.0388)	(0.0230)	(0.0961)	(0.0255)
Skilled agricultural	-0.0014	-0.584	-0.0383	-0.1803	0.0472
	(0.0037)	(0.1124)	(0.0650)	(0.3028)	(0.0921)
Machine operator	-0.0170***	-0.3403***	0.1952***	0.7188***	-0.0470641*
	(0.0015)	(0.0607)	(0.0288)	(0.0874)	(0.)

In brackets, Standard Errors estimates. (***), (**) and (*) denote significance at 0.01, 0.05 and 0.1, respectively

In particular, the increase in wage inequality might be almost fully explained by the low efficiency of the Italian labour market structure in contrasting it with adequate labour policies and support measures.

To complete the analysis, it could be interesting to identify which are the factors that more contribute to the differentials over time. Table 7 reports the results for a selection of variables. For both composition and wage structure effects, high-skilled employees with a permanent contract have an equalising effect in wage inequality in that they contribute to increase wage levels. High-educated employees reduce wage inequality and dispersion only in the wage structure.

Instead, in the composition effect, employees with a medium level of education contribute in increasing inequality less than their high-educated counterparts. Finally, the RIF-regression decomposition confirms that being female increases wage inequality, essentially due to their lower average salaries, reinforcing the role of composition effect in generating the observed gaps over time in wage levels and inequality.

Table 6 – *RIF decompositions for the five statistics. Gap 2005-2013.*

	Gini	Variance	Median	10^{th} perc	90^{th} perc
Total Gap	0.0064***	0.1879***	0.5305***	0.2021***	0.5814***
Composition Effect	0.0004	0.0026	0.0593***	0.0209*	0.0774***
	(6.25%)	(1.38%)	(11.18%)	(10.34%)	(13.32%)
Wage structure	0.0060***	0.1853***	0.4712***	0.1812***	0.5039***
	(93.75%)	(98.62%)	(88.82%)	(89.66%)	(86.68%)

*Significant at 10%; **Significant at 5%; ***Significant at 1%. Percentages (share) are in brackets.

4. Conclusions

The analysis of wage inequality has been conducted for five statistics, namely the Gini index, the variance, the median and the two extreme deciles (q10 and q90) on log-wage. Applying the so called Recentered Influence Function regression, we have analysed the main drivers of the logarithm of individual gross wage and decomposed the changes occurred over time in the income inequality. In addition, the decomposition into composition effect, which captures the impact due to individual attributes, and the wage structure that depends on the characteristics of the country highlights which are the factors that contribute the more to the inequality over time.

The analysis reveals what are the main weakness of Italian labour market and it could be used by policy makers to address more efficient policies voted at reducing wage inequalities among Italian employees.

In this work, we carried out the twofold (wage structure and composition effect) decomposition. It is well suited to our objective because it allows us to decompose the temporal gap in the share due to the role of employees' individual endowments and the share that captures how endowments are rewarded by the labour market. Our future goal may be to perform the threefold decomposition introducing the specification error (Firpo et al., 2011), which detects the simultaneous leverage produced by both effects. In the same way, we also should explore the role of other covariates (e.g., activity sector) to the changes of wages and wage inequality over time.

Table 7 – *RIF decomposition of the five statistics on log-wage by some variables.*

Variables	Measures	Composition effect		Wage structure	
		parameter	p-value	parameter	p-value
Gender (male)	Gini	-0.00009***	(0.00003)	0.00083*	(0.00050)
	Variance	-0.00320***	(0.00093)	0.03621***	(0.01401)
	Median	-0.00574***	(0.00116)	0.00721	(0.00901)
	Q10	-0.00097	(0.00113)	-0.06741***	(0.02620)
	Q90	-0.00726***	(0.00158)	-0.02995	(0.01837)
Experience	Gini	-0.00065***	(0.000012)	-0.00902***	(0.00130)
	Variance	-0.01534***	(0.00350)	-0.23370***	(0.03670)
	Median	0.04064***	(0.00271)	0.10229***	(0.02394)
	Q10	0.04682***	(0.00642)	0.22133***	(0.07883)
	Q90	0.03890***	(0.00380)	-0.00986	(0.04321)
Medium Education	Gini	-0.00015***	(0.00005)	0.00199***	(0.00053)
	Variance	-0.00425***	(0.00148)	0.03337**	(0.01464)
	Median	-0.00798***	(0.00131)	-0.01655*	(0.00979)
	Q10	-0.00524***	(0.00192)	0.01690	(0.02168)
	Q90	-0.01515***	(0.00276)	0.06304**	(0.02783)
Low Education	Gini	0.00026**	(0.00012)	0.00177***	(0.00056)
	Variance	0.00995***	(0.00362)	0.02215	(0.01541)
	Median	0.03290***	(0.00291)	-0.01554	(0.01066)
	Q10	0.02550***	(0.00567)	0.03890	(0.02635)
	Q90	0.05263***	(0.00538)	0.07216***	(0.02605)
Permanent job	Gini	-0.00023**	(0.00011)	-0.00979***	(0.00107)
	Variance	-0.00549**	(0.00259)	-0.28782***	(0.02997)
	Median	0.00223**	(0.00106)	0.08608***	(0.01821)
	Q10	0.00844**	(0.00403)	0.21293**	(0.00403)
	Q90	0.00048	(0.00030)	-0.06174**	(0.02439)
Full time	Gini	0.00108***	(0.00011)	0.00279***	(0.00107)
	Variance	0.01937***	(0.00222)	0.00501	(0.02958)
	Median	-0.01592***	(0.00159)	0.07159***	(0.01619)
	Q10	-0.04267***	(0.00505)	-0.54725***	(0.00505)
	Q90	-0.00523***	(0.00099)	-0.01576	(0.02284)

*Significant at 10%; **Significant at 5%; ***Significant at 1%. Percentages (share) are in brackets.

Appendix

Table A1 – List of variables

Dimension	Variables	Description
Individual Characteristics	Gender	*Dummy for gender (ref.: male)*
	Couple	*Dummy for marital status (ref.: married):* *- Never married: value 1 if employee has never been married and 0 otherwise* *- Other married: value 1 if employee has experienced marriage in the past and 0 otherwise*
	Health	*Dummy for General health (ref.: suffer)* *- Good health: value 1 if employee do not suffer from any chronic illness or condition and 0 otherwise*
Human Capital	Working experience	*Number of years since starting the first regular job that a person has spent at work*
	Education	*Dummies for high level of education (ref.: higher levels):* *- low- and medium-level (ISCED97: from pre-primary to, post-secondary non-tertiary education)* *- high-level (first and second stage of tertiary education)*
Job characteristics	Type of contract	*Dummies for type of contract:* *- Permanent job: value 1 if employee has permanent contract and 0 otherwise*
	Economic status	*Dummies for employment status:* *- Full time: value 1 if employee is full time and 0 otherwise*
Occupation	Professional status	*Ten dummies for professional status (ISCO classification)* *- elementary workers (ref); Senior official; Manager of small enterprise; Professionals; Teaching professional; Technicians; Clerks; Service Workers; Skilled Agricultural; Machine Operators.*

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SUMMARY

A RIF regression approach to estimate the structural changes in the Italian employment composition

This paper investigates how microeconomic characteristics affect wage levels and wage inequality in Italy, before and during the economic crisis. We use EU-SILC (European Union Survey on Income and Living Conditions) data at individual level (the unit of analysis are employees aged 16-64) for 2005 and 2013.

After analysing how the structure of employment has changed between 2005 and 2013 in Italy, we perform the Recentered Influence Function (RIF) regression of Gini index, variance, median and two extreme deciles (q10 and q90) on (log of) gross individual wage.

The RIF regression allows us to estimate the impact of changes on covariates on the whole unconditional distribution of the measures of interest. Thus, the changes in wage inequality are decomposed into two components: the composition effect, which captures the impact due to individuals' endowments, and the wage structure that depends on the labour market characteristics of the Country. Finally, the composition effect and the wage structure are computed for each covariate, highlighting the factors that contribute the more to the inequality over time.

The five statistics confirm that the greater weight is associated with the return effect. In particular, the analysis reveals that the increase in wage inequality might be almost fully explained by the low efficiency of the Italian labour market structure in contrasting it with adequate labour policies and support measures.

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