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Vanishing social classes? Facts and figures of the Italian labour market

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Vanishing social classes?
Facts and figures of the Italian labour market*

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Abstract

This paper analyses medium-term labour market trends from 1983 to 2018 in Italy relying on the "Rilevazione dei contratti di lavoro" from INPS archive which provides information on average salaries by professional category, age, gender, and geographical origin. Within an overall pattern of exacerbated inequalities, documented by means of different indicators, the empirical analysis highlights how the *within*-component of the wage variation prevails in the gender, age and geographical dimensions. By contrast, the *between*-component in terms of professional categories (trainees, blue-collar jobs, white-collar jobs, middle managers, executives) is the only between-variation attribute to prevail, corroborating the role played by class schema in explaining wage inequality. Regression-based inequality estimations confirm the role played by social classes. Stratification of wage losses is recorded being largely concentrated among blue-collar professional categories, women, youth, and in the Southern regions.

JEL Classification: E24, J31, J50.

Keywords: Inequality, wages, occupations.

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1 Introduction

From the 1980s onward both sociology and economics have witnessed a gradual marginalization of the role and centrality of social classes as lens of analysis in understanding, on the one hand, the structural transformation in the employment composition and, on the other hand, the socio-economic conditions and income evolution (Pugliese, 2008). With reference to Italy, with the exception of the pioneering contribution on the Italian occupational structure by Sylos Labini (2014, 1974), social classes have been largely dismissed in recent analyses, while inequality has revamped and gained a great deal of attention in the public and scholarly debate. Certainly, the underlying difficulty to operationalize the notion of social classes might have reinforced its abandonment in social sciences.

Nonetheless, the analysis via social classes, framed in terms of occupational categories, is still crucial to understand the undergoing transformations of society (Wright, 1998; Grusky and Weeden, 2001). Least but not last, social classes and occupational categories have been shown to be particularly relevant in analyzing the COVID-19 pandemic phase, especially in terms of access to telework (Cetrulo et al., 2020c) and, more in general, in studying educational opportunities, healthcare access, and intergenerational transmission of status (Albertini, 2013). Furthermore, the interaction between micro-level occupational structures and macro-level class schemes has been recently adopted as an interpretative lens in examining the anatomy of Italian occupations (Cetrulo et al., 2020a).

Hereby, using administrative data on Italian wages and jobs (INPS Longitudinal Sample – *Rilevazione dei contratti di lavoro*), we decline the notion of social classes via the underlying employment relations they entail and we focus, among the group of employees, on the different occupational hierarchical ladders, in line with recent research on social classes (Albertini, 2013). We look at the Italian labour market in the medium-run (1983-2018), and we intersect three interrelated dimensions: social classes – intended as the dynamics of the blue-collar, white-collar, managerial and business executive macro-occupational categories –, their remuneration in terms of wages, and their attributes in terms of industrial characterization, gender, age, type of job contract, and regional distribution.

Our results, within an overall picture of declining real wages, reduced number of working weeks and increasing number of jobs, highlight severe processes of divergences in terms of (i) wage distribution between white-collars and blue-collars versus executives, (ii) top versus bottom decile of the wage distribution, (iii) sectoral dynamics, (iv) gender and age divides. If the gap with respect to the top of the employment distribution tends to increase over time, some patterns of convergence versus the low-end appear, particularly after the 2008 crisis, in terms of (i) reducing the blue–white-collar wage gap, and of (ii) decreasing bottom–median wage gaps.

In terms of periodization, while some patterns of divergence exploded with the 2008 crisis, in particular the 'proletarization' of middle-wage occupations, some others, such as declining wages and jobs for the youth versus the elderly, definitely pre-date the 2008 crisis. Indeed, the gradual process of market flexibilization started at the beginning of the 1990s has resulted in a strong increase of part-time and short-term contracts, particularly among women in Southern Italy which record the lowest wage across all worker categories.

Within a general trend of exacerbated wage inequalities, the empirical analysis highlights how the within-component of the wage variation prevails in the gender, age and geographical dimensions. By contrast, the between-component in terms of professional categories (trainees, blue-collar jobs, white-collar jobs, middle managers, executives) is the only prevailing between-variation attribute, thereby corroborating evidence that the professional dimension still represents the greatest source of wage inequality. Regression-based inequality estimations confirm the role played by social classes. Stratification of wage losses is recorded being largely concentrated among blue-collar professional categories, women, youth, and in the Southern regions.

Our analysis is based on wage data of employed jobs and therefore does not take into account (i) other sources of income that contribute in explaining income inequality, (ii) employers' jobs, (iii) autonomous jobs. Although this might represent a limitation in understanding the overall dynamics of social classes, we believe worthy restricting the focus to wages only, since our interest lies in identifying eventual patterns of convergence/divergence in wages resulting from different positions along the hierarchy of employment relationship. In addition, considering the presence of managerial positions in our dataset and the increasing decision-making role exerted by the latter in business organizations, managers and executives represent the hierarchical ladder most akin to employers.

Finally and contrary to the purported pattern of sheer polarization that mainstream labour economics has put forward (Acemoglu and Autor, 2011), we do not find descriptive evidence of market-based competitive forces driving inequality which should be reflected in U-shaped wage and employment changes along wage percentiles: changes in wages by wage distribution do not follow changes in occupations by wage distribution. On the contrary, we detect a remarked tendency towards wage compression, resulting in a generalised negative wage growth, except for the very top percentile. This evidence leaves room for other institutionally and structurally based determinants of inequality, far from market-based forces (primarily technology and education).

The remainder of the paper is organised as follows. Section 2 describes the employed dataset, while Section 3 discusses facts and figures of the Italian labour market. Determinants of wage inequality are explored in Section 4. Section 5 presents our conclusions.

2 Data

We rely on the Italian Institute of Social Security Longitudinal Sample – *Rilevazione dei contratti di lavoro*, a high-quality micro-aggregated level data based on administrative records. As its name suggests, the dataset has a longitudinal structure and is based on a large representative sample of employees in the private sector – with the exception of agricultural and domestic jobs – from 1982 to 2018. Therefore, it does not include information on public employees or any type of self-employed jobs.

For each year the *Rilevazione dei contratti di lavoro* open archive[1] contains information on the number of jobs, yearly or weekly gross salaries and weeks of work (especially relevant for part-time and intermittent jobs) as reported by private-sector employers, together with a number

[1]INPS Open Data are available at: https://www.inps.it/OpenData/default.aspx?lastMenu=46293&iMenu=1&iNodo=46293&ifaccettaargomento=2

of socio-professional characteristics of the job, such as gender, age, typology of employment, region and economic sector of activity.

While the micro-level version of this dataset reports individual data, our analysis is based on the publicly available data, which contains information averaged over different segments of the workforce. Hence, we are not able to follow individual workers' employment histories, but we observe more aggregated characteristics of the labour force.

Each observation of our dataset is characterized by five of the aforementioned socio-professional variables – region (20 Italian regions), geographical area (North-West, North-East, South, Center, Islands), gender, age cohort (under 30, 30-50, over 50 years old), and occupational status (trainee, blue-collar, white-collar, middle managers, executives) – that identify specific segments of the labour force. In each year, the theoretical maximum number of segments given by all the combinations of the socio-professional characteristics is 600 (20 regions, 5 occupations, 3 age groups, 2 genders). However, when excluding missing values and considering the fact that the executive occupational category was introduced only in 1996, we obtain a total of 17371 observations with the actual maximum number of cells being 559 in 2003 and the minimum 344 in 1995. For all those combinations, in each year, is performed an average of the taxable amount of each worker's wage, the weeks actually remunerated in the year, the labour market entry age, the percentage of part-time (since 1985) and permanent (since 1998) jobs, the percentage of jobs in 1-digit ATECO 2007 economic sectors (i.e., Mining and Quarrying; Manufacturing; Metallurgy, Chemical and Pharmaceutical industries; Energy; Water Supply; Sewerage and Machinery; Construction, Wholesale and Retail Trade; Transport; Information and Communication together with Financial and Insurance Activities; Professional Services; Education and Human Health Activities; Other Services). For instance, a single cell of our dataset may detail for under 30 years old, white-collar women working in Sicily in 2018 the number of jobs on which the averages of the gross real salary and the weeks of work were performed, together with information on sectoral and type of employment shares.

To construct our sample, we focus primarily on the occupational structure as interpretative lens for the undergoing transformations in the Italian labour market, and on the interaction of the macro-occupations with the geographical area, type of employment, gender, age cohort and sectors in determining the distribution of wages, that are expressed in real terms in constant 2016 euros.

Given that we do not look at the individual dimension, to maximise the informative content of the data, we take into account the possibility of secondary or tertiary jobs and compute the averages across all the employment relationships in each segment of the labour force, rather than considering only primary jobs. Indeed, following the increasing weakening of the labor market regulation and the steady rise of non-standard jobs, accounting for primary jobs only and not for total jobs would determine an under-estimation of the real number of employment relations activated for a given category of worker in a given year.

To motivate our choice, Figure 1 presents the ratio between the number of first over total number of jobs (that may include secondary or tertiary jobs). The trend is clearly decreasing since 1980s, ranging from 95% in 1982 to 77% in 2018. However, the pace of the fall changes distinctively in three different periods, reflecting the process of job-fragmentation and the appearance of open-ended contracts: up to 1995 (5% drop), from 1995 to 2008 (13% drop), after

2008 (constant trend). Considering that secondary and tertiary jobs are concentrated among low paid occupations, their exclusion would upward bias the analysis.[2]

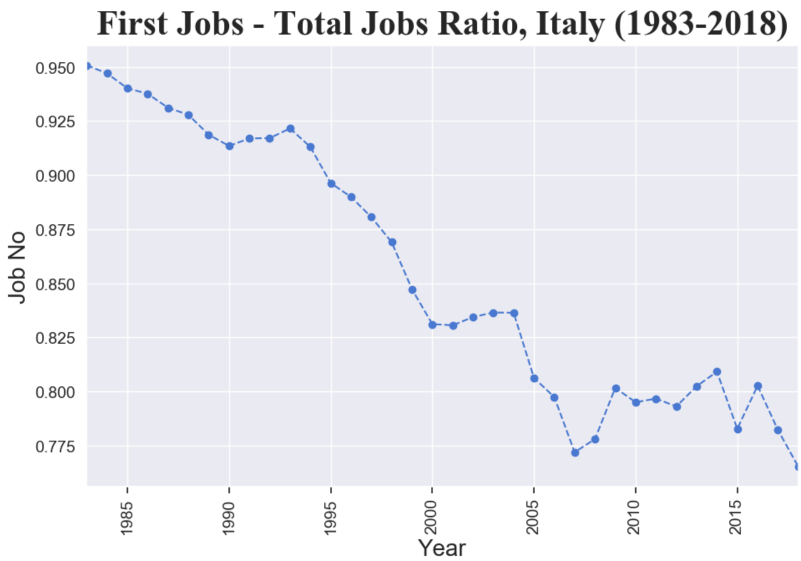


Figure 1: Ratio between number of first jobs and total number of jobs. Italy, 1983–2018.

Finally and as mentioned above, in our analysis we focus exclusively on yearly earnings. Despite the crucial role played by other sources of income, such as wealth (Acciari et al., 2020), we deem an analysis on wages extremely informative as they represent the principal source of disposable income for the majority of workers (Quintano et al., 2009), a major trigger of unequal distribution dynamics (Galbraith and Kum, 2003), and ultimately reflect the actual remuneration of productive labour in the market. Concerning the unit of scale, weekly and yearly wages can strongly differ as shown in Figure 2, since the latter are affected by both the level of hourly wages and the total amount of working weeks in a year. However, yearly figures are a more comprehensive measure inasmuch they incorporate the effect of potential wage reduction due to intermittent working activity, e.g. characterised by employment discontinuity or underemployment (as in the case of involuntary part-time or casual jobs).

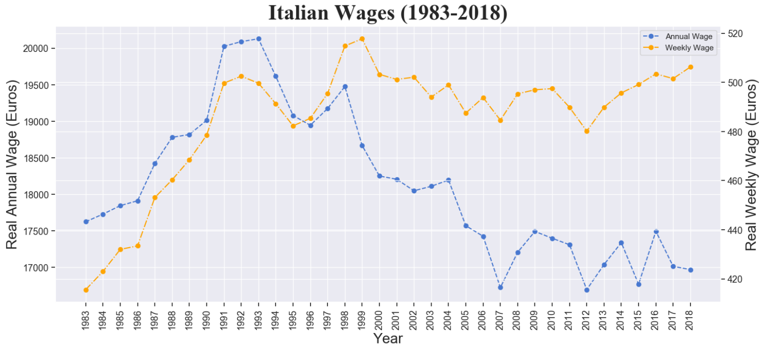
Table 2 shows descriptive statistics on the number of jobs and the average wage earned for each subgroup belonging to the different population groups described above, summarizing the increasing participation of women into the labour market (8,221 million in 2018 with respect to 2,261 million in 1983); the reduction in youth employment from 2003, as due to both longer educational careers, first-entry job regulated by atypical contracts, and increasing inactivity rates; the leading role of Northern regions that show both higher wages and a larger workforce; and the sharp fall of blue-collars' average wages (from 13 thousands euro in 1983 to 10 thousands euro in 2018) compared to the substantial increase in wages of middle managers and executives.[3]

[2] As robustness exercise, the empirical analysis has been replicated applying as statistical weight the number of first jobs, confirming our results. Such robustness exercise is available upon request.

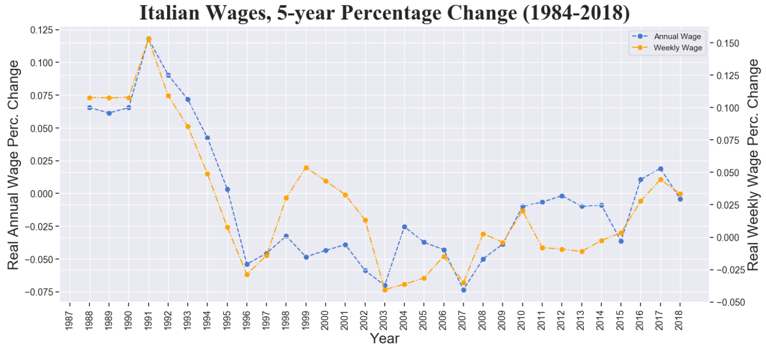
[3] Our database collects information on the private sector only, therefore the number of observed jobs differs from the total number of employees as reported by ISTAT (see: `http://dati.istat.it/Index.aspx?QueryId=31493`), last retrieved 26 July 2021.

			1983	1993	2003	2013	2018
Total		*Average Real Wage*	17626	20129	18111	17040	16971
		Number of First Jobs	6643516	9142393	12630946	13489724	14830056
		Number of Jobs	6987301	9920339	15099242	16810611	19378263
Occupation	**Trainee**	*Average Real Wage*	7381	7449	7809	8540	8737
		Number of First Jobs	359412	459197	775217	650119	705056
		Number of Jobs	394058	558196	1005564	997419	1092714
	Blue-collar	*Average Real Wage*	15565	15994	13927	12139	11892
		Number of First Jobs	4139724	5448182	7290505	7507121	8336025
		Number of Jobs	4304989	5915699	8819540	9590153	11353633
	White-collar	*Average Real Wage*	21609	26601	22565	21400	21998
		Number of First Jobs	2067665	3114180	4126493	4781543	5213611
		Number of Jobs	2208584	3319380	4785366	5626490	6298740
	Manager	*Average Real Wage*	–	–	54158	55271	58755
		Number of First Jobs	–	–	310204	432165	458048
		Number of Jobs	–	–	347185	467760	505339
	Executive	*Average Real Wage*	69229	99264	112994	118452	125573
		Number of First Jobs	76715	120834	128527	118776	117316
		Number of Jobs	79670	127064	141587	128789	127837
Gender	**Male**	*Average Real Wage*	19575	22536	20678	19699	19487
		Number of First Jobs	4521452	5978812	7817494	7860608	8568385
		Number of Jobs	4725507	6474057	9309306	9690644	11156455
	Female	*Average Real Wage*	13554	15607	13983	13421	13557
		Number of First Jobs	2122064	3163581	4813452	5629116	6261671
		Number of Jobs	2261794	3446282	5789936	7119967	8221808
Geographical Area	**South**	*Average Real Wage*	14626	16885	15385	12545	12493
		Number of First Jobs	998473	1320880	2012641	2209947	2445527
		Number of Jobs	1054164	1411646	2311533	2760613	3149497
		Number of Jobs	448716	672132	1015887	1190746	1278266
	Center	*Average Real Wage*	18065	20919	18342	16770	16666
		Number of First Jobs	1291519	1781923	2465992	2772321	3089940
		Number of Jobs	1364723	1916578	2929199	3474541	4029264
	North-West	*Average Real Wage*	19597	22684	20330	19985	19946
		Number of First Jobs	2568139	3241840	4209843	4353810	4739277
		Number of Jobs	2681517	3503732	5077166	5364486	6170386
	North-East	*Average Gross Wage*	16967	18747	17459	17746	17561
		Number of First Jobs	1366117	2182235	3057714	3206845	3565032
		Number of Jobs	1438181	2416251	3765457	4020225	4750850
Age Cohort	**Under 30**	*Average Real Wage*	12713	13980	11359	9067	8494
		Number of First Jobs	2673776	3786099	4194559	3020003	3378076
		Number of Jobs	2876618	4226286	5389661	4235625	5088250
	Adults 31-50	*Average Real Wage*	21011	23942	20795	18496	18246
		Number of First Jobs	3055080	4258624	6885981	7827848	7737063
		Number of Jobs	3175961	4543798	8001183	9518095	9881949
	Over 50	*Average Real Wage*	21239	27662	26841	23552	23898
		Number of First Jobs	914660	1097670	1550406	2641873	3714917
		Number of Jobs	934722	1150255	1708398	3056891	4408064

Table 1: Yearly average real wages (gross), number of jobs and number of first jobs by workforce subgroup.



(a)



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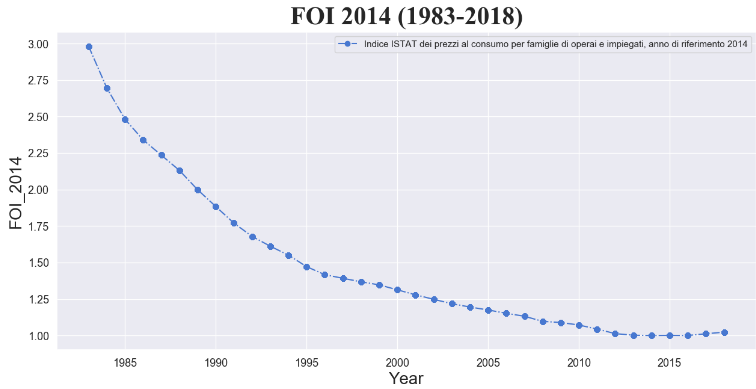


(c)

Figure 2: Italy, 1983–2018, wage compression trend. **(a)** Real average wage (annual in blue, weekly in orange). **(b)** Real average wage 5-year percentage change (Annual in blue, Weekly in orange). **(c)** FOI, price index used to compute real wages.

3 Facts and figures of the Italian labour market

Since the 1980s inequality in both income and wage distributions has been increasing at a worrying pace (Franzini and Raitano, 2019). The last three decades were marked by major crises (Brandolini et al., 2018), namely the currency crisis in 1992 and the double-dip recession, first with the explosion of the Great Recession in 2008 and then followed by the national debt crisis and the austerity phase. At the same time, profound changes have taken place in the labour market in terms of deregulation of job contracts (Piasna and Myant, 2017), deterioration of social dialogue and weakening of industrial relations at national and European level (Leonardi and Pedersini, 2018; Baccaro and Howell, 2011). In line with these processes, the Italian labour market underwent a gradual precarisation, in compliance with the European Employment Strategy launched by the European Council in 1994 and sanctioned in the well known OECD (1994) Jobs Study.

Exploiting the longitudinal dimension of our database, we start by describing a series of long-run trends that we deem appropriate to characterize the dynamics of the labour market in Italy over the period of observation. Dominant trends in the labour market can be summarised as follows: WAGE COMPRESSION, SERVITIZATION, JOBS FLEXIBILIZATION AND FRAGMENTA-

TION, AGEING LABOUR FORCE, FEMINIZATION, GEOGRAPHICAL DIVERGENCE, EXPLODING INEQUALITY. Let us motivate empirically such trends.

Figure 2 shows the time evolution of real wages, namely nominal wages deflated over time by the consumer price index FOI (*Indice nazionale dei prezzi al consumo per famiglie di operai e impiegati*). While consumer inflation, shown in the bottom part of the panel, monotonically shrinks, in the dynamics of real wages, both yearly and weekly (in blue and orange respectively), three different phases can be detected:

- an increasing trend in the decade 1983-1993;
- an overall declining trend since 1993;
- a strong decoupling between yearly and weekly wages after 1998.

Such phases are intimately linked to a series of legislative changes that have interested the Italian labour market. Historically, the process of gradual wage suppression started during the 1983-1984 period, with the government coalition led by the Socialist Party, reducing by three points the alignment between wage and inflation, with the aim of keeping the latter under control, the so-called *San Valentino agreement*, that was signed between the Craxi government and two of the three main Italian trade unions, with the exclusion of CGIL (*Confederazione Generale Italiana del Lavoro*). This adjustment was object of a referendum launched in 1985 which saw the prevalence of consensus for freezing wage growth and keeping inflation under control.[4]

The abolition of automatic wage indexation to inflation was accompanied by numerous debates and rifts between trade unions and eventually occurred after one decade, in 1992, when Italy was preparing its entry into the currency union, with an agreement between the Amato government and all three main unions. That year signed the beginning of a reconfiguration of the wage bargaining process, the so-called cooperation period (*periodo della concertazione*), and of the wage policy (*politica dei redditi*) undertaken by the succeeding government led by Ciampi.

Wage compression was successfully pursued, as shown by the 5-year percentage change in real wages (Figure 2 (b)), which from the peak in 1991, recording a 12% growth, reached a negative value of (-0.5%) in 1996. Such a negative wage growth became a dominant trait of the labour market onwards, with other two minima, the first in 2003, just two years after the entry in the common currency union, with the introduction of the *Legge Biagi* and the second in 2007 with the beginning of the Great Recession. Wage growth was then positive only during the two modest recovery years, 2016 and 2017, and turned again negative in 2018.

The pillar of these reforms, and the first in response to the EU institutions' indications, was the *Pacchetto Treu* in 1997 that multiplied the possible types of contractual regulations, introducing temporary contracts and strengthening part-time ones (existing since 1984). The *Legge*

[4]One of the outcome of the "hot autumn" season in 1969 – characterized by intense social conflict between trade unions and employers – was a revision of the wage indexation mechanism (*scala mobile*) in 1975 with the introduction of a mechanism aimed at ensuring full wage indexation. The so called *punto unico di contingenza* provided for the payment of a contingency allowance equal for all workers, regardless of the job level. While at the beginning Italian employers seemed to accept this "100% inflation hedging mechanism" (Graziani, 1998, p.126) thanks to the possibility of discharging the increasing labor cost on a devaluation of the national currency, with the entry into the EMS and the consequent stabilization of the exchange rate between the lira and the mark, they became great opponents of it.

Biagi followed in 2003, further increasing the number of contractual regulations, allowing for short employment duration and introducing *de facto* forms of mini-jobs by means of outsourcing contracts (*co.co.co*), project-based contracts (*co.co.pro*), occasional or intermittent contracts (*lavoro occasionale*, *lavoro accessorio*).

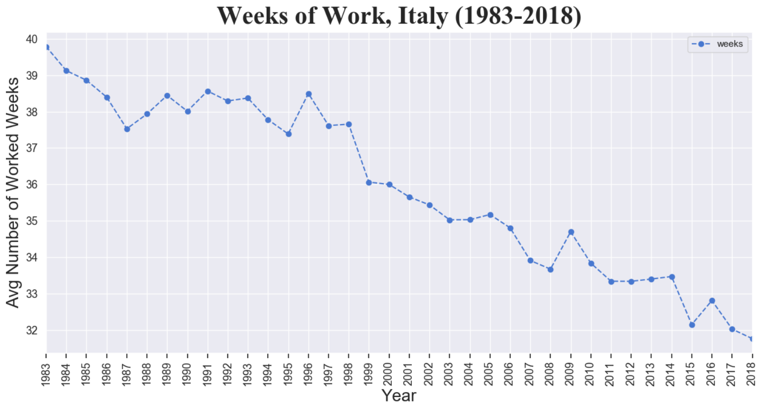
The following liberalization reform was the *Legge Fornero* in 2012, which weakened the effectiveness of labour protection instruments, further encouraged open-ended contracts and reformed the pension system increasing retirement age. Two years later in 2014 the *Jobs Act* was implemented, the last major labour market reform and final straw of the flexibilisation process, meant at easing firing processes and abolishing restrictions for firms with more than 15 employees. The Jobs Act definitely suppressed the remaining protections from invalid dismissals and introduced a less rigid typology of contract with time variable protections for employees (*contratto a tutele crescenti*).

These series of reforms, which were supposed to foster employment growth, did not produce the expected effect (Fana et al., 2016) but instead weakened the innovative capabilities of Italian firms (Cetrulo et al., 2019; Reljic et al., 2021). Moreover, they successfully resulted into an evident contraction in the number of worked weeks contrasted however by an increasing number of jobs, as shown in Figure 3 (a) and (b). Inclusion of atypical contractual forms, absent in our dataset, would have even further exacerbated the picture. Such diverging trends hint at a strong fragmentation of the temporal unit of working activity – the employment contract – which exploded in number but dramatically shortened in time.

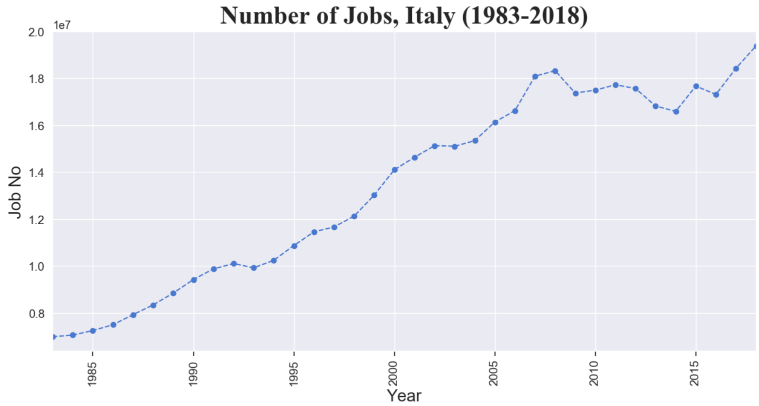
Nevertheless, such increasing number of jobs is distinctly concentrated in specific sectors. Panel (c) of Figure 3 documents the well-known process of deindustrialization, with shares in manufacturing (orange line), chemical, metallurgy and pharma (green line) strongly declining from respectively 0.20% and 0.25% of total private employment in 1983 to a share of approximately 10% in 2018. In contrast, a trend of servitization is clearly evident, with increasing shares of retail trade (purple line), transport (brown line), education and human health activity (yellow line), accounting for more than 50% of employees in 2018.

Figure 4 presents the breakdown by geographical area, divided into North-East, North-West, South, Center and Islands. Job shares, shown in panel (a), remain roughly constant, with the exception of the North-West declining shares and the slightly increasing shares in the South. However, the increasing share of jobs in the South corresponds to the introduction of temporary jobs in 1998. Furthermore, in panel (b) we detect a marked pattern of wage divergence accelerating since 1998, a rebound of the North-East since 2007, and a huge decline in the South and the Islands, with average wages ranging form 20 thousand euros in the North to 12 thousands in the South and the Islands. The geographical wage gap however is also marked within the same geographical area, between temporary/part-time and permanent/full-time jobs, as shown in panel (c). The lowest gap is found for the Islands, the highest is instead registered in the North-West, antipodal areas in terms of wage levels.

A growing participation in the labour market from the female component is visible in panel (a) of Figure 5, with a share raising from 35% in 1983 up to 42% in 2018. However, the increasing demand of female jobs did not mapped into increasing real wages: the latter remain almost flat in real terms and the gender-pay gap (of approximately 6 thousands euros) does not show any contraction in the period of analysis. When looking at the wage dynamics by gender and



(a)



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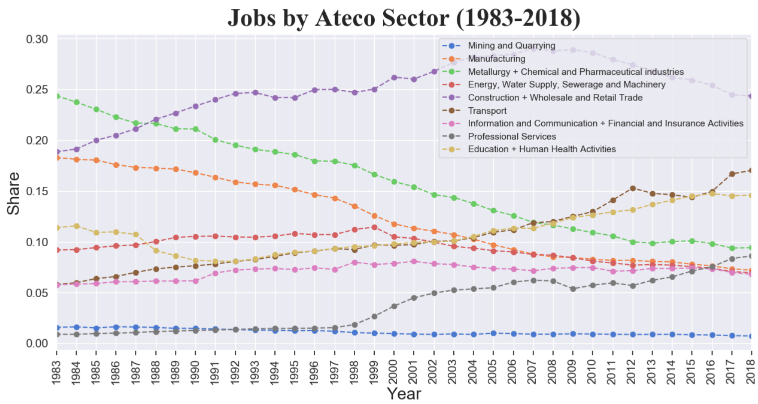
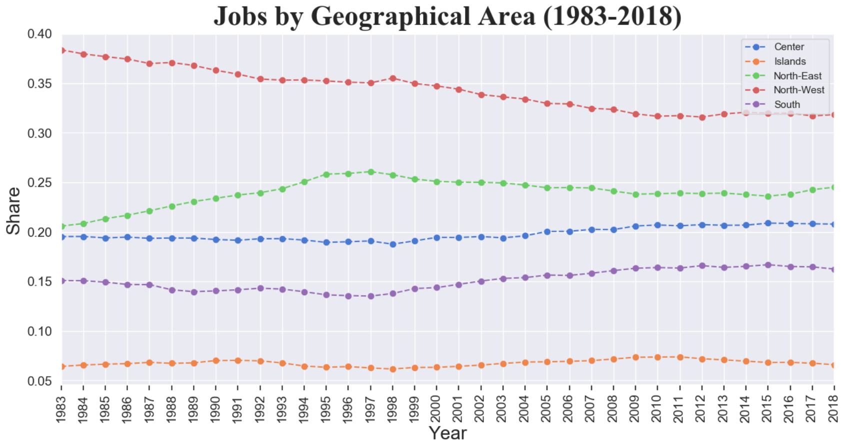
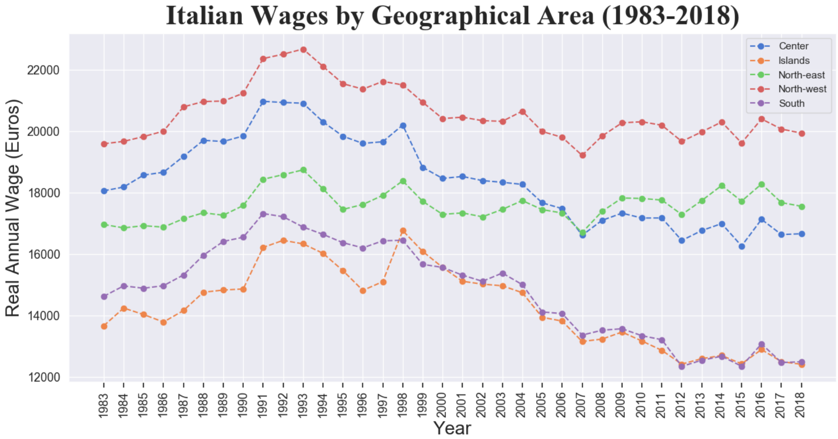


(c)

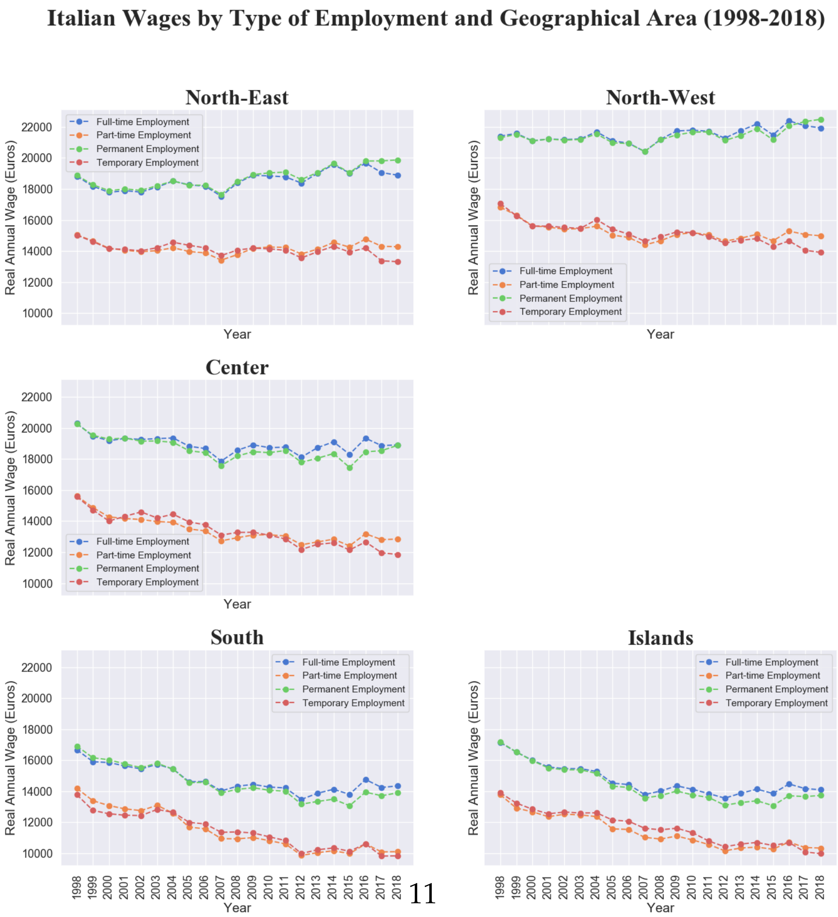
Figure 3: Italy, 1983–2018. Precarisation, fragmentation and deindustrialisation trends. **(a)** Average number of weeks of work in a year. **(b)** Number of jobs. **(c)** Number of jobs by different aggregations of 1-digit Ateco industrial sectors (Mining and Quarrying; Manufacturing; Metallurgy + Chemical and Pharmaceutical industries; Energy, Water Supply, Sewerage and Machinery; Construction + Wholesale and Retail Trade; Transport; Information and Communication + Financial and Insurance Activities; Professional Services; Education + Human Health Activities; Other Services).


Jobs by Geographical Area (1983-2018)
Share
Year
Center
Islands
North-East
North-West
South

(a)


Italian Wages by Geographical Area (1983-2018)
Real Annual Wage (Euros)
Year
Center
Islands
North-east
North-west
South

(b)


Italian Wages by Type of Employment and Geographical Area (1998-2018)
North-East
North-West
Center
South
Islands
Real Annual Wage (Euros)
Year
Full-time Employment
Part-time Employment
Permanent Employment
Temporary Employment

(c)

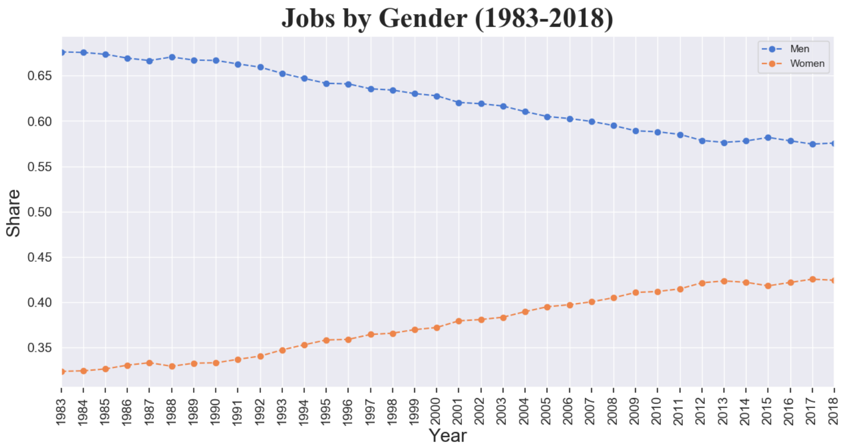
employment type, a declining trend is recorded in temporary/part-time jobs for male and female jobs, albeit with temporary female jobs experiencing the lowest remuneration across all categories.

Moving to the ageing labour market trend, Figure 6 (a) shows an increasing emergence of jobs done by 31-50 years old workers since 1992, and a corresponding declining trend in the share of jobs performed by workers under 30. Although such a trend might also be due to a higher education rate retarding the entry age in the labour market, since 1998 the growing fraction of jobs performed by workers over 50, that increasingly populated the labour market, appears quite alarming and also reflects the entry in the labour market with atypical contractual forms. The older segment also enjoys remarkable wage premium, as shown in panel (b). If the wage-age premium is not surprising, what is worrying is the declining remuneration of under 30s, which in 2018 earn on average less than 10 thousand euros per year. Panel (c) presents the breakdown of the three age cohorts by type of contract: while the wage gap between full-time/permanent contracts and part-time/temporary ones is visible for the two older cohorts, the remunerations of workers under 30, independently from their contract type, record a steep and monotonic convergence to the bottom.

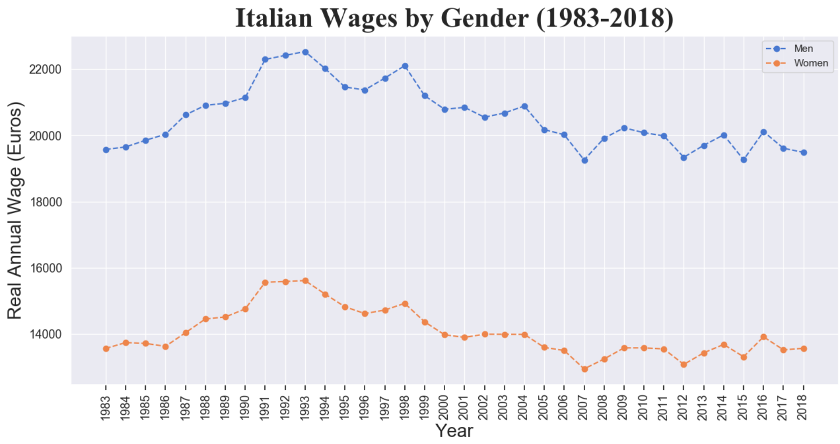
The observed patterns of wage divergence are mirrored by the movement of the synthetic inequality indicators presented in Figure 7 (a) which displays the time evolution of real wages in the 10th, 50th, 90th and 99th percentiles. While the median percentile declines and the bottom is roughly constant, the two top percentiles show clear increasing trends with a decreasing distance between P99 and P90 after 2005 and a growing distance from P50 and P10. Panel (b) presents the 90-10 wage percentile ratio: a visible and steep increasing trend is reported documenting divergence toward the top. Convergence towards the bottom between the 50th and 10th percentile is shown in panel (c), providing evidence in favour of a 'proletarization' hypothesis since 2000.

Are the divergence at the top and convergence towards the bottom linked to the wages of different occupational categories? Figure 8 presents the dynamics of the wage-gap between executives and blue-collars (panel a), executives and white-collars (panel b), white- and blue-collars (panel c). The latter statistics, which are generically not used as proxy of the inequality dynamics, give us a glimpse of the role of occupational categories in affecting inequality and indirectly on the relative bargaining power of the bottom occupational classes vis-à-vis the top ones. A clear pattern of lost bargaining power of blue- and white-collars over executives' earnings appears, with the executive average pay increasing from 5 to more than 10 times that of blue-collars, and from 3 to 5.5 times that of white-collars. Remarkably, and consistently with the 90-50 wage gap, white- and blue-collars increasingly present similar wages, with the gap reducing from 0.7 up to 0.5.

Overall, together with a wage compression and job fragmentation story, we have documented patterns of divergence deriving from many alternative sources, namely geographical origin, age, gender and occupational divides. Our results confirm both the analysis provided by Rosolia (2010) on the longitudinal INPS database (WHIP) over the period 1985-2004, where the strong relation between socio-demographic characteristics and income gaps emerges; and the study by Bloise et al. (2018) that, using individual INPS LOSAI data over the period 1985-



(a)



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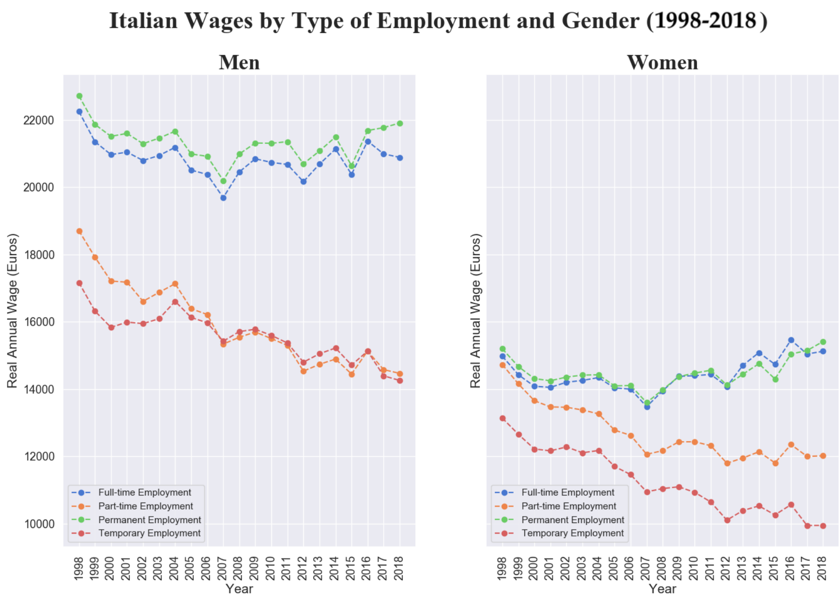
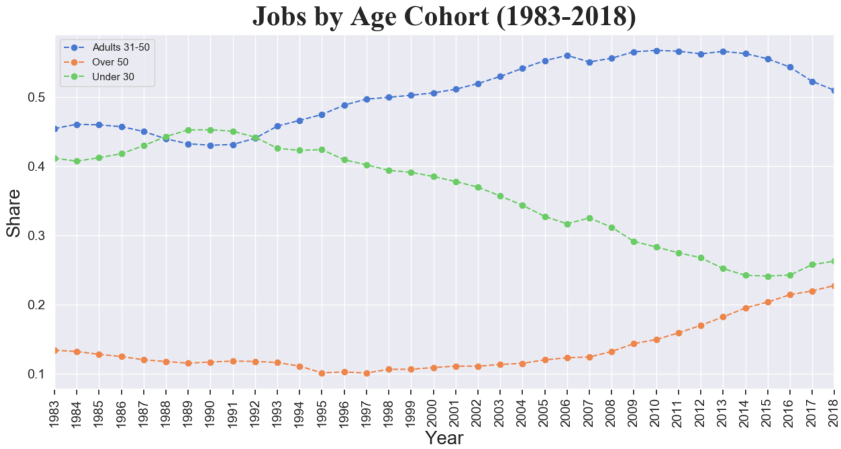
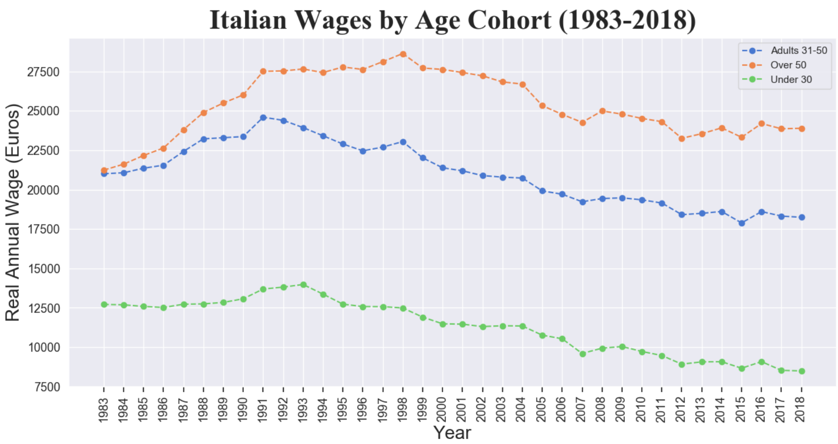


(c)

Figure 5: Italy, 1983–2018, feminization of the labour force and gender wage divide. **(a)** Real average wage by gender (Women in orange, Men in blue). **(b)** Number of jobs by gender. **(c)**: Real average wage by gender and type of employment.



(a)



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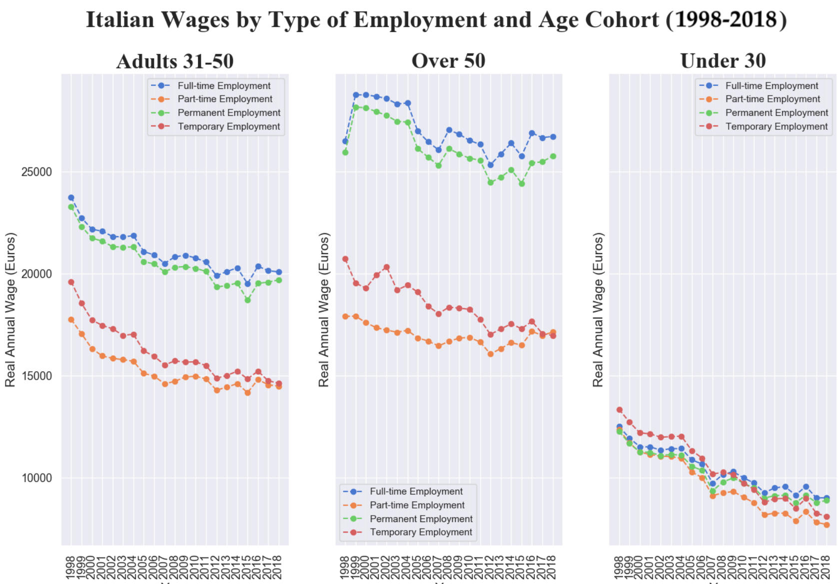


(c)

Figure 6: Italy, 1983–2018, ageing labour force trend. **(a)** Real average wage by age cohort (Young under 30, Adults between 31 and 50, and Over 50). **(b)** Number of jobs by age cohort. **(b)** Real average wage by age cohort and type of employment.

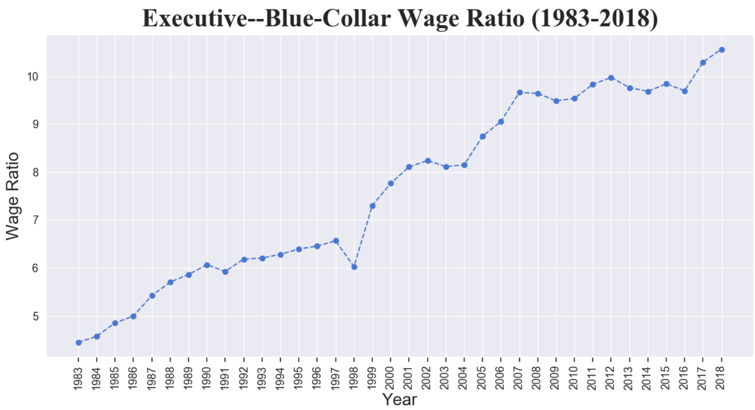
Figure 7: Italy, 1983–2018. **(a)** Real average wage centiles over time. **(b)** P90-P10 and **(c)** P50-P10 wage ratios.

2014, observe not only a general increase in inequality but also a rising polarization across groups, in particular for what concerns the distance between top and bottom income earners.

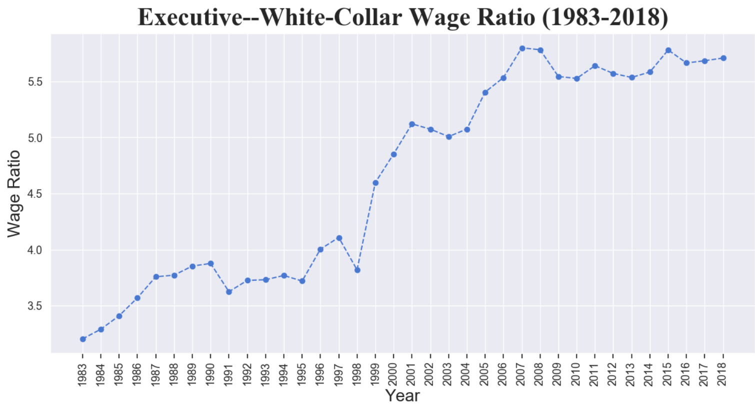
Given the evidence presented so far, we have detected a strong influence exerted by socio-demographic characteristics on patterns of wage divergence, however without a conclusive understanding of the role played by each one of them. In the following we attempt to address such a task.

4 Determinants of inequality

While in the above we have observed a clear trend of increasing inequality, especially the two processes of divergence at the top and convergence at the bottom, in this section we explore the determinants of inequality by distinguishing the role played by the gender, age, geographical area and occupational category of the workforce. In order to do so, firstly we present an a priori decomposition exercise in Subsection 4.1, secondly we propose a regression-based analysis in Subsection 4.2, and thirdly in Subsection 4.3 we study the association between negative wage episodes and our inequality determinants. Finally, Subsection 4.4 discusses our findings vis-à-vis the routinization hypothesis.



(a)



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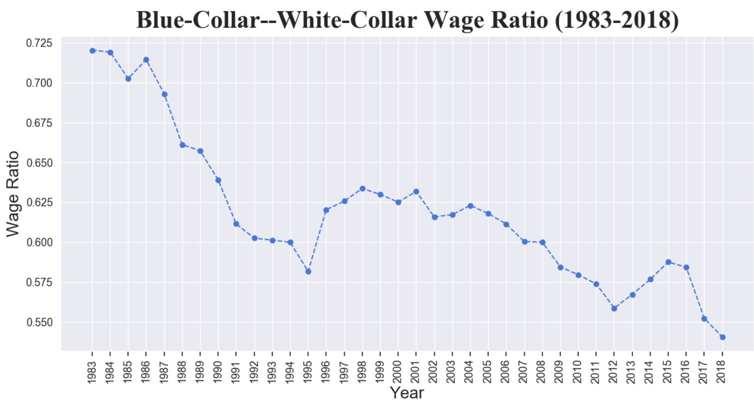


(c)

Figure 8: Italy, 1983–2018. **(a)** Executive-Blue Collar wage ratio. **(b)** Executive-White Collar wage ratio. **(c)** Blue Collar-White Collar wage ratio.

4.1 Inequality decomposition: within and between components

With the aim of appreciating different characteristics of the overall, within- and between-group inequality distribution, we compare the trends of a number of inequality indicators, each of which is particularly sensible to specific and distinct features of the earnings distribution. In particular we focus on the Gini coefficient and different Generalised Entropy indices ($GE(\alpha)$). For a population of n individuals and a discrete wage distribution $\mathbf{y} \in \mathbb{R}^n_+$, where each worker has wage y_i, $(i = 1, \cdots, n)$ and wages are indexed in non-decreasing order ($y_i \leq y_{i+1}$), the Gini coefficient formulation we employ is defined as follows:

$$G = \frac{n+1}{n} - \frac{2}{n \sum\limits_{i=1}^{n} y_i} \left(\sum_{i=1}^{n} (n+1-i)\, y_i \right). \tag{1}$$

$G = 0$ in the case of perfect equality, i.e. when all individuals have the same wage, and $G = 1$ in a situation of maximum inequality, i.e. when a single individual earns the totality of wages. The Gini coefficient tends to be more sensitive to wage differences around the mode than in the lower or higher tails of the distribution (Green et al., 1994).

Concerning the Generalised Entropy indices we focus on $GE(\alpha)$ with $\alpha \in [0, 1, 2]$, where $GE(0)$, $GE(1)$, $GE(2)$ correspond respectively to the Mean Logarithmic Deviation (MLD), the Theil Index and the Half Square of the Coefficient of Variaton (1/2 SCV).

Mathematically, considering a population of n individuals, with wage y_i $(i = 1, \cdots, n)$, arithmetic mean wage m, sample weight, if present, equal to w_i, with $f_i = w_i/N$ and $N = \sum w_i$ ($N = n$ when $w_i = 1$), these widely used inequality indicators are defined as follows:

$$GE(\alpha) = \begin{cases} \frac{1}{\alpha(\alpha-1)} \sum_{i=1}^{n} f_i \left[\left(\frac{y_i}{m} \right)^{\alpha} - 1 \right], & \alpha \neq 0, 1, \\ \frac{1}{n} \sum_{i=1}^{n} f_i \frac{y_i}{m} \ln \frac{y_i}{m}, & \alpha = 1, \\ \frac{1}{n} \sum_{i=1}^{n} f_i \ln \frac{m}{y_i}, & \alpha = 0 \end{cases} \tag{2}$$

where α is a real parameter that regulates the weight given to the distance between each individual's wage and the average. For large values of α, $GE(\alpha)$ is particularly sensitive to wage differences at the top of the distribution, by contrast for small α it responds more to inequality at the bottom of the distribution (Jenkins, 2009, 1995). $GE(\alpha) = 0$ in the case of complete equality, while larger real values of the index indicate higher inequality in the distribution.

A distinct positive growth of inequality is shown by all indicators taken into consideration, albeit at different paces, as implied by their underlying mathematical and parametric constructions (Figure 9). Table 2 presents their point values in 1983, 1993, 2003, 2013 and 2018, the starting years of each decade plus the last observation in our data-set. Table 3 instead displays their percentage variations in the time intervals 1983-1993, 1993-2003, 2003-2013, 2013-2018 and over the entire observation window. The change is much higher for all GEs (> +110%) rather than for Gini, that, being more sensitive to changes in the middle of the distribution, increases "only" by 50%. The highest percent changes are recorded for GE(1) and GE(2), thus confirming that inequality at the top of the distribution has increased the most over our time window. The greatest change is however recorded in the first decade (1983-1993) for all indicators.

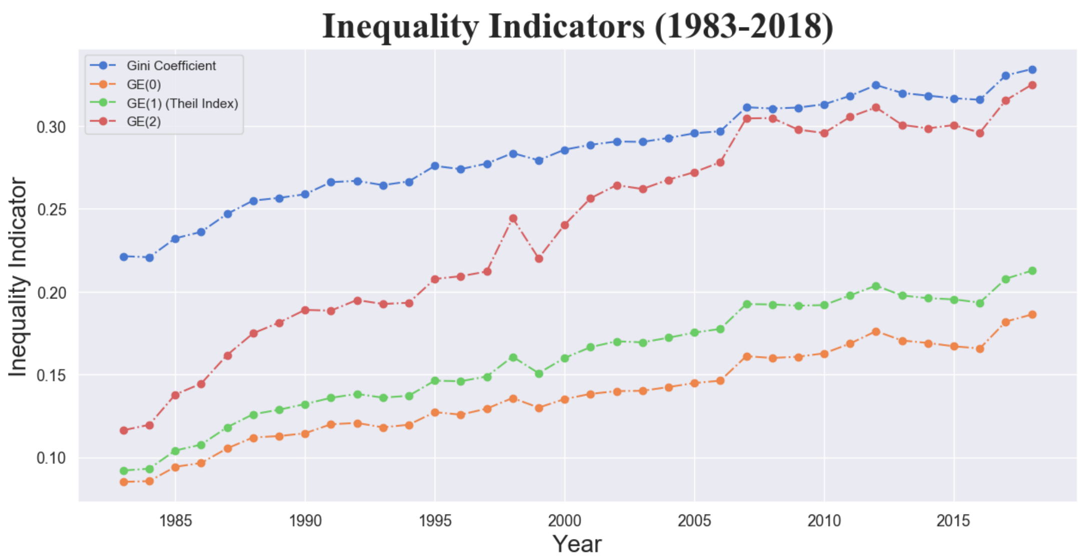


Figure 9: The Gini Coefficient and the selected general entropy indicators $GE(\alpha),\ \alpha \in [0, 1, 2]$ trends over the period 1983-2018.

Year	Gini	MLD (GE(0))	Theil (GE(1))	1/2 SCV (GE(2))
1983	221	85	92	116
1993	264	118	135	192
2003	290	140	169	261
2013	319	170	197	300
2018	334	186	212	324

Table 2: Values multiplied by 1000 of the Gini Coefficient and the selected general entropy indicators $GE(\alpha),\ \alpha \in [0, 1, 2]$ in 1983, 1993, 2003, 2013 and 2018.

Time Interval	Gini	MLD (GE(0))	Theil (GE(1))	1/2 SCV (GE(2))
1983-1993	19	39	46	65
1993-2003	9	19	25	36
2003-2013	1	21	16	15
2013-2018	5	9	8	8
1983-2018	51 7	119	130	179

Table 3: Percentage variation of the Gini Coefficient and the selected general entropy indicators $GE(\alpha),\ \alpha \in [0, 1, 2]$ in the time intervals 1983-1993, 1993-2003, 2003-2013, 2013-2018 and over the entire time window 1983-2018.

Next, we develop a decomposition analysis of inequality by four workforce sub-groups defined by the occupational category, gender, age and geographic area of origin of each considered segment. We refrain from the use of the contractual regulation types, whether part-time or temporary, since for each category we do not have direct attribution but percentage of workers with a specific type of job contract. Alternatively, we should have ex-ante imputed to each category a type of job contract, according to a principle of prevalence (e.g. average blue-collar women in Piedmont, beyond fifty, the totality of whom considered as full-time workers, while average white-collar women in Lombardy in the service sector beyond thirty all considered temporary workers). Such type of attribution by prevalence, given the within-category variability, although investigated, was not doable.

In order to detect whether the overall change in inequality derives from changes within or between each sub-group, we rely on the decomposition method developed by Jenkins (1995), building on the seminal work of Shorrocks (1982, 1984). Similar analyses have been conducted for Italy in Franzini and Raitano (2019) regarding income inequality and in Raitano (2021) regarding wage inequality.

The four attributes on which we base our workforce partitions are deeply important for understanding the overall dynamics of wage inequality. According to Goldthorpe (2002)'s class schema, occupational categories open the possibility to grasp the role played by class position in wage differentials. The gender factor takes into account the increasing relevance of female employment, occupational segregation and gender wage gap (Bettio et al., 2013). Age is associated with different career prospects and degrees of job stability with a distinct impact on the wage level (Rosolia and Torrini, 2007). The geography of wage inequality in Italy is linked to a profound North-South divide, characterised by strong labour market segmentation and differences in industrial structure (Sbardella et al., 2021) and infrastructures (Viesti, 2021).

To carry out the decomposition exercise, we focus exclusively on the generalised entropy indices as they are easily decomposable across population groups. For the sake of brevity but with the aim of grasping differences both at the top and the bottom of the distribution, we show our results only for the Mean Logarithmic Deviation GE(0) and the Half Square of the Coefficient of Variation GE(2).

If individuals (employment relationships in our case) are grouped in a mutually exclusive and exhaustive way, inequality can be separated into a *within-group* component – the weighted sum of the inequalities in each group – and a *between-group* component – computed assuming that each employment relation's wage corresponds to its group's average income. Therefore, following Jenkins (1995), if we consider that the population is divided into m groups, $g_1, g_2, ..., g_m$, each with n_k individuals with $k = 1, ..., m$, then for $GE(\alpha)$ Equation 4.1 can be rewritten as:

$$GE(\alpha) = GE^W(\alpha) + GE^B(\alpha) \tag{3}$$

where $GE^W(a)$ is the within group inequality and $GE^B(a)$ is the between group inequality. Looking in particular at the GE(0) and GE(2) Equation, we can write:

$$\begin{aligned} GE(0) = GE(0)^W + GE(0)^B = \textstyle\sum_k^m v_k\, GE(0)^{(k)} + \sum_k^m v_k\, log(1/s_k) \\ GE(2) = GE(2)^W + GE(2)^B = \textstyle\sum_k^m v_k\, s_k^2\, GE(2)^{(k)} + \sum_k^m v_k [s_k^2 - 1] \end{aligned} \tag{4}$$

where $v_k = \frac{n_k}{n}$ is the population share of group k, $s_k = \frac{y_k}{\bar{y}}$ is the ratio of the average group wage to overall average wage, $GE(\alpha)^{(k)}$ $(\alpha = 0, 2)$ is the inequality index for each group k and accounts for the inequality between the members of the group, that is assumed to be a separate population from the other groups.

Table 4 presents the decomposition analysis accounting for the *between* and the *within* components of overall wage inequality. While we report the results for some selected time-

		1983	1993	2003	2013	2018
Gender	*GE(0) Within*	71	103	123	153	170
	GE(0) Between	14	15	17	17	16
	GE(2) Within	103	179	245	284	310
	GE(2) Between	13	13	16	16	14
Age Cohort	*GE(0) Within*	55	79	91	116	119
	GE(0) Between	30	39	49	54	67
	GE(2) Within	89	156	218	257	271
	GE(2) Between	27	36	43	43	53
Geographical Area	*GE(0) Within*	78	111	134	156	172
	GE(0) Between	7	7	6	14	14
	GE(2) Within	110	186	256	287	311
	GE(2) Between	6	6	5	13	13
Occupational Category	*GE(0) Within*	39	39	43	60	70
	GE(0) Between	46	79	97	110	116
	GE(2) Within	45	52	51	53	63
	GE(2) Between	71	140	210	247	261

Table 4: GE(0) and GE(2) within group and between group inequality in 1983, 1993, 2003, 2013 and 2018 (values multiplied by 1000).

windows, the decomposition exercise has been consistently replicated over the entire time period. Thanks to such decomposition, we are able to study the magnitude of the within and between group components and to distinguish the groups characterised by higher degrees of internal inequality ($GE(\alpha)^{(k)}$ $(\alpha = 0, 2)$) from those for which inequality with respect to the other groups is higher.

Among our partitions, occupational categories constitute the group characterised by the higher between component, which explains most of the overall inequality both using the Mean Logarithmic Deviation and the Half Square Coefficient of Variation, consistently with Raitano (2021). The trend is increasing over time, meaning that the degree of wage inequality has been rising across occupations; nevertheless, our proxy of job class constitutes the only partition where the between component overcomes the within component over the entire time period. Indeed, class schema results to be very effective in explaining wage inequality and is more relevant than the other workforce characteristics.

This finding confirms that considering class position in terms of occupational hierarchies allows to account for a not negligible degree of wage inequality, as underlined for instance by Quintano et al. (2009) and Albertini (2013) for Italy and by Penissat et al. (2020) for European countries. This is true despite the fact that our occupational category group is based on a very broad classification, able to distinguish among only five types of occupations. Therefore, it is not directly comparable with more refined and accurate socio-economic models that exploit higher degrees of disaggregation (Weeden and Grusky, 2005; Goldthorpe, 2002) that often include additional factors linked to the work process, such as the degree of autonomy and power exercised along segments of organizations (Wright, 2000, 1998) or account for the role of social capital (Savage, 2015). The importance of socio-economic groups and the occurrence of a distributional shift in favour of specific groups such as middle managers and executives have been indeed assessed in the literature (Brandolini et al., 2018), however without placing the issue of class inequality at the center of the analysis.

Differently from what happens for occupational categories, within group inequality prevails in the other partitions. In the case of gender this suggests that, despite the presence of a distinct gender wage gap, stronger patterns of wage inequality can be found within the female and male groups rather than among women *vs* men. Geographical areas and age cohorts exhibit increasing degrees of within inequality that are systematically higher than the between component.

4.2 Regression based inequality decomposition

Two methods to decompose inequality metrics have been proposed in the literature, the *a priori* decomposition, presented above, and a *regression* approach. As discussed by Cowell and Fiorio (2011) these, rather than being alternative approaches, may be regarded as complementary. Both methods do not provide causal interpretations, but are however useful to get a clear picture of i) the degree of inequality within and between groups, ii) the role played by each factor characterising the groups in explaining the level of inequality. To precisely estimate the relative contribution played by each considered job characteristic in explaining the level of wage inequality, here we carry out a regression based inequality decomposition.

Here, in particular, we rely on Field's regression decomposition method (Fields and Yoo, 2000; Fields, 2003) that, also thanks to its flexibility, has been widely adopted in the inequality literature. For instance, O'Donoghue et al. (2018) use a Fields' method to study the impact of several variables on wage inequality in Ireland during the Great Recession; Manna and Regoli (2012) focus on Italian households income and wealth over the period 1998-2008; and Wan and Zhou (2005) study the determinants of income inequality in rural China showing that geography and capital inputs have the highest explanatory power.

By following Fields (2003), as a first step to carry out the regression-based inequality decomposition let us consider a wage generating function for a population of n wage recipients and k determinants of inequality:

$$\begin{gathered} log(y_i) = aZ_i \\ a = [\alpha \quad \beta_1 \quad \beta_2 \quad ... \quad \beta_k \quad 1] \\ Z_i = [1 \; x_{i1} \; x_{i2} \quad ... \quad x_{ik} \; \epsilon_i] \end{gathered} \tag{5}$$

where y_i $(i = 1, ..., n)$ denotes the wage of employee i, x_{ij} $(j = 1, ..., k)$ the j-th explanatory variable, b_j its coefficient and ϵ_i the error term. After some transformations, it is possible to define the share of the wage log-variance (the relative factor inequality weight) that can be attributed to the j-th explanatory factor s_j as follows:

$$s_j(log(y)) = \frac{cov[a_j Z_j, log(y)]}{\sigma^2(log(y))} \tag{6}$$

where $\sigma^2(log(y))$ is the variance of the dependent variable and $cov[a_j Z_j, log(y)]$ is the covariance between the j-th explanatory factor and the dependent variable. If $s_j > 0$ the contribution of factor x_j increases inequality, while it decreases inequality for $s_j < 0$. Moreover, when the residual ϵ_i is excluded from Z, the sum of all relative factor inequality weights is equal exactly to $R^2(log(y))$.

Therefore, for each year, we run a regression of the log yearly wages as a linear function of the variables that characterize our sub-groups of employment relations: gender (with the base group being male employees), age cohort (the base group being employees under 30), geographical area (the base group being employees situated in Southern Italy), occupation (the base group being blue-collars). For ease of readability, we present the results of the regression decomposition only for the five years considered in the previous exercise (1983, 1993, 2003, 2013 and 2018), but they are consistent across the whole 1983-2018 time window. The estimation of the coefficients is done via OLS.

To distinguish co-variates on the basis of their importance in explaining inequality, we focus on the factor inequality weights reported in Table 5. According to estimation results presented in the Appendix, all variables have statistically significant coefficients, confirming their importance as wage distribution determinants. This is also confirmed by the fact that in our observation period not only the residual shows low values, always below 9%, but its magnitude is also decreasing over time, going as low as 2.4% in 2013 and 2.5% in 2018, indicating the growing relevance of our determinants.

The occupational category factors display the highest factor weights as inequality-enhancing (with respect to the base group of blue-collars). Occupational categories are then followed by the age and gender attributes, which seem to play a significant role in explaining inequality, whereas lower weights are associated to geographical areas. Over time we register the reducing weight of the middle-age fraction of employees and the increasing one of the older segment, the constant weight of female jobs and the increasing role played by white-collars and middle managers. Along the line of Fields (2003), to facilitate the interpretation of the factors and ease of visualisation, in Figure 10 we sum up the relative contributions of each group components to verify which workforce partition contributes the most to inequality during the years under analysis. Consistently with the disaggregated weights, the occupational category group (in blue) plays the leading role in explaining inequality, followed by age cohort group (green) and gender (yellow).

	1983	1993	2003	2013	2018
Residual	8.60	5	4.3	2.4	2.5
Female	14.70	11.80	14	14	12.1
White Collars	14.90	28.50	22.6	24.7	25.30
Executive	12.80	16.40	14.1	10.9	8.9
Trainees	13.90	12.10	4.4	-1.4	-1.9
Middle Managers	-	-	14.40	17.10	15,90
30-50 Years Old	20.50	15.50	15	13	12.8
Over 50 Years Old	4.80	5.70	8.7	12.3	18.1
Central Italy	0.60	0.5	0	-0.3	-0.3
Islands	0.90	0.5	0.2	0.1	0.2
North Eastern Italy	-0.60	-1.1	-0.3	1.8	1.5
North Western Italy	8.80	5.10	2.6	5.4	4.8
Total	100	100	100	100	100

Table 5: Factor inequality weights (%) for each considered variable across the entire workforce from Fields' wage inequality regression decomposition.

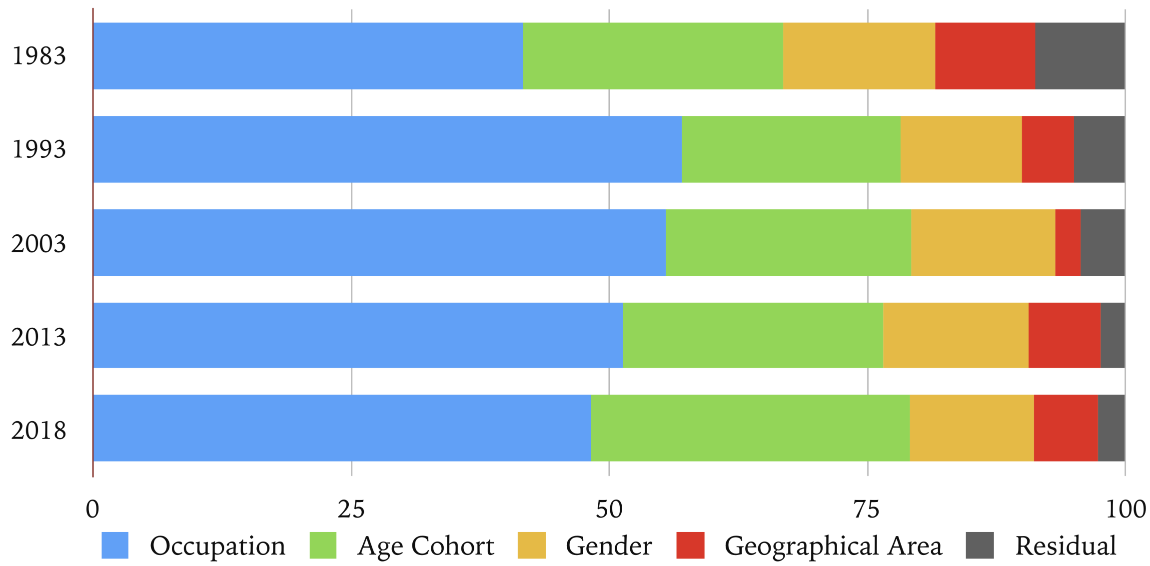


Figure 10: Total factor inequality weights (%) for each variable.

4.3 Wage losses by population subgroups

Beyond the exploding inequality trend, the period under analysis records enormous wage losses in real terms (cf. Figure 2). Here we investigate how these have manifested among the groups detailed in the previous analysis and which workforce partition has suffered the most.

In order to do so, firstly we attribute a panel structure to our dataset, whereby the repeated observation corresponds to a category given by the combination of gender (2 types), age class (3 types), region (20 types) and occupational category (5 types). Then, for each category we compute the annual wage growth and negative wage growth episodes. The objective of this analysis is to detect the extent to which such categorical attributes are correlated with the event of a wage loss and if the observed differences across groups are statistically significant.

Table 6 presents for five periods (1983-1984, 1993-1994, 2003-2004, 2013-2014, 2017-2018) the occurrence of a wage loss event according to each different group, both showing the total number and the percentage of jobs. To check for the presence of a possible conditional dependency, we compute the Pearson's χ^2 statistic and the χ^2 likelihood ratio, and test whether the distribution of the events across population groups is independent from the partitions.[5] Both tests look at the differences between observed and theoretical frequencies under the null hypothesis that variables manifest independently, and therefore differences between theoretical and empirical frequencies are not statistically significant. While the Pearson χ^2 test computes the squared difference between them, the likelihood ratio χ^2 computes the ratio of the two.

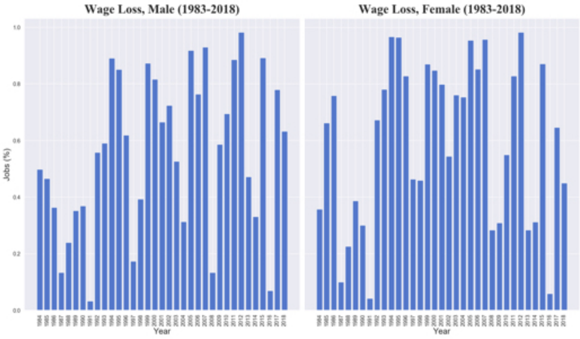
Considering, e.g., the two-way frequency of female and male workers, a significant Pearson χ^2 test implies that the difference between the distribution of a wage loss among female and male workers is significant. In all the years under analysis, we find strong evidence of dependence (we reject the null hypothesis of independence) thus implying that the probability of recording a wage loss is not independent from categorical attributes such as gender, age, geographical area and occupational category.

Figure 11 shows the distribution of wage loss events for each of the four determinants of inequality. Firstly, the event is not rare as in all years under analysis we find a marked presence of blue areas in the plots. Additionally, wage losses are more concentrated across female and youth jobs with respect to male and older jobs. Among the occupational category subgroups, blue-collars and white-collars record the highest percentage of wage losses, whereas Northern regions are generically more resilient to loss events.

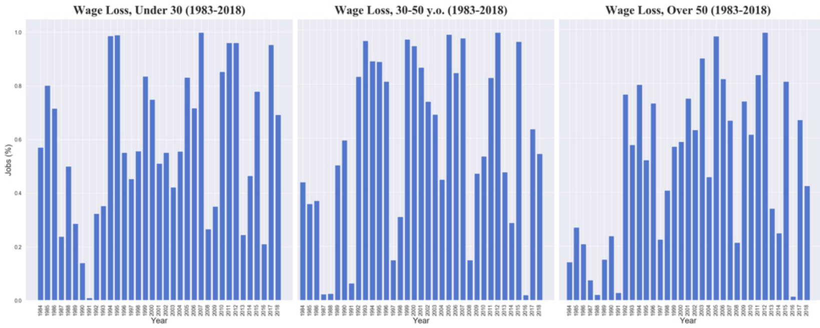
4.4 Why inequality is not a matter of technology

So far we have focused on structural determinants but we have been silent about the role played by skills and technology, the two most prominent responsible of wage inequality according to mainstream economics: first the skill bias technical change (SBTC) (Acemoglu, 2002; Katz and Murphy, 1992; Autor et al., 1998) and afterwards the routine-biased technical change (RBTC) (Autor et al., 2006, 2003; Spitz-Oener, 2006) approaches have become the dominant frameworks to explain inequality as a purely market problem. According to the first variant, the rising wage inequality detected in the U.S. since the end of the 1970s was primarily due to an increasing demand for graduated vis-à-vis non-graduated workers. However, given the impossibility of explaining the growth in low skill jobs, a new variant of the "canonical model" was proposed, focusing the attention on the set of tasks embodied in each job activity rather than the skills and on the substitution effect of new technology on highly routinized activities (Acemoglu and Autor, 2011; Autor and Dorn, 2013). Therefore, the RBTC theory interpreted rising inequality as the result of the increasing adoption of computers, able to substitute those types of human activities consisting in performing repetitive tasks – easily translatable into standards and codes – concentrated in the middle part of the occupational categories. Ac-

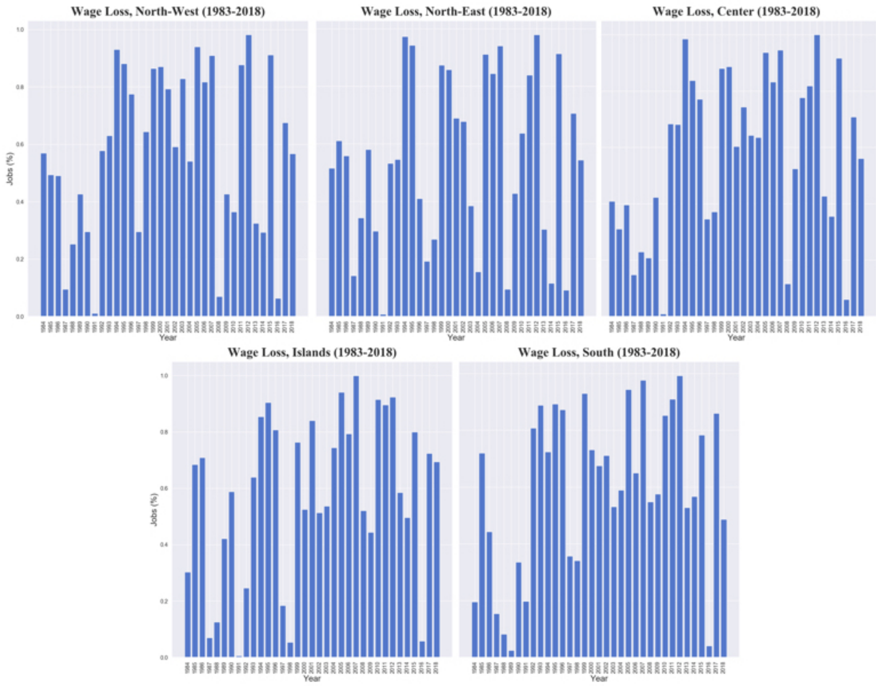
[5]Results are reported in Table 6.3 in the Appendix.



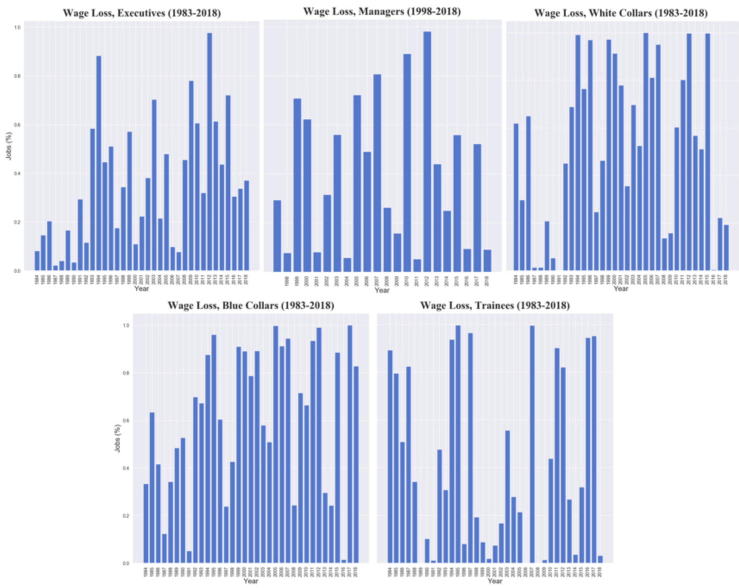
(a) Gender



(b) Age Cohort



(c) Geographical Area



(d) Occupation

Figure 11: Wage loss events by population subgroups.

			1983-1984		1993-1994		2003-2004		2013-2014		2017-2018	
			Wage Loss	*No Wage loss*	*Wage Loss*	*No Wage loss*	*Wage Loss*	*No Wage loss*	*Wage Loss*	*No Wage loss*	*Wage Loss*	*No Wage loss*
Gender	*Female*	Total	817,103	1,471,117	3,496,842	118,505	4,506,501	1,469,782	2,183,352	4,816,306	3,696,829	4,524,884
		%	36	64	97	3	75	25	31	69	45	55
	Male	Total	2,376,143	2,391,379	5,902,912	723,078	2,934,370	6,427,113	3,174,910	6,411,931	7,054,192	4,102,214
		%	50	50	89	11	31	69	33	67	63	37
Age Class	*Under 30 years old*	Total	1,640,055	1,234,317	4,273,143	57,990	2,927,300	2,342,289	1,867,241	2,148,484	3,523,683	1,564,492
		%	57	43	99	1	56	44	46	54	69	31
	31-50 years old	Total	1,421,036	1,829,821	4,224,020	552,695	3,712,132	4,596,343	2,686,362	6,652,674	5,364,089	4,517,860
		%	44	56	88	12	45	55	29	71	54	46
	Over 50 years old	Total	132,155	798,358	902,591	230,898	801,439	958,263	804,659	2,427,079	1,863,249	2,544,746
		%	14	86	80	20	46	54	25	75	42	58
Geographical Area	*Central Italy*	Total	562,762	815,88	1,934,602	29,473	1,908,525	1,098,807	1,217,912	2,212,351	2,258,875	1,770,324
		%	41	59	98	1	63	37	36	64	56	44
	Islands	Total	140,347	323,134	565,226	96,683	783,073	269,602	571,890	581,682	886,419	391,847
		%	30	70	85	15	74	26	50	50	69	31
	North-Eastern Italy	Total	757,976	713,083	2,498,417	68,334	586,790	3,206,401	453,869	3,488,475	2,579,679	2,171,146
		%	52	48	97	3	15	86	12	88	54	46
	North-Western Italy	Total	1,524,013	1,155,180	3,365,941	252,823	2,770,665	2,353,877	1,560,438	3,759,135	3,495,838	2,674,548
		%	57	43	93	0,7	54	46	29	71	57	43
	Southern Italy	Total	208,148	855,219	1,035,568	394,27	1,391,818	968,208	1,554,153	1,186,594	1,530,210	1,619,233
		%	20	80	72	28	59	41	57	43	49	51
Job Class	*Blue collars*	Total	1,452,605	2,893,153	5,374,197	763,090	4,524,299	4,359,145	2,297,499	7,144,097	9,402,865	1,950,768
		%	33	67	88	12	51	49	24	76	83	17
	White collars	Total	1,386,681	853,159	3,389,947	28,508	2,565,243	2,319,362	2,852,288	2,731,902	1,219,095	5,079,645
		%	62	38	99	1	53	47	51	49	19	81
	Executives	Total	6,548	74,255	111,353	14,757	30,538	111,303	55,224	71,326	47,448	80,326
		%	8	92	88	12	22	78	44	56	37	63
	Trainees	Total	347,412	419,29	524,257	35,228	300,322	777,690	35,146	927,880	35,176	1,057,469
		%	89	11	94	6	28	72	4	96	3	97
	Middle Managers	Total					20,469	329,395	118,105	353,032	46,437	458,890
		%					6	94	25	75	10	90

Table 6: Wage loss distribution by segments

cordingly, the RBTC hypothesis predicts that middle jobs were at higher risk of being replaced by computers during the 2000s and by robots and artificial intelligence nowadays. As consequence, middle-skilled workers would have shifted towards simpler manual or more complex abstract tasks, with an ensuing relative increase in the bottom tails of the distribution. The resulting occupational polarization due to human-replacing technologies should have therefore automatically turned into wage polarization, since wages are expected to closely follow job demand.

An enormous literature spurred in search of the evidence for such polarization, which empirically should have manifested into a U-shaped curve when looking both at employment and wage variations, as measured by wage percentiles (used as a proxy of skills) (Goos et al., 2009; Michaels et al., 2014). Thereafter, economic policies addressing inequality have generally been fully skill-oriented: taming inequality became a matter of education.

A strong critique to the latter theory has been put forward by an institutional approach to labour markets (Dosi et al., 2018; Mishel and Bivens, 2021) and has been questioned even by more mainstream contributions (Stansbury and Summers, 2020). A series of theoretical criticisms to this forms of technological determinism include: (i) a temporal mismatch between computer adoption and rising wage inequality (Card and DiNardo, 2002); (ii) lack of evidence, even acknowledged by the proponents of the theory (Autor, 2015), of the purported U-shaped pattern in every decade since the end of 1970s in the U.S. (Mishel and Bivens, 2017); (iii) contradictory results on the emergence of a job polarization pattern across European economies and presence of heterogeneity (Fernández-Macías and Hurley, 2017); (iv) institutional features behind inequalities away from technology, related to macro-economic policies, structural change, international trade competition, labor market regulation (Mishel and Bivens, 2021) work organisation (Holm et al., 2020) and firms' strategy of outsourcing (Weil, 2014); (v) a more comprehensive notion of wage and employment intended not simply as the result of demand and supply dynamics, but rather as the outcome of bargaining and conflicts; (vi) relevant differences between wage and skills level (usually proxied in terms of wage rank) empirically confirmed by declining college premia, increasing number of underpaid over-skilled workers (Cappelli, 2015) and growing inequality at the top of the income distribution (Atkinson et al., 2011; Mishel and Bivens, 2021); (vii) lack of perfect substitutability between computers and routine tasks;[6] viii) reductionist view of the labour activity in itself.[7]

Despite the criticism that has been raised, in this final part of our empirical analysis we perform a last exercise to detect the potential presence of polarisation in the Italian economy and to check for the indirect role of technological change in the rising wage inequality we have detailed above. Therefore, by following Acemoglu and Autor (2011) we perform a locally weighted Gaussian-smoothing regression of changes in employment and wage shares by wage percentile rank (used in this context as a proxy for occupational skill). For each wage percentile i the employment share is defined as $\frac{E_{i,t}}{E_t}$, where $E_{i,t}$ is total employment in percentile i and year t, and E_t is total employment in year t. For each starting year t_0 we then plot the change $\left(\frac{E_{i,t}}{E_t} - \frac{E_{i,t_0}}{E_{t_0}}\right)$. The shares thus sum to one across percentiles ($\sum_{i=0}^{100} \frac{E_{i,t}}{E_t} = \frac{E_t}{E_t} = 1$) and changes in shares sum to zero. A similar procedures is followed for wages.

Results are presented in Figure 12. We replicate the analysis for three periods (1983-1994), (1995-2006), (2007-2018) and show changes in employment (panel (a)) and in wages (panel (b)) by 1983 (the starting year of our data-set) wage percentiles.

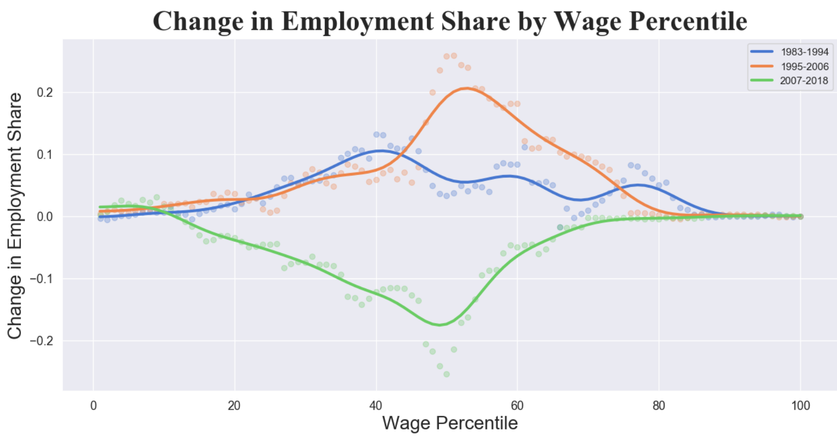
Firstly, no U-shaped pattern is present tout-court in employment changes: while in the previous two decades we do find evidence of a rather hump-shaped pattern (i.e., evidence of increases, and not decreases, in the middle part of the income distribution), in the last decade we record a decrease in the middle part, but with no increase neither in the lower nor in the upper part of the wage distribution, as predicted by the routine-bias technical change model. With reference to wage changes, we clearly see a gradual downward wage compression occurring over the almost four decades of analysis: while in the first period wages were rising relatively more for higher paid occupations, negative wage growth started to be recorded for low-paid occupations already in the period 1995-2006. A generalised negative wage growth is found along the entire wage distribution, except for wages at the very top in the last period.

5 Conclusions

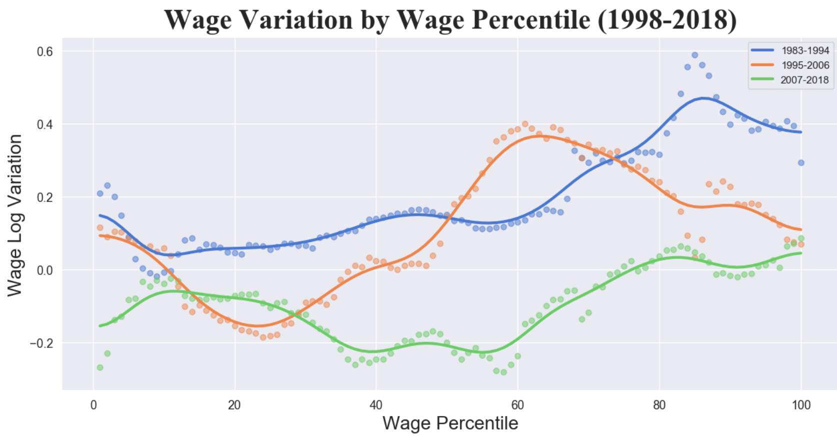
By using administrative data on the Italian labour market, this paper has documented a series of medium-run trends within an overall picture of exploding inequality at the top and

[6] In Acemoglu and Autor (2011) the authors make the example "of software that connects spelling and identifies grammatical errors" (p.82) as machines that substitute routine task. However, machine learning still requires human supervision and direct intervention (Tubaro and Casilli, 2019; Casilli, 2020).

[7] On the one hand, although the labour process in manufacturing might be viewed as standardised, manual workers do perform a large number of cognitive activities related to the control of production and tracking of errors (Pfeiffer, 2016; Cetrulo et al., 2020a), which are barely routinised. On the other hand, standardization is present in all activities, even those that apparently are very fare from routinisation, as writing papers, proving theorems or coding software.



(a)



(b)

Figure 12: Italy, 1983–2018. **(a)** Employment polarization. The figure plots 10-year changes in employment shares by 1983 wage percentile rank (1983-1994 in blue, 1995-2006 in orange, 2007-2018 in green). **(b)** Wage polarization. Real average wage 10-year logarithmic change (1983-1994 in blue, 1995-2006 in orange, 2007-2018 in green).

convergence toward the bottom, namely WAGE COMPRESSION, SERVITIZATION, JOB FLEXIBILIZATION AND FRAGMENTATION, AGEING LABOUR FORCE, FEMINIZATION, GEOGRAPHICAL DIVERGENCE. Among such potential determinants of inequality we have shown that the occupational category is the only factor presenting a higher between component vis-à-vis the within component, documenting that social classes, represented here by macro-occupational categories as intended by the early work of Sylos Labini (1974), are still the main determinant of divergence, notwithstanding the role played by age, gender and area of origin.

The Italian PNRR (*Piano Nazionale per la Ripresa e la Resilienza*), aimed at promoting a period of deep transformation of the Italian economy by investing almost 200 billions of euros in six years, has identified clearly three main divergent patterns in the labour market which require urgent action, namely (i) generational asymmetries, (ii) gender asymmetries, (iii) geographical asymmetries. Although we acknowledge the need to tame the latter divergences, the elephant in the room is represented by occupational asymmetries that are the root cause of the exploding 90-10 wage gap ratio, that is inequality at the top.

Inequality, we have shown, is an institutional result: it is largely due to wage compression strategies started with the period of cooperation (*periodo della concertazione*) in 1993 and perpetuated by a series of structural reforms meant at making flexible the labour market in line with the neo-liberal orthodox consensus. Almost thirty years of such policies gave us back a country marked by deep stratification processes, wherein social and economic risks, such as wage losses, are largely concentrated among young, female, blue-collars, in disadvantaged areas. Such stratification reverberates from the economic to the social dimension, and with cumulation of income, occupational and safety risks on the shoulder of the very same most vulnerable categories (Cetrulo et al., 2020b,c).

Evidence of institutionally based roots of inequality, away from technological deterministic prediction of sheer polarization, has been recently put forward also by Mishel and Bivens (2021) who, by focusing on the U.S., strongly advocate for a rebalancing of labour power as the only effective redistributive policy measure to revert inequality trends:

> Neither slow productivity growth nor inevitable economic forces can explain U.S. wage problems. Rather, wage suppression reflects the failure of economic growth to reach the vast majority. It was a "failure by design" (Bivens, 2011), engineered by those with the most wealth and power. The dynamics are primarily located in the labor market and the strengthening of employers' power relative to their rank-and-file workforce (which increasingly includes those workers with a four-year college degree). In other words, the dynamics that have challenged the growth of living standards for the vast majority are based on workers not sharing in economic gains [...]. [(Mishel and Bivens, 2021), p. 2-3]

If from a policy perspective our paper stresses the role of redefining power relationship between top and middle-bottom occupational categories, from an analytical perspective, although suffering from the absence of individual longitudinal data, it puts under the spotlight the role played by social classes in understanding the ongoing labour market trends. This enlarges the scope of investigation of inequality and stratification and calls for a deep reconsideration of the role of occupations as main determinants of divergence, actually more relevant, and by far, than individual attributes as gender, age and geographical location.

Some limitations are however important to highlight. First, the very notion of social class is very complex to empirically operationalize. In general, whenever possible, the literature has used full-digit level disaggregation of occupational data, but it has also linked political and social attitudes (e.g., consumption habits) as determinants of social classes (Weeden and Grusky, 2005). Our investigation lacks such detailed information, which however might also dilute in too many rivulets the identification of social classes. Second, the period under analysis is a hotbed of institutional changes with the national political agenda being shaped by the necessity of complying with the European so-called "external constraint" (Baccaro and D'Antoni, 2020). Indeed, with the exit of Italy from SME in 1992 and the urgency of entering back as soon as the fluctuations of lira were again under control, Italian governments put in place several policies in order to restore the competitiveness of the country. A strict control of the public debt was implemented, mainly through a massive reduction in public spending; the intervention of the State in the economy was downsized with the privatization of national companies owned by IRI such as Telecom and Alfa Romeo; the banking system was reformed (Graziani, 1998). Third, such structural changes combined with the re-entering of the national currency into the SME in 1996 clearly affected the overall productive structure of the country and influenced firms' strategies (Landini et al., 2020). While big firms' relevance was declining, industrial districts composed of small and interconnected firms were rising, also as the result of employers' interest to restructure and delocalize "at local level" the production in order to weaken trade unions' power and therefore relieve pressure on wage increases (Graziani, 1998). Considering that wage bargaining processes, or the lack of them, largely occur in workplaces, our results are silent about the workplace role in affecting inequality (Tomaskovic-Devey et al., 2020) and more broadly social classes, as they are about firm internal labour market policies and wage setting-schemes.

Future lines of research entail the understanding of the role played by sectoral and technological specialization in affecting inequality trends at the regional level in order to further explore the North-South divide, but also analyses meant at tackling determinants of functional income inequality, analysing, e.g., the dynamics of the labour share in the medium-run.

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6 Appendix

6.1 Descriptive figures

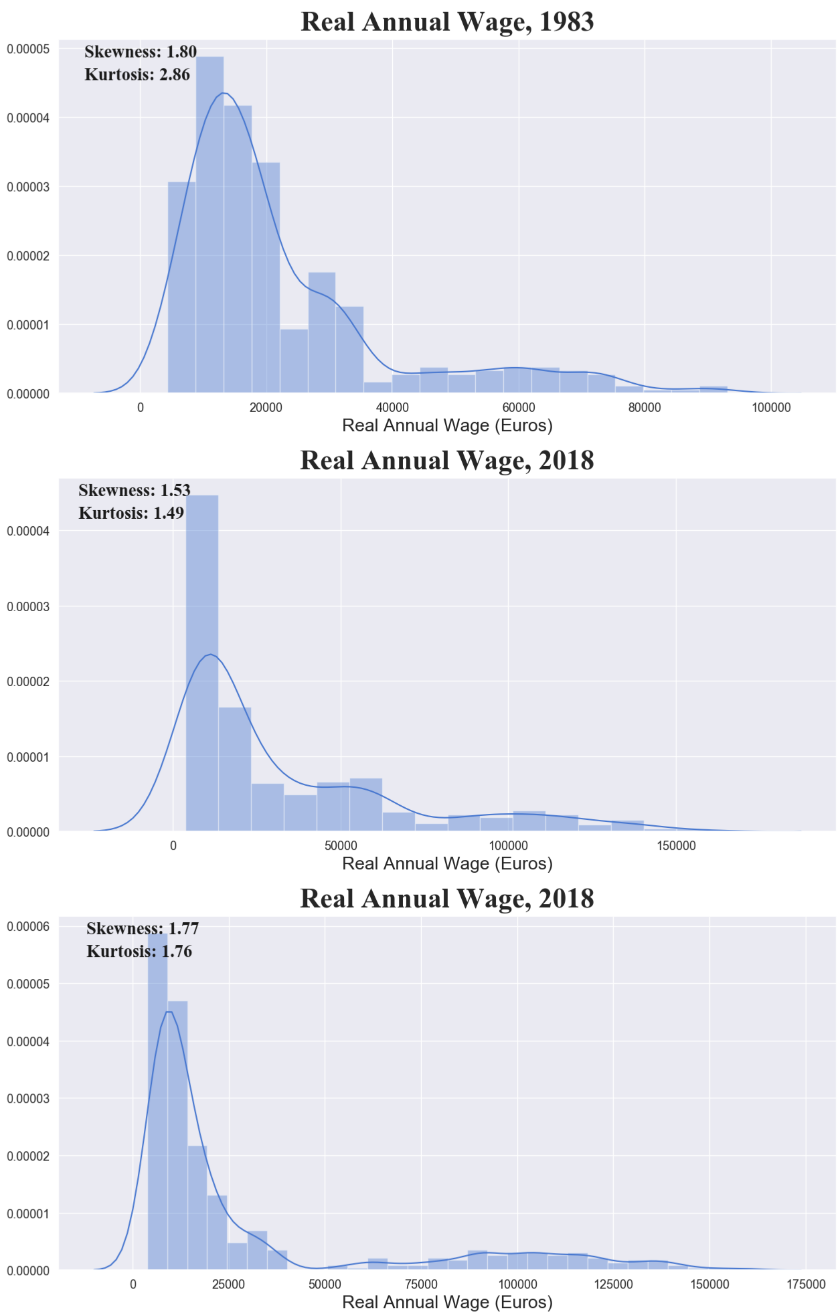

Figure 13: Italy, 1983–2018. **(a)** Real gross average wage distribution, Gaussian KDE in 1983; **(b)** 2018; **(c)** excluding executives 2018.

6.2 Regression-based inequality decomposition

Total workforce

Log Yearly Wage 1983	Coef.	Std. Err.	t	P>|t|	[95% Conf. Interval]
Female	-.3360131	.0130721	-25.70	0.000	-.3617118 -.3103145
White Collars	.3516309	.0132352	26.57	0.000	.3256115 .3776502
Executives	1.277227	.0560667	22.78	0.000	1.167004 1.387449
Trainees	-.4924298	.0271987	-18.10	0.000	-.5459001 -.4389595
30-50 Years Old	.354491	.0133622	26.53	0.000	.328222 .3807599
Over 50 Years Old	.3203695	.0192573	16.64	0.000	.2825114 .3582276
Central Italy	.2009248	.020298	9.90	0.000	.1610206 .2408289
Islands	-.0860071	.0278459	-3.09	0.002	-.1407498 -.0312644
North Eastern Italy	.2310217	.0200602	11.52	0.000	.1915851 .2704582
North Western Italy	.2999016	.0180021	16.66	0.000	.264511 .3352921
_cons	9.302424	.0181377	512.88	0.000	9.266767 9.338081
N	411				
Adjusted R-squared	0.9114				

Table 7: Econometric regression on Log Yearly Wage 1983.

Decomp.	100*s_f	S_f	100*m_f/m	CV_f	CV_f/CV(total)
Residual	8.6438	0.0036	-0.0000	-6.04e+14	-1.46e+16
Female	14.7076	0.0061	-1.1222	-1.4472	-34.8585
White Collars	14.9002	0.0062	1.1468	1.4727	35.4740
Executives	12.8056	0.0053	0.1503	9.3228	224.5580
Trainees	13.9438	0.0058	-0.2865	-4.0954	-98.6463
30-50	20.5255	0.0085	1.6625	1.0968	26.4188
Over 50	4.8118	0.0020	0.4422	2.5478	61.3678
Centre	0.5774	0.0002	0.4049	2.0322	48.9505
Islands	0.9154	0.0004	-0.0570	-3.8220	-92.0593
North Eastern Italy	-0.5902	-0.0002	0.4906	1.9667	47.3715
North Western Italy	8.7591	0.0036	1.1875	1.2687	30.5596
Total	100.0000	0.0415	100.0000	0.0415	1.0000

Table 8: Regression-based decomposition of inequality in Log Yearly Wage 1983.

Log Yearly Wage 1993	Coef.	Std. Err.	t	P>|t|	[95% Conf. Interval]
Female	-.3608618	.0111256	-32.44	0.000	-.3827339 -.3389897
White Collars	.5299623	.0113552	46.67	0.000	.5076387 .5522858
Executives	1.583107	.0459912	34.42	0.000	1.492692 1.673523
Trainees	-.5091363	.023455	-21.71	0.000	-.5552471 -.4630255
30-50 Years Old	.3401489	.011386	29.87	0.000	.3177649 .3625329
Over 50 Years Old	.3857652	.0174467	22.11	0.000	.3514662 .4200643
Central Italy	.1625902	.0179258	9.07	0.000	.1273494 .1978309
Islands	-.0705613	.0238629	-2.96	0.003	-.1174741 -.0236485
North Eastern Italy	.1654493	.0171409	9.65	0.000	.1317516 .199147
North Western Italy	.2467609	.0161534	15.28	0.000	.2150045 .2785173
_cons	9.393638	.0157269	597.30	0.000	9.36272 9.424555
N	410				
Adjusted R-squared	0.9488				

Table 9: Econometric regression on Log Yearly Wage 1993.

Decomp.	100*s_f	S_f	100*m_f/m	CV_f	CV_f/CV(total)
residual	4.9922	0.0023	0.0000	9.60e+13	2.05e+15
Female	11.7914	0.0055	-1.2803	-1.3723	-29.3737
White Collars	28.5416	0.0133	1.8110	1.4119	30.2218
Executives	16.3930	0.0077	0.2071	8.7899	188.1472
Trainees	12.0849	0.0056	-0.2926	-4.1004	-87.7686
30-50 Years Old	15.4713	0.0072	1.5911	1.0891	23.3124
Over 50 Years Old	5.7427	0.0027	0.4568	2.7646	59.1766
Central Italy	0.4820	0.0002	0.3208	2.0460	43.7954
Islands	0.4531	0.0002	-0.0488	-3.7139	-79.4962
North Eastern Italy	-1.0885	-0.0005	0.4115	1.7644	37.7679
North Western Italy	5.1363	0.0024	0.8901	1.3549	29.0023
Total	100.0000	0.0467	100.0000	0.0467	1.0000

Table 10: Regression-based decomposition of inequality in Log Yearly Wage 1993.

Log Yearly Wage 2003	Coef.	Std. Err.	t	P>|t|	[95% Conf. Interval]
Female	-.4090858	.0094812	-43.15	0.000	-.4277124 -.3904591
White Collars	.5543072	.0101205	54.77	0.000	.5344245 .57419
Executives	1.8362	.0464718	39.51	0.000	1.744902 1.927499
Trainees	-.2180298	.0194036	-11.24	0.000	-.25615 -.1799096
Middle Managers	1.191567	.0301086	39.58	0.000	1.132416 1.250718
30-50 Years Old	.3878121	.0103008	37.65	0.000	.3675753 .408049
Over 50 Years Old	.509484	.0157425	32.36	0.000	.4785563 .5404117
Central Italy	.0927542	.0152335	6.09	0.000	.0628265 .1226818
Islands	-.0436096	.0205359	-2.12	0.034	-.0839544 -.0032648
North Eastern Italy	.1372863	.0144755	9.48	0.000	.1088477 .165725
North Western Italy	.1754438	.0137834	12.73	0.000	.148365 .2025226
_cons	9.24379	.013717	673.89	0.000	9.216842 9.270738
N	525				
Adjusted R-squared	0.9559				

Table 11: Econometric regression on Log Yearly Wage 2003.

Decomp.	100*s_f	S_f	100*m_f/m	CV_f	CV_f/CV(total)
residual	4.3137	0.0022	-0.0000	-1.24e+14	-2.48e+15
Female	13.9683	0.0070	-1.6232	-1.2692	-25.3179
White Collars	22.6114	0.0113	1.8178	1.4695	29.3129
Executives	14.1250	0.0071	0.1782	10.2881	205.2227
Trainees	4.3639	0.0022	-0.1502	-3.7473	-74.7502
Middle Managers	14.3957	0.0072	0.2835	6.5247	130.1521
30-50 Years Old	15.0218	0.0075	2.1265	0.9428	18.8061
Over 50 Years Old	8.7032	0.0044	0.5965	2.8024	55.9004
Central Italy	-0.0126	-0.0000	0.1862	2.0403	40.6984
Islands	0.1882	0.0001	-0.0304	-3.7269	-74.3422
North Eastern Italy	-0.2966	-0.0001	0.3543	1.7366	34.6405
North Western Italy	2.6180	0.0013	0.6104	1.4063	28.0526
Total	100.0000	0.0501	100.0000	0.0501	1.0000

Table 12: Regression-based decomposition of inequality in Log Yearly Wage 2003.

Log Yearly Wage 2013	Coef.	Std. Err.	t	P>|t|	[95% Conf. Interval]
Female	-0.472304	.007747	-60.97	0.000	-0.487 - -0.457
White Collars	0.6509091	.0083336	78.11	0.000	0.634 - 0.667
Executives	2.025904	.0427336	47.41	0.000	1.941 - 2.109
Trainees	0.128903	.0172828	7.46	0.000	0.094 - 0.162
Middle Managers	1.3665	.0229033	59.66	0.000	1.321 - 1.411
30-50 Years Old	0.5239184	.0096293	54.41	0.000	0.505 - 0.542
Over 50 Years Old	0.6508425	.0120905	53.83	0.000	0.627 - 0.674
Central Italy	0.1940378	.0122788	15.80	0.000	0.169 - 0.218
Islands	-0.0202988	.0166329	-1.22	0.223	-0.052 - 0.012
North Eastern Italy	0.3077266	.0118942	25.87	0.000	0.284 - 0.331
North Western Italy	0.3243027	.0113114	28.67	0.000	0.302 - 0.346
_cons	8.863065	.0120032	738.39	0.000	8.839 - 8.886
N	540				
Adjusted R-Squared	0.9753				

Table 13: Econometric regression on Log Yearly Wage 2013.

Decomp.	100*s_f	S_f	100*m_f/m	CV_f	CV_f/CV(total)
residual	2.4186	0.0014	-0.0000	-8.36e+13	-1.46e+15
Female	14.0112	0.0080	-2.0897	-1.1677	-20.4340
White Collars	24.7073	0.0141	2.2758	1.4112	24.6944
Executives	10.9045	0.0062	0.1621	11.3916	199.3423
Trainees	-1.3606	-0.0008	0.0799	3.9854	69.7410
Middle Managers	17.0695	0.0098	0.3972	5.9164	103.5308
30-50 Years Old	12.9800	0.0074	3.0988	0.8761	15.3314
Over 50 Years Old	12.2709	0.0070	1.2363	2.1231	37.1524
Central Italy	-0.2967	-0.0002	0.4189	1.9610	34.3149
Islands	0.1232	0.0001	-0.0150	-3.6252	-63.4375
North Eastern Italy	1.7519	0.0010	0.7688	1.7853	31.2416
North Western Italy	5.4202	0.0031	1.0811	1.4621	25.5848
Total	100.0000	0.0571	100.0000	0.0571	1.0000

Table 14: Regression-based decomposition of inequality in Log Yearly Wage 2013.

Log Yearly Wage 2018	Coef.	Std. Err.	t	P>|t|	[95% Conf. Interval]
Female	-.4681434	.0081762	-57.26	0.000	-.4842049 -.4520818
White Collars	.6842877	.0088642	77.20	0.000	.6668747 .7017006
Executives	2.071677	.0487108	42.53	0.000	1.975988 2.167366
Trainees	.2224362	.0184795	12.04	0.000	.1861347 .2587377
Middle Managers	1.421381	.0250223	56.80	0.000	1.372227 1.470536
30-50 Years Old	.6039673	.010097	59.82	0.000	.5841326 .623802
Over 50 Years Old	.7642786	.0119016	64.22	0.000	.7408988 .7876584
Central Italy	.1842535	.0130152	14.16	0.000	.158686 .2098209
Islands	-.0306534	.0180946	-1.69	0.091	-.066199 .0048921
North Eastern Italy	.3050324	.0125661	24.27	0.000	.2803474 .3297175
North Western Italy	.3210475	.0120214	26.71	0.000	.2974323 .3446626
_cons	8.770863	.0126168	695.17	0.000	8.746079 8.795648
N	545				
Adjusted R-squared	0.9748				

Table 15: Econometric regression on Log Yearly Wage 2018.

Decomp.	100*s_f	S_f	100*m_f/m	CV_f	CV_f/CV(total)
residual	2.4683	0.0015	0.0000	5.85e+13	9.70e+14
Female	12.1131	0.0073	-2.0792	-1.1659	-19.3261
White Collars	25.3352	0.0153	2.3283	1.4423	23.9075
Executives	8.9335	0.0054	0.1431	12.2826	203.5905
Trainees	-1.8550	-0.0011	0.1313	4.0945	67.8682
Middle Managers	15.8846	0.0096	0.3880	6.1168	101.3897
30-50 Years Old	12.7836	0.0077	3.2240	0.9812	16.2638
Over 50 Years Old	18.1324	0.0109	1.8199	1.8445	30.5742
Central Italy	-0.2786	-0.0002	0.4010	1.9536	32.3812
Islands	0.1603	0.0001	-0.0212	-3.7664	-62.4301
North Eastern Italy	1.4800	0.0009	0.7828	1.7563	29.1114
North Western Italy	4.8425	0.0029	1.0701	1.4644	24.2731
Total	100.0000	0.0603	100.0000	0.0603	0.0603

Table 16: Regression-based decomposition of inequality in Log Yearly Wage 2018.

6.3 Wage loss analysis

		1983-1984		1993-1994		2003-2004		2013-2014		2017-2018	
Gender	*Pearson*	1.2e+05	Pr = 0.000	1.8e+05	Pr = 0.000	2.8e+06	Pr = 0.000	6.9e+03	Pr = 0.000	6.4e+05	Pr = 0.000
	LR test	1.3e+05	Pr = 0.000	2.1e+05	Pr = 0.000	2.9e+06	Pr = 0.000	6.9e+03	Pr = 0.000	6.4e+05	Pr = 0.000
Age Class	*Pearson*	5.3e+05	Pr = 0.000	5.6e+05	Pr = 0.000	1.6e+05	Pr = 0.000	5.0e+05	Pr = 0.000	7.1e+05	Pr = 0.000
	LR test	5.7e+05	Pr = 0.000	6.3e+05	Pr = 0.000	1.6e+05	Pr = 0.000	4.9e+05	Pr = 0.000	7.2e+05	Pr = 0.000
Geographical Area	*Pearson*	5.1e+05	Pr = 0.000	9.8e+05	Pr = 0.000	2.4e+06	Pr = 0.000	1.7e+06	Pr = 0.000	1.7e+05	Pr = 0.000
	LR test	5.3e+05	Pr = 0.000	8.1e+05	Pr = 0.000	2.6e+06	Pr = 0.000	1.8e+06	Pr = 0.000	1.7e+05	Pr = 0.000
Job Class	*Pearson*	8.5e+05	Pr = 0.000	4.0e+05	Pr = 0.000	5.3e+05	Pr = 0.000	1.6e+06	Pr = 0.000	8.4e+06	Pr = 0.000
	LR test	8.9e+05	Pr = 0.000	5.3e+05	Pr = 0.000	6.0e+05	Pr = 0.000	1.6e+06	Pr = 0.000	9.2e+06	Pr = 0.000