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IZA DP No. 16693

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DECEMBER 2023

I Z A Institute of Labor Economics

Initiated by Deutsche Post Foundation

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DECEMBER 2023

ISSN: 2365-9793

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ABSTRACT

The Role of Industries in Rising Inequality*

We analyse thirty years of Italian private sector employment data (1985-2018) to study the dynamics of rising earnings inequality. The total variance surged by 10 log points, with 55% occurring between industries, particularly in a few low-paid service sectors. Workers with low earnings ability showed increased likelihood of working in industries with low average firm premium (sorting) together with other low-earning workers (segregation). Strikingly, parallels with the US emerge. In both, inequality increased predominantly between industries and concentrated within a small number of sectors. Italy's increase primarily stems from low-paying sectors, diverging from the more balanced growth observed in the US across high-paying and low-paying industries. Our findings suggest that despite institutional differences similar underlying forces are at work.

JEL Classification: E02, E25, J01

Keywords: earnings inequality, industries, sorting, segregation

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* We thank Alan Manning, John Moore, Mike Elsby, Claudio Michelacci, Jonathan Thomas, John Van Reenen, Lorenzo Cappellari, Bernardo Fanfani, Salvatore Lattanzio and Salvatore Morelli. We also thank participants at the 2023 EEA-ESEM, EALE, ESPE, AIEL and SIEP conferences, 2023 CEP-LSE Labour Workshop, 2022 VisitINPS workshop, the VisitINPS seminar, and the 2022 MacCaLM conference for their useful comments. All remaining errors are our own. The findings and conclusions expressed are solely those of the authors and do not represent the views of INPS. La realizzazione del presente articolo è stata possibile grazie alle sponsorizzazioni e le erogazioni liberali a favore del programma "VisitINPS Scholars".

1 Introduction

While it is well established that earnings inequality has increased sharply since the 1980s, the features of this increase remain a matter of debate (Hoffmann et al. 2020). A large body of literature has focused on understanding the role of firms and has shown that the large majority of the rise in earnings inequality took place between firms.[1] A question which is overlooked, with the exception of Haltiwanger et al. (2022) for the US, is whether earnings inequality is growing mainly between firms in the same industry, or between firms in different industries. To the best of our knowledge, no such study exists for Europe. Determining whether the factors driving inequality are primarily rooted in industry-level dynamics or are connected to the heterogeneity across firms within the same sectors is crucial for shaping effective policy strategies. Our analysis unveils the importance of changes in the organization of production between industries, and comprehensively illustrates the characteristics of the increase in earnings inequality in the European context. This perspective has received little attention in the inequality literature, which focuses on the heterogeneous composition of skills and tasks across firms and industries. Our results complement this established view since structural changes, such as the adoption of new technologies or globalization, which influence the demand for workers with particular skill sets, bring about different changes in the organization of production depending on the type of industry (Haltiwanger et al. 2022).

To investigate this issue, we use a social security administrative dataset covering the universe of private-sector employment in Italy. We first document the evolution of real annual earnings in Italy in the last thirty years, which we show to be characterised by a lack of growth and rising dispersion. We perform several variance decompositions, estimate an AKM model (Abowd et al. 1999) and calculate the industry-enhanced AKM variance decomposition (Haltiwanger et al. 2022) to assess the role of industries and firms in explaining the observed increase in earnings variance. Specifically, we explore the extent of sorting

[1] Song et al. (2019), Barth et al. (2016) and Haltiwanger et al. (2022) for the US, Faggio et al. (2010) for the UK, Card et al. (2013) for West Germany and Alvarez et al. (2018) for Brazil.

(high-wage workers are more likely to work in industries with high average firm effects) and segregation (high-wage workers are more likely to work together in the same industry).

It is an open question whether the increase in earnings inequality is ascribable to higher dispersion in the rate of pay or how much an individual works over the year (Depalo and Lattanzio 2023). This is particularly relevant for Italy, where the labour market is highly segmented (Tealdi 2019, Di Porto and Tealdi 2022) and some industries adopt temporary contracts to a greater extent than others (Felgueroso et al. 2017). Therefore, across industries, we decompose the variance of annual earnings into the variance of weeks worked, the variance of wage rates and their covariance.

We document a rise in the variance of log annual earnings of about half the size of the US and around 10 log points.[2] Interestingly, similar to the US, we find that the large majority of the total increase in annual earnings variance between 1985 and 2018 took place between industries (55%), corresponding to approximately 5.3 log points. Less than half of it took place within firms (27%) and the remaining 18% between firms within the same industry. This large increase in the between-sector variance component is even more concentrated than in the US, with a small number of industries playing a disproportionate role (14 out of 523 sectors in Italy compared to 30 out 301 sectors in the US)[3]. However, while in Italy the key industries driving inequality are low-paying service sectors related to food and drink, accommodation, social care, cleaning of buildings and work agencies, and account for 4.2 log point out of the total 10 log point increase, in the US the driving industries are equally split between low-paying and high-paying. In Italy, these low-paying sectors contributed towards greater inequality by both attracting more employment and experiencing declining relative earnings.

We also find that the growth in earnings inequality is mainly due to the rising dispersion in the worker-specific component of pay and to the increased (positive) sorting of workers

[2] When applying the same sample selection and comparing to the results of Song et al. (2019) who cover a similar period to us.

[3] Comparing to the results of Haltiwanger et al. (2022) for the USA.

into firms and industries. Comparing AKM-based variance decomposition over time, we show that industries are increasingly different in the average earnings ability of their workers (segregation) and workers with low earnings ability are more likely to work in industries with low average firm pay premiums (sorting).

When breaking down annual earnings into weeks worked and pay rates, we observe a growing variation in wage rates and a strengthening positive correlation between pay rates and weeks worked. This intensifies over time and is primarily attributed to the between-sector component. These findings emphasize the important role of industries in dual labour markets. Sectors with low rates of pay are also the ones employing part-time and temporary workers, thus amplifying the effect of earnings dispersion between sectors.

This paper contributes to the literature by providing a comprehensive analysis of the features of increased earnings inequality, by specifically investigating the role of industries. This complements the recent literature which has focused on firm heterogeneity within industries (Autor et al. 2020, Freund 2022). The patterns that we find are consistent with shifts in industry-level labour demand and subsequent reallocation of workers across industries. These shifts could be the result of different forces: structural transformation, routine-biased technical change or trade (Acemoglu and Autor 2011, Autor and Dorn 2013). Our findings could also be partially accounted for by the rise of domestic outsourcing (Autor 2003).

We are the first to shed light on the role of industries in rising inequality in a country with an institutional setting different from the US, but similar to many European countries. Despite stark differences (national collective agreements, union representation), we find patterns which are very similar to the ones found by Haltiwanger et al. (2022) for the US. This is suggestive evidence that the underlying forces are likely similar.

We also contribute to the small and emerging literature examining the contribution of wage rates and labour supply quantities to the annual earnings inequality (Depalo and Lattanzio 2023, Bovini et al. 2023). Our findings are related to the literature on dual labour markets in Europe (Saint-Paul 1996, Bentolila et al. 2020), and in Italy (Picchio 2008, Tealdi

2019, Bianchi and Paradisi 2023). The significant increase in the dispersion of weeks worked among young men, likely caused by the introduction of temporary contracts in Italy, played a limited role in the overall rise in earnings inequality.

The remainder of the paper is organized as follows. Section 2 describes the data. Section 3 presents descriptive analysis of annual earnings inequality in Italy. In Section 4 we explore the role of firm and worker heterogeneity and sorting of workers across firms and industries. In Section 5 we study the role of labour supply quantities, rate of pay and their covariance to the growth of annual earnings inequality. In Section 6 we discuss the possible explanations of our findings. Finally, Section 7 concludes.

2 Data

We use a matched employer-employee administrative dataset provided by the Italian Social Security Institute (INPS),[4] which contains the universe of Italian social security records of private-sector employees (excluding agriculture) between 1975 and 2018. We focus on the period 1985-2018. The data includes information on labour earnings (no upper limit), the number of weeks worked, unique worker and firm identifiers, the location of the firm, type of contract and demographic information of the worker (gender, year, and place of birth). Uniquely, the database includes information on the sector (NACE industry classification at 4 digits) of the worker and the firm.[5] We sum income across all employment spells in a given year for each worker and we link each worker to the firm that accounts for the largest share of her income. We also set a threshold level of annual earnings below which all observations are dropped to remove any bias brought about by individuals who are not

[4] Istituto Nazionale della Previdenza Sociale.

[5] A firm which operates in multiple sectors, e.g., a car company which produces cars (manufacturing) and also sells them to customers (retail), receives multiple identifiers from the Social Security Institute, one for each sector it is engaged in; workers are registered under this sector-specific firm identifier. In contrast, administrative data from other countries typically only includes the primary sector of the firm. To ensure comparability with other studies, we assign to the firm the sector to which the majority of the firm's workforce belongs.

strongly attached to the labour market. Although Italy does not have a statutory national minimum wage, we compute the threshold level by multiplying the lowest hourly rate of pay in 2018 (which amounts to 6.77 Euro)[6] by 13 working weeks (one quarter) by 40 hours a week.[7] We adjust this threshold for all the other years (1985-2018) using the nominal wage growth series provided by the OECD[8].

We restrict the sample to individuals between the age of 20 and 60 and to firms with at least 10 workers for our baseline analysis.[9] The latter criteria ensures that the number of observations is sufficient to calculate a meaningful within-firm variance and it is consistent with other studies in the literature, thus assuring comparability of results. Nevertheless, our results are robust to lowering the minimum firm size threshold to 5 workers per firm or removing the restriction altogether (Section 3.5).

The original INPS data set (the entire universe) contains about 640,000 firms and approximately 6.9 million workers in 1985 and 1.5 million firms and 14.8 million workers in 2018 (Table 1(a)).[10] Our sample contains approximately 88,000 firms and 4.6 million workers in 1985 and approximately 192,000 firms and 9.2 million workers in 2018. The restrictions, especially the firm size requirement, imply that our sample includes about 13% of the total number of firms and two-thirds of the total number of workers. Firms are on average larger in our sample due to the imposed minimum firm size: the median number of workers per firm in 2018 is 3 in the universe and 17 in our sample; the mean firm size in 2018 is 10 in the original data and 47.8 in our sample (Table 1(b)). The mean annual earnings are higher in the sample than in the original data set due to the imposed minimum threshold of annual

[6] According to the Italian statistical office, the gross hourly wage of a worker in the bottom decile of temporary contract workers in the 2-digit NACE industry "81: services to buildings and landscape activities" was 6.77 Euro in 2018.

[7] Our threshold level of earnings, which amounts to 3520 Euro in 2018, is comparable to the one chosen for the US, e.g., Song et al. (2019) set it at $3,770 in 2013.

[8] https://data.oecd.org/lprdty/labour-compensation-per-hour-worked.htm.

[9] Song et al. (2019) use a cutoff of 20 workers per firm. We set a lower cutoff due to the high percentage of workers employed in small firms in Italy.

[10] The rise in the number of private sector employees between 1985 and 2018 is due to the higher participation rate of women, population growth and immigration. Figure A4 displays labour force participation by gender. We can see a steady increase in the participation of women, while the rate for men is flat.

Table 1: Descriptive statistics.

(a) Observations

	Number of firms	Number of workers
Universe - 1985	643,160	6,934,287
Our Sample - 1985	87,852	4,580,723
Universe - 2018	1,480,243	14,836,334
Our Sample - 2018	191,930	9,182,330

(b) Distribution of firm size

	Mean	sd	10%	50%	90%
Universe - 1985	10.78	164.58	1	3	15
Our Sample - 1985	52.14	409.38	10	18	77
Universe - 2018	10.02	213.71	1	3	14
Our Sample - 2018	47.84	481.85	10	17	67

(c) Distribution of annual earnings

	Mean	sd	10%	50%	90%
Universe - 1985	20,320	16,518	3,425	19,983	34,407
Our Sample - 1985	24,806	16,830	8,901	23,124	38,095
Universe - 2018	21,729	22,253	2,697	19,135	41,050
Our Sample - 2018	27,050	23,229	8,426	23,633	46,675

Note: The universe includes all private sector employees (excluding agriculture). Our sample includes workers between the age of 20 and 60 working in firms with at least 10 employees and with annual earnings above the minimum threshold. Earnings are expressed in 2018 euros.

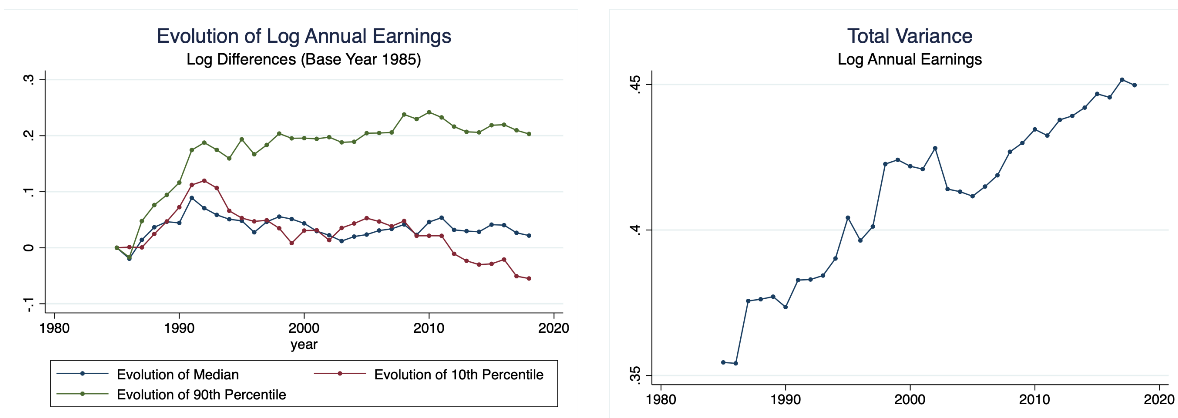
earnings (Table 1(c)).

3 Descriptive Analysis of Earnings Inequality

3.1 Evolution of annual earnings in Italy

The evolution of the annual earnings distribution in Italy is characterised by little growth in the average, but a significant increase in the dispersion. Mean real annual earnings stood at 24,806 euros in 1985 and 27,050 euros in 2018 (Table 1(c)). Median earnings saw virtually no growth in the 33-year window, changing from 23,124 euros in 1985 to 23,633 euros in 2018 (Figure 1). Conversely, the 90th percentile of earnings increased by 20 log points, with most of the growth happening between 1985 and 1995; the 10th percentile increased between 1985 and the mid-1990s, but fell persistently afterwards, ending up 6 log points lower compared to 1985.

Figure 1: Growth of earnings dispersion: percentile ratios and total variance.



(a) Evolution of Log Annual Earnings.

(b) Overall Inequality.

Note: In the left-hand graph annual earnings are normalised to zero in 1985 (base year). Our measure of inequality is the variance of log annual earnings.

Summing up, between 1985 and mid-1990s, the increased dispersion was mainly due to the fast growth in earnings at the top of the distribution, while between 1995 and 2018 the increased dispersion was mainly driven by falling earnings at the bottom.[11] Total variance of log annual earnings rose from 0.35 in 1985 to 0.45 in 2018 (Figure 1), representing an

[11] The 90th to 50th percentile ratio of annual earnings grew mainly between 1985 and 2003, while the 50th to 10th percentile ratio grew mainly after 2005 (Figure A1).

increase of 9.6 log points. This increase was persistent and not episodic, i.e., the dispersion was rising throughout the period. Although the growth in earnings inequality in Italy is about half the level of the US throughout the period under consideration (Song et al. 2019), it is still quite remarkable and worth investigating.

3.2 Variance Decomposition

Our first analysis to study the role of firms in accounting for the increased earnings inequality in Italy is to perform the variance decomposition into the between-firm and within-firm components:

$$\underbrace{\frac{1}{N}\sum_{\forall i}(y_{ij}-\bar{y})^2}_{\text{total variance}} = \underbrace{\sum_{\forall j}\frac{n_j}{N}(\bar{y}_j-\bar{y})^2}_{\text{between-firm variance}} + \underbrace{\sum_{\forall j}\frac{n_j}{N}\frac{\sum_{\forall i|i\in j}(y_{ij}-\bar{y}_j)^2}{n_j}}_{\text{within-firm variance}}, \tag{1}$$

where y_{ij} denotes the log annual earnings of worker i at firm j in a given year, N denotes the total number of workers, n_j is the number of workers employed at firm j, $\bar{y}_j = \frac{1}{n_j}\sum_{\forall i|i\in j} y_{ij}$ is the value of average log annual earnings at firm j and $\bar{y} = \frac{1}{N}\sum_{\forall i} y_{ij}$ is the economy-wide average of log annual earnings. Then, we further decompose the between-firm variance in the between-sector and the between-firm-within-sector components to investigate the role of industries:[12]:

[12] In addition to directly calculating (2), the results of this variance decomposition can also be obtained by first controlling for the sector (either by running regression with sector fixed effects and taking residuals or by demeaning the data by sector averages) and then performing the between- versus within-firm variance decomposition on the resulting data (more detailed explanation is in the Appendix, Section 9.1). This produces between-firms-within-sector variance and within-firm variance. All three methods are equivalent and generate the same outcomes.

$$\underbrace{\frac{1}{N}\sum_{\forall i}(y_{ijs}-\bar{y})^2}_{\text{total variance}} = \underbrace{\sum_{\forall s}\frac{n_s}{N}(\bar{y}_s-\bar{y})^2}_{\text{between-sector variance}} + \underbrace{\sum_{\forall s}\frac{n_s}{N}\sum_{\forall j|j\in s}\frac{n_j}{n_s}(\bar{y}_j-\bar{y}_s)^2}_{\text{between-firm-within-sector variance}} + \underbrace{\sum_{\forall j}\frac{n_j}{N}\frac{\sum_{\forall i|i\in j}(y_{ijs}-\bar{y}_j)^2}{n_j}}_{\text{within-firm variance}}, \tag{2}$$

where y_{ijs} denotes the log annual earnings in a given year of a worker i employed in firm j which belongs to sector s, n_s is the number of workers employed in sector s and $\bar{y}_s$ gives the average log annual earnings of sector s.

3.3 Inequality between firms and sectors

We perform the full variance decomposition presented in Equation (2) for every year from 1985 until 2018 (Table 2). We find that the total variance grew from 0.35 in 1985 to 0.45 in 2018. The growth of the between-sector variance accounts for 55.8% of the total variance increase, the between-firm-within-sector variance accounts only for 17.9%, while the remaining 26.3% is due to the rise of the within-firm component.[13][14]

Similar to other countries,[15] we find that the majority of the rise in earnings inequality in Italy between 1985 and 2018 took place between firms, and this was overwhelmingly driven by the rising dispersion of average earnings across industries, but only partially driven by the rising dispersion of average earnings across firms within industry. The between-firm variance also became a larger relative component of the total variance of log annual earnings. The dispersion in average earnings across firms represented 45.6% of the total variance in 1985,

[13]When we instead use the sector of the worker for our analysis, the findings are very similar to the baseline ones. Results are available upon request.

[14]Although all three components were growing over time (Figure 2), the between-sector component grew as a share of total variance, while the shares of both the between-firm-within-sector and the within-firm components fell during the period considered (Table 2).

[15]US (Song et al. (2019), Barth et al. (2016)), the UK (Faggio et al. (2010)) and West Germany (Card et al. (2013)).

Table 2: Sectors and firms: full variance decomposition.

(a) Variance change over time

	Between sector	Between firms within sector	Within firm	Total
1985	0.083	0.079	0.193	0.355
2018	0.136	0.096	0.218	0.450
Change	0.053	0.017	0.025	0.095
% of total increase	55.8%	17.9%	26.3%	100.0%

(b) Variance shares

	Between sector	Between firms within sector	Within firm
1985	23.3%	22.2%	54.4%
2018	30.2%	21.4%	48.4%

Note: see Equation (2) for definitions. Industries are defined according to the 4 digit NACE classification.

and rose to 51.6% in 2018 (Table 2).[16]

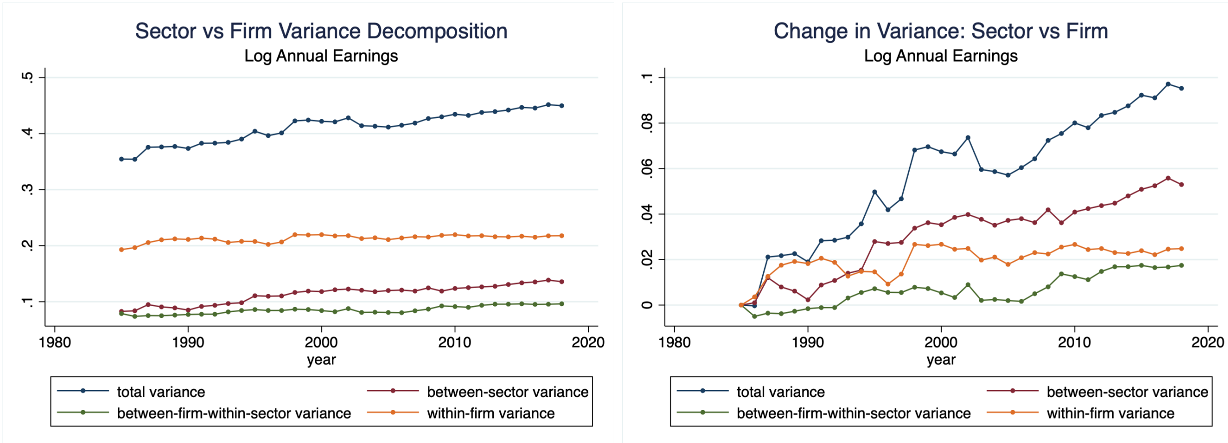
The level of aggregation of the sector does not matter for this result: the increase in between sector variance represents 57.9%, 54.7% and 55.8% of the total variance increase with 2 digit, 3 digit and 4 digit industry categories, respectively (Table 3). Thus, inequality grew mainly between broad industries.[17]

To understand the role of gender in explaining the previous results, we split the sample and calculate the variance decomposition for men and women separately. Overall, the results for men are consistent with the baseline sample (Figure A2). The patterns for women are different. While earnings dispersion is higher for women, it has not increased over time (Table A2). The total variance of log annual earnings in the female sample was 0.42 in 1985 and 0.45 in 2018. The limited rise in earnings dispersion among women is overwhelmingly

[16] The same patterns hold up for all firm size categories. The definitions of firm size categories come from OECD and are: small firm: 10-49 employees; medium firm: 50-249 employees; large firm: over 250 employees. Results available from the authors upon request.

[17] Additionally, the explanatory power of industry in any given yearly cross-section varies very little with the level of aggregation (Table 3).

Figure 2: Sector and firm: full variance decomposition.



(a) Levels. (b) Change Relative to 1985.

Note: See Equation (2) for definitions. In the right-hand graph the variance is normalised to zero in 1985 (base year). Industries are defined according to the 4-digit NACE classification.

due to rising within-firm dispersion. This is the net effect of an increase in between-sector variance and a much larger fall in between-firm-within-sector variance (Figure A3).

Table 3: Between versus within 2, 3 and 4 digit sectors: variance decomposition.

(a) Variance change over time

	Between sector			Total
	2 digit	3 digit	4 digit	
1985	0.065	0.077	0.083	0.355
2018	0.120	0.130	0.136	0.450
Change	0.055	0.052	0.053	0.095
% of total increase	57.9%	54.7%	55.8%	100.0%

(b) Variance shares

	Between sector		
	2 digit	3 digit	4 digit
1985	18.2%	21.8%	23.3%
2018	26.6%	28.8%	30.2%

Note: The between versus within variance of annual earnings is reported. Industries are defined according to the NACE classification. There are 88 2-digit sectors, 268 3-digit sectors and 593 4-digit sectors.

3.4 The industries driving growth in inequality

In this section, we identify the sectors which are responsible for the growth in between-industry inequality. We calculate the contribution of individual sectors to the between-sector variance growth using the following expression:

$$\underbrace{\Delta var(\bar{y}_s - \bar{y})}_{\substack{\text{between-sector} \\ \text{variance growth}}} = \sum_{s=1}^{523} \underbrace{\Delta \underbrace{\left(\frac{n_s}{N}\right)}_{\substack{\text{employment} \\ \text{share}}} \underbrace{(\bar{y}_s - \bar{y})}_{\substack{\text{relative} \\ \text{earnings}}}^2}_{\substack{\text{sector s's contribution} \\ \text{to between sector} \\ \text{variance growth}}}, \tag{3}$$

where N is total employment, n_s is employment in sector s, $\bar{y}$ denotes economy-wide average earnings and $\bar{y}_s$ are average earnings in sector s. We define the contribution of sector s to between-sector variance increase as $\Delta\left(\frac{n_s}{N}\right)(\bar{y}_s - \bar{y})^2$.

The contribution of a sector to between-sector variance growth consists of two parts: changes in relative earnings and changes in employment share (Equation 3). When the average earnings in a high-paying (low-paying) industry increase (decrease) over time, this increases between sector variance. On the contrary, if average earnings move closer towards the economy average, inequality falls. Inequality will also grow when there is an increase in employment shares of industries which have average earnings far from the economy average, either paying very high or very low earnings. On the contrary, if employment is shifting towards industries that pay close to the economy average, inequality will fall. Finally, changes in relative earnings of an industry will have a larger impact on inequality if that sector represents a larger share of employment.

We identify five 4-digit sectors with individual relative contributions of more than 5% that jointly account for 66% of the increase in between-sector variance (and thus about a third of the overall earnings inequality increase), while only representing 3% of employment in 1985 (Table 4).[18] Additional nine sectors with individual contributions between 2.6% and 5% together account for 33% of the rise in between-sector variance, while collectively having an employment share of 5% in 1985. Thus, 14 out of the total of 523 industries together account for around 99% of the growth in between-sector variance (roughly 55% of the overall rise in inequality), while representing only around 8% of total employment in 1985[19].

The remaining 509 industries have offsetting contributions with a joint impact close to zero. This consists of 188 industries with a positive impact on between-sector variance growth[20] that jointly represent around 67% of the total increase. There are further 246 industries with roughly zero impact on the change in between-sector variance, and 75 industries with a negative impact on between-sector variance growth with joint contribution of -67%.[21] The growth in earnings inequality was extremely concentrated: less than 3% of industries (14 out of 523) accounted for around two thirds of the positive contributions to

[18]There are 523 industries at 4-digit level. We restrict the analysis to those industries that exist in the data in both 1985 and 2018. The omitted sectors together account for only a small fraction of the increase in between-sector variance and thus their omission does not have an important effect on the results.

[19]Results are similar when restricting the sample to just men (Table A4).

[20]Each individual contribution is between 0.05% and 2.6% of the increase in between-sector variance.

[21]Similar results are found when performing the analysis using 2-digit sectors (see the Online Appendix).

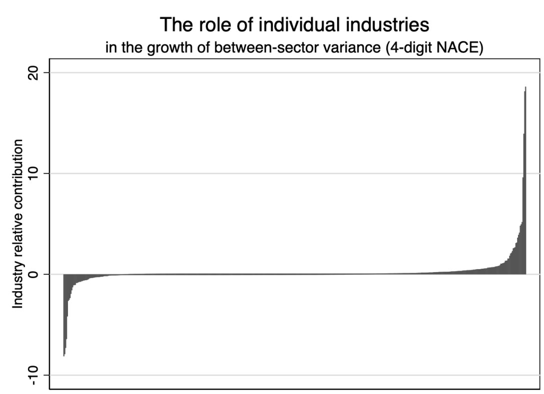
Table 4: Contribution of 4-digit sector groups to between sector variance growth (grouped based on individual sector share).

Individual sector share of between sector variance growth	Number of sectors	Total employment share in 1985	Total contribution to between sector variance growth	Total share of between sector variance growth
> 5%	5	2.8%	0.034	65.5%
2.6% to 5%	9	4.9%	0.017	33.0%
0.05% to 2.6%	188	43.5%	0.035	67.3%
-0.05% to 0.05%	246	15.1%	0.001	1.6%
< -0.05%	75	33.7%	-0.035	-67.4%
Total	523	100.0%	0.051	100.0%

Note: See Equation (3) for the definition of the contribution of a particular sector to between-sector variance growth. We keep all sectors which are present in the data in both 1985 and 2018.

the rise of between-sector variance, while representing only 7.7% of total employment in 1985 (Figure 3). We provide detail on the top 14 (4-digit) industries in Table 5[22].

Figure 3: The relative role of individual industries in the growth of between-sector variance (in percentage points).



Note: the graph depicts the contribution of each 4-digit sector to the growth of the between-sector variance. A small number of industries provide large negative contributions, the vast majority of industries have contribution close to zero and a small number of industries provide very large positive contributions to the rise of the between-sector variance.

The industry with the largest contribution is "Other Human resources provision" which accounts for around 19% of the between-sector variance growth (Table 5). This is a particular sector which includes employment agencies providing workers to different industries.

[22]The top inequality-increasing industries are almost identical when restricting the sample to just men (Table A5).

This leads to a question whether the observed increase in between-sector variance may be overstated. To address this concern, we conduct a robustness exercise in Section 3.5 where we exclude the entire industry, demonstrating that the results remain consistent.

The second most important sector is "Restaurants and mobile food service activities" which accounts for 18% of the between-sector variance growth, followed by "Other cleaning activities" (14%), "Other non-residential social work" (10%) and "Other food service activities" (5%). These top five industries experienced a decline in their annual earnings relative to the economy average and a massive increase in their employment share between 1985 and 2018 (Table 5).

Table 5: Top 14 sectors in terms of increasing between-sector variance.

NACE code	Industry title	Employment share 1985	Employment share 2018	Relative earnings 1985	Relative earnings 2018	Share of between sector variance growth
7830	Other human resources provision	0.0%	4.9%	0.41	-0.44	18.6%
5610	Restaurants and mobile food service activities	0.4%	2.6%	-0.28	-0.61	18.2%
8129	Other cleaning activities	1.5%	3.2%	-0.54	-0.60	13.9%
8899	Other non-residential social work	0.5%	2.6%	-0.22	-0.44	9.6%
5629	Other food service activities	0.5%	1.0%	-0.27	-0.55	5.2%
5510	Hotels and similar accommodation	1.1%	2.1%	-0.42	-0.47	5.0%
5630	Beverage serving activities	0.2%	0.8%	-0.28	-0.56	4.8%
8121	General cleaning of buildings	0.0%	0.3%	-0.51	-0.80	4.1%
3514	Trade of electricity	0.1%	0.5%	0.75	0.72	3.9%
4910	Passenger rail transport, interurban	0.1%	0.7%	-0.11	0.54	3.6%
6209	Computer service activities	0.2%	2.0%	0.13	0.29	3.2%
8790	Other residential care activities	0.1%	0.9%	-0.34	-0.43	3.1%
3312	Repair of machinery	2.6%	2.5%	0.06	0.25	2.7%
2120	Manufacture of pharmaceutical preparations	0.5%	0.4%	0.34	0.69	2.6%

Note: Relative earnings is the gap between the average log earnings of a particular industry and the economy average. Sectors are disaggregated at 4 digits. See Equation (3) for definitions.

Among the top 14 industries with the largest contributions to the rise of between-sector variance, there are five high-paying industries which account for 16% of between-sector variance growth and nine low-paying industries which account for 83% of the growth in between-sector variance (Table 6). Thus, in Italy low-paying sectors play a dominant role. Conversely, in the US the contributions of high and low-paying sectors is more balanced.[23]

[23] These same patterns hold when using broad 2-digit industries (Table B5 in the Online Appendix).

Table 6: Sector contributions to between sector variance growth, by average earnings.

Sector relative earnings	Number of sectors	Total employment share in 1985	Total contribution to between sector variance growth	Total share of between sector variance growth	Shift-share: employment	Shift-share: earnings
			Top 14 sectors			
High paying	5	3.6%	0.008	16.0%	43.6%	57.5%
Low paying	9	4.2%	0.042	82.5%	68.8%	32.3%
			The remaining 509 sectors			
High paying	316	63.1%	0.021	41.2%		
Low paying	193	29.2%	-0.020	-39.7%		
Total	523	100.0%	0.051	100.0%	17.0%	85.4%

Note: See Equation (3) for definitions of relative earnings and of the contribution of a particular sector to between-sector variance growth. The sector is high paying (low paying) if its average relative earnings are positive (negative) where the average is taken over the 1985 and 2018 values. The total contribution of a particular sector to between-sector variance growth is decomposed into the role of employment and earnings changes as defined in Equation (4). To calculate the shares we sum the employment and earnings components across sectors and divide each by the corresponding sum of the total contribution to between sector variance growth. Sectors are disaggregated at 4 digits.

Using the shift-share decomposition proposed by Haltiwanger et al. (2022), we disentangle the contribution of changes in employment shares and in relative earnings. Specifically, the contribution of sector s to the between-sector variance growth (Equation (3)) is decomposed into the employment and earnings components in the following way:

$$\underbrace{\Delta\left(\frac{n_s}{N}\right)(\bar{y}_s-\bar{y})^2}_{\substack{\text{sector s's contribution}\\ \text{to between sector}\\ \text{variance growth}}} = \underbrace{\overline{(\bar{y}_s-\bar{y})^2}\Delta\left(\frac{n_s}{N}\right)}_{\text{employment contribution}} + \underbrace{\overline{\left(\frac{n_s}{N}\right)}\Delta(\bar{y}_s-\bar{y})^2}_{\text{earnings contribution}}, \tag{4}$$

where $\overline{(\bar{y}_s-\bar{y})^2}$ and $\overline{\left(\frac{n_s}{N}\right)}$ denote averages of 1985 and 2018 relative earnings and employment share, respectively. The employment component of the contribution of a given sector represents the effect of the change in the employment share of that industry on the between-sector variance when keeping the relative earnings of the industry fixed, while the earnings component characterises the changes in the relative earnings in the industry, while

Moreover, these patterns hold when we restrict the sample only to males. Results are available upon request.

keeping the employment share of the industry constant.[24]

Focusing on the top 14 sectors with the largest contribution to the growth of inequality, the contribution of the high-paying industries is mainly driven by changes in relative earnings (Table 6). In contrast, the contribution of the low-paying sectors is mainly due to changes in employment shares. Interestingly, both patterns are similar to the ones reported in Haltiwanger et al. (2022) for the US.[25]

To have a picture at the economy level, we apply the shift-share decomposition (Equation (4)) to every industry, and sum employment and earnings components across industries (Equation (5)) and we show that the majority of the rise in earnings inequality is accounted for by changes in relative earnings, rather than by changes in employment shares.

$$\underbrace{\Delta var(\bar{y}_s - \bar{y})}_{\substack{\text{between-sector} \\ \text{variance growth}}} = \underbrace{\sum_{s=1}^{523} \overline{(\bar{y}_s - \bar{y})^2} \Delta\left(\frac{n_s}{N}\right)}_{\text{total employment contribution}} + \underbrace{\sum_{s=1}^{523} \overline{\left(\frac{n_s}{N}\right)} \Delta(\bar{y}_s - \bar{y})^2}_{\text{total earnings contribution}}. \tag{5}$$

Shifts in employment, holding relative earnings of industries constant, account in total for just 17% of the rise in between-sector variance (Table 6).[26] This is the net effect of changes in employment shares across all industries (for growing industries the employment component is positive, for shrinking industries it is negative). Differently from the results of the previous exercise when looking at the top 14 industries, the growing dispersion of relative earnings across industries is the primary source of the growth of between-sector variance in the economy as a whole.

3.5 Robustness

The first robustness we present is the decomposition analysis as described in Section 3.4, where we relax the sample restriction of a minimum of 10 workers per firm. We report

[24] Employment and earnings components can both be positive or negative.

[25] We find the same pattern when performing the analysis with 2-digit industries (Online Appendix).

[26] Using 2-digit industries we find a similar figure of around 24%.

results when applying a cutoff of 5 workers per firm (Online Appendix, Section 9.6) and when no firm size restriction is applied (Section 9.7). Our findings are unchanged: around 55% of the rise in inequality took place between industries, the degree of concentration is similar and the key industries are the same as in the baseline results. The only difference is that the "Restaurant" sector becomes even more important as a driver of the between-sector earnings inequality, and a new low-paying sector emerges, i.e., "Hairdressing and other beauty treatment".

A possible concern is that administrative data over long time periods can change significantly due to change in the administrative coverage non-related to economic factors. For instance, workers in the entertainment sector were not present in our social security data until early 2000. Therefore, the second robustness focuses on the continuity of the industry coverage over time. As in Citino et al. (2023), we restrict the sample to only those sectors with no change in the coverage of INPS data since 1985. Results are very similar to the baseline specification (Section 9.8).

It is well known that the share of informality in Italy is large. Some of the growth in the INPS population of private sector employment (Table 1(a)) could be due to a decline in informality following amnesty reforms. This could potentially bias our results. Figure A5 shows that the aggregate informality rate, defined as employment in the informal sector as a share of total employment, is approximately constant over the period of study. Exploring changes in informality by industry, we find that except for "Accommodation and food service activities", there is no trend over time (Figure A5). For this reason, we repeat the analysis dropping observations in that specific sector.[27] While the main findings still hold, not surprisingly, the growth in the total variance is slightly smaller (0.08 vs 0.10) and the contribution of the between-sector variance to the overall inequality growth is lower (49% vs 56%) (Section 9.9).

[27] In this case we remove two 2-digit NACE sectors that play a prominent role in our baseline results, "Accommodation" (NACE code 55) and "Food and beverage service activities" (NACE code 56).

The final check deals with the considerable rise in employment via work agencies in Italy as represented by the rising employment share of the sector "Other human resources provision". Unfortunately, there is no data available to link workers in this sector to the client companies that they work for; therefore, we repeat the analysis removing all workers in the 2-digit sector "Employment activities", which includes the aforementioned 4-digit industry (Section 9.10). This change has minimal effects on our results.

4 Decomposing Earnings using AKM

4.1 Empirical framework of worker and firm effects

To explore the extent to which high-wage (low-wage) workers sort into industries with better (worse) wage policies and/or are more likely to cluster in the same industry, we perform an AKM analysis (Abowd et al. 1999) with the aim of calculating the industry-enhanced AKM variance decomposition developed by Haltiwanger et al. (2022). Specifically, we estimate an AKM model for five 7-year intervals: 1985-1991, 1992-1998, 1999-2005, 2006-2012 and 2013-2019. Per each panel, as in our previous analysis, we keep one observation per worker in a given year, we sum earnings across all job spells in a year, allocate each worker to the firm that is the most significant source of earnings in that seven-year interval and apply the same sample restrictions (Section 2). Subsequently, we create the largest connected set within each panel. This results in around 34 million worker-year observations (around 7 million workers and 162 thousand firms) in the 1985-1991 panel and 59 million observations (around 11 million workers and 300 thousand firms) in the 2013-2019 panel (Online Appendix, Table B8).[28] Thus, allowing for the standard assumptions, we estimate the following AKM model:

$$y_t^{i,j,s,p} = \theta^{i,p} + \psi^{j,s,p} + X_t^{i,p}\beta^p + \epsilon_t^{i,j,s,p}, \tag{6}$$

[28] By restricting to the largest connected set we only lose less than 1% of observations.

where $\theta^{i,p}$ is typically interpreted as capturing the underlying worker earning ability, $\psi^{j,s,p}$ captures the persistent earnings differences between firms after accounting for variation in worker ability across firms. The vector of time-varying observable characteristics includes controls for year-fixed effects and worker age.[29] Using Equation (6), the variance of annual earnings in a given interval can be decomposed into the variance of worker effects, the variance of firm effects, the variance of observable time-variant characteristics, their covariances and the variance of residuals. Following Haltiwanger et al. (2022), we extend the standard variance decomposition to account separately for dispersion between industries, between firms within industries and within firms:

$$
\begin{aligned}
Var(y_t^{i,j,s}) = \; & \underbrace{Var(\bar{\psi}^s)}_{between-sector\ pay\ premia} + \underbrace{2Cov(\bar{\psi}^s, \bar{\theta}^s) + 2Cov(\bar{\psi}^s, \bar{X}^s\beta)}_{between-sector\ sorting} \\
& + \underbrace{Var(\bar{\theta}^s) + Var(\bar{X}^s\beta) + 2Cov(\bar{\theta}^s, \bar{X}^s\beta)}_{between-sector\ segregation} + \underbrace{Var(\psi^{j,s} - \bar{\psi}^s)}_{between-firm\ within-sector\ pay\ premia} \\
& + \underbrace{2Cov(\bar{\theta}^{j,s} - \bar{\theta}^s, \psi^{j,s} - \bar{\psi}^s) + 2Cov(\psi^{j,s} - \bar{\psi}^s, \bar{X}^{j,s}\beta - \bar{X}^s\beta)}_{between-firm\ within-sector\ sorting} \\
& + \underbrace{Var(\bar{\theta}^{j,s} - \bar{\theta}^s) + Var(\bar{X}^{j,s}\beta - \bar{X}^s\beta) + 2Cov(\bar{\theta}^{j,s} - \bar{\theta}^s, \bar{X}^{j,s}\beta - \bar{X}^s\beta)}_{between-firm\ within-sector\ segregation} \\
& + \underbrace{Var(\theta^i - \bar{\theta}^{j,s}) + Var(X_t^i\beta - \bar{X}_t^{j,s}\beta) + 2Cov(\theta^i - \bar{\theta}^{j,s}, X_t^i\beta - \bar{X}_t^{j,s}\beta) + Var(\epsilon_t^{i,j,s})}_{within-firm\ person\ effect,\ observables,\ their\ covariance\ and\ residual},
\end{aligned}
\tag{7}
$$

where $\bar{\theta}^s$ is the average worker effect at sector s, $\bar{X}^s\beta$ is the average effect of observable characteristics at sector s and $\bar{\psi}^s$ is the average firm effect at sector s. The equivalent objects defined for firm j in sector s are $\bar{\theta}^{j,s}$, $\bar{X}^{j,s}\beta$ and $\psi^{j,s}$. The variance of firm fixed effects ($Var(\psi^{j,s}) = Var(\bar{\psi}^s) + Var(\psi^{j,s} - \bar{\psi}^s)$) is composed of the variance of average firm

[29] We follow Card et al. (2016) in centering age around 40, we then include a quadratic and cubic transformation of worker age, but not the linear term.

effects between sectors ($Var(\bar{\psi}^s)$), and the variance of firm effects between firms within sectors ($Var(\psi^{j,s} - \bar{\psi}^s)$).

The between-sector sorting ($2Cov(\bar{\psi}^s, \bar{\theta}^s) + 2Cov(\bar{\psi}^s, \bar{X}^s\beta)$) captures the extent by which highly paid workers are employed in sectors with a high average pay premium. We distinguish this from the between-firm within-sector sorting ($2Cov(\bar{\theta}^{j,s} - \bar{\theta}^s, \psi^{j,s} - \bar{\psi}^s) + 2Cov(\psi^{j,s} - \bar{\psi}^s, \bar{X}^{j,s}\beta - \bar{X}^s\beta)$), which reflects the degree to which workers who have relatively high earning ability in a specific sector, work in firms which pay a relatively high pay premium in the sector.

The between-sector segregation ($Var(\bar{\theta}^s) + Var(\bar{X}^s\beta) + 2Cov(\bar{\theta}^s, \bar{X}^s\beta)$) captures the extent to which high-paid workers cluster together with other high-paid workers in the same industry. The greater the differences in the average worker fixed effects across industries, the greater the between-sector segregation, as sectors differ more in the type of workers they employ.

Segregation that takes place between firms within sectors ($Var(\bar{\theta}^{j,s} - \bar{\theta}^s) + Var(\bar{X}^{j,s}\beta - \bar{X}^s\beta) + 2Cov(\bar{\theta}^{j,s} - \bar{\theta}^s, \bar{X}^{j,s}\beta - \bar{X}^s\beta)$) reflects the extent to which within sectors similar workers (in terms of earnings ability) cluster together in the same firm.

Finally, the within-firm variance is composed of i) variance of worker fixed effects within firms ($Var(\theta^i - \bar{\theta}^{j,s})$), ii) variance of time-variant characteristics within-firms ($Var(X^i_t\beta - \bar{X}^{j,s}_t\beta)$), iii) covariance between worker effects and time-variant characteristics within-firms ($2Cov(\theta^i - \bar{\theta}^{j,s}, X^i_t\beta - \bar{X}^{j,s}_t\beta)$), and iv) variance of residuals ($Var(\epsilon^{i,j,s}_t)$).[30]

4.2 Results of AKM-based Decompositions

Table 7 displays results of the industry-enhanced AKM variance decomposition (Equation (7)), for the first interval (1985-1991), the last interval (2013-2019) and the change between

[30] The full decomposition of variance of earnings also includes covariance of residuals with worker effects and with time-variant characteristics, $2Cov(\theta^i - \bar{\theta}^{j,s}, \epsilon^{i,j,s}_t)$ and $2Cov(X^i_t\beta - \bar{X}^{j,s}_t\beta, \epsilon^{i,j,s}_t)$. However, the estimated residual from 6) is by design orthogonal to worker effects and time-variant characteristics, so these two covariances are equal to zero which we also confirm empirically.

the two periods.[31] [32] Interestingly, 60% of the 8 log point increase in the total variance of log annual earnings between the first and the last periods is accounted for by the rising between-sector variance, 33% by the rising between-firm-within-sector variance and around 7% is due to rising within-firm variance. More than 90% of the growth in earnings inequality took place between firms and a large majority took place between industries. Strikingly, the contribution of industry is similar to the estimate for the US (60% vs 62%).

Notably, 31% of the aforementioned between-sector variance increase (60%) is due to sorting and 34% is due to segregation, while the variance of the sector pay premiums (average firm effects) declined and has a negative contribution of approximately -5%.

Thus, the majority of the rise in Italian earnings inequality is due to an increase in the sorting of highly paid workers to high-pay industries and due to increasing differences in average worker quality across industries (measured by average worker fixed effect), as highly-paid workers cluster in the same industries. Equivalently, workers with low earnings ability are more likely to work with other low-income workers in the same industry and more likely to work in industries with particularly low firm premiums[33]. Therefore, the growth of the between-sector variance is entirely due to the change in the allocation of workers across industries and not due to increasing heterogeneity in firm wage policies across industries.[34]

The 33% contribution of between-firm-within-sector variance consists mainly of sorting (39%), less of segregation (around 6%) and a declining dispersion of firm pay premiums (-12%). Therefore, the increasing positive sorting of workers across firms within sectors plays an important role in driving the rise in earnings inequality, while the declining variance of

[31] Results of the standard AKM decomposition are reported in Section 9.4.

[32] We use 4-digit industries as in Section 3, however, results are similar when using 2-digit industries. Results are available in the Online Appendix, Table B11.

[33] Focusing on the top 14 sectors with the largest contribution to the rise of earnings inequality (Section 3.4), we find that low-paying industries experienced declines in the average worker earnings ability (as measured by worker fixed effects), while the opposite happened in high-paying sectors, with relatively little change in the average firm effects (Table A7).

[34] The role of between-industry sorting is highlighted by the fact that the correlation of average firm fixed effect and average worker effect across industries is just 0.10 in the 1985-1991 period, but it is 0.69 in the 2013-2019 period. With 2-digit industries, the correlation is even higher, 0.30 in the first interval and 0.85 in the last interval.

Table 7: Industry-enhanced AKM variance decomposition.

	Interval 1 1985-1991		Interval 5 2013-2019		Growth 1 to 5	
	Var.	Share	Var.	Share	Change	% of total var. change
	(1)	(2)	(3)	(4)	(5)	(6)
Total variance	0.341	-	0.422	-	0.081	-
Between-sector	**0.077**	**22.6%**	**0.126**	**29.9%**	**0.049**	**60.5%**
Sector pay premium	0.023	6.9%	0.020	4.6%	-0.004	-4.7%
Sector sorting	0.030	8.7%	0.055	12.9%	0.025	30.5%
Sector segregation	0.024	6.9%	0.051	12.2%	0.028	34.3%
Between-firm-within-sector	**0.057**	**16.7%**	**0.084**	**19.9%**	**0.027**	**33.3%**
Firm pay premium	0.048	14.0%	0.038	9.0%	-0.010	-12.1%
Firm sorting	-0.037	-11.0%	-0.006	-1.4%	0.032	39.1%
Firm segregation	0.047	13.7%	0.052	12.2%	0.005	5.8%
Within-firm	**0.207**	**60.7%**	**0.213**	**50.5%**	**0.006**	**7.4%**
Person effect	0.123	36.0%	0.154	36.5%	0.031	38.8%
Time-variant characteristics	0.017	5.1%	0.013	3.2%	-0.004	-5.1%
Covariance of the above two	-0.005	-1.5%	-0.013	-3.0%	-0.008	-9.4%
Residuals	0.072	21.1%	0.058	13.7%	-0.014	-17.3%

Note: See Equation (7) for definitions. Industries are disaggregated at 4-digit level.

firm fixed effects within industries moves in the opposite direction. At the same time, the sorting of workers to firms plays an important role both between sectors and between firms within sectors, while increasing segregation is a predominantly between-sector phenomenon.

The variance of the worker fixed effect within firms increased significantly and represents around 39% of the overall rise in earnings inequality. This was offset by the falling variance of the residuals (-17%), of the time-variant characteristics within firms (-5%) and of the covariance between worker fixed effect and time-variant characteristics within firms (-9%).

This is the reason why the within-firm component of variance only accounts for around 7% of the total increase in earnings variance.[35]

Summing up, inequality grew because of the rising dispersion of the worker-specific component of pay (worker effects) and the rising positive sorting, while the dispersion of pay premiums declined. Consistently with our previous results, much of the rise in the variance of worker effects and the increase in sorting took place between industries (Section 3.3).

5 Weekly earnings vs weeks worked

A notable difference between European labour markets and the US lies in the extensive use of temporary employment contracts. This feature could increase the dispersion in time worked (Picchio 2008, Bentolila et al. 2020, Bianchi and Paradisi 2023, Daruich et al. 2023). This is particularly relevant to our analysis because some industries adopt temporary contracts to a greater extent than others (Felgueroso et al. 2017) and the relative share changes over time.

In this section, we quantify changes in the dispersion of annual earnings, differentiating between variances in working hours and pay rates. Moreover, we analyse how these measures vary within and between industries.[36] This is a novel contribution, as there is no other paper in the literature performing such analysis.

We perform the decomposition of annual earnings as:

$$Y_t^i = W_t^i H_t^i, \tag{8}$$

[35]Results of the industry-enhanced AKM variance decomposition on the sample of men only are presented in Table A6.

[36]In the Italian social security data we observe the number of weeks worked per each job spell and for part-time job spells the full-time equivalent number of weeks is provided. If an individual works 50% of full-time hours per week for 10 weeks, this is equivalent to working 5 weeks full-time. For each individual, we sum this across job spells in a given year to calculate the total number of full-time equivalent (FTE) weeks worked per year.

where Y_t^i are total annual earnings of worker i in year t, H_t^i is the total number of FTE (full-time equivalent) weeks worked by worker i in year t, and W_t^i is the average weekly earnings of worker i in year t. We directly measure Y_t^i and H_t^i from the data and we calculate W_t^i as $W_t^i = Y_t^i / H_t^i$.

The variance of log annual earnings is then given by:

$$Var(y_t^i) = Var(w_t^i) + Var(h_t^i) + 2Cov(w_t^i, h_t^i), \tag{9}$$

where y_t^i are log annual earnings, w_t^i is the log of average weekly earnings and h_t^i is the log of FTE weeks worked in a year. The three components of the variance of log annual earnings are: i) variance of average weekly earnings in that year, $Var(w_t^i)$, capturing inequality in the rate of pay; ii) variance of FTE weeks worked in that year, $Var(h_t^i)$; and iii) covariance of weekly earnings and weeks worked in that year, $2Cov(w_t^i, h_t^i)$, which captures the extent to which those on higher rate of pay also work more during the year.

Interestingly, we find that the main driver of the increase in variance of annual earnings is the rising positive covariance between weekly earnings and weeks worked in the year (Table 8), which increased from 0.027 in 1985 to 0.091 in 2018, representing 66.7% of the increase in variance of annual earnings. In contrast, the variance of the full-time equivalent weeks worked in a year, $Var(h_t^i)$, fell from 0.167 in 1985 to 0.155 in 2018, accounting for -12.5% of the total increase in annual earnings variance. The variance of log weekly earnings, $Var(w_t^i)$, increased substantially from 0.159 to 0.203, accounting for 45.8% of the growth in annual earnings variance. Thus, the two drivers of rising annual earnings inequality are (i) growing inequality in the rate of pay and (ii) growing association between the rate of pay and labour supply quantities. Increasingly, workers on higher rates of pay work more during the year and those on low pay work less (either work part-time or have more gaps in employment)[37].

[37] We interrogate this result further in section 9.5 in the Appendix, looking at the change in each component over time and splitting the sample by gender and age.

Table 8: Decomposing annual earnings into full-time equivalent weeks worked and average weekly earnings.

(a) Variance change over time

	Weekly earnings variance	Weeks worked variance	2*Covariance of weeks and earnings	Annual earnings variance
1985	0.159	0.167	0.027	0.353
2018	0.203	0.155	0.091	0.449
Change	0.044	-0.012	0.064	0.096
% of total increase	45.8%	-12.5%	66.7%	100.0%

(b) Variance shares

	Weekly earnings	Weeks worked	2*Covariance of weeks and earnings
1985	45.0%	47.3%	7.6%
2018	45.2%	34.5%	20.3%

Note: See Equation (9) for definitions. Industries are disaggregated at 4-digit level.

Next, we perform the decomposition into between-sector, between-firm-within-sector and within-firm, for each component of Equation 9.[38] Of the rise in variance of weekly earnings (wage inequality), 36.2% is accounted for by the between-sector component, 23.4% by the between-firm-within-sector component and 38.3% by the within-firm component. Thus the majority of the rise in Italian wage inequality took place between firms, but only just above a third was between industries. However, 56.7% of the rise in covariance between weekly earnings and weeks worked is accounted for by the between-sector component. Increasingly, those sectors that employ workers for only a part of the year also offer low rate of pay[39]. We can see this growing positive association between the rate of pay and labour supply at industry level on Figure A9, comparing 1985 and 2018.

The between-sector variance of annual earnings increased by 0.053 between 1985 and

[38]For the variance of weekly earnings (Table A8 and Figure A6), the variance of weeks worked (Table A9 and Figure A7) and the covariance of weekly earnings and weeks worked (Table A10 and Figure A8).
[39]This result holds when restricting the sample to only men.

2018 (Table 2), due to the increase in the between-sector variance of weekly earnings and the increase in the between-sector covariance component. In contrast, the between-sector variance of weeks worked was roughly constant.[40] Thus, the dispersion of annual earnings across industries grew due to: 1.) an increase in the dispersion of wage rates across industries, and ii) an increase in the positive association between the average weeks worked and the average rate of pay across industries.[41]

Table 9: Top 14 sectors contributing to the increased between-sector variance.

NACE code	Industry title	Relative log weekly earnings		Relative log weeks worked		Relative log annual earnings	
		1985	2018	1985	2018	1985	2018
7830	Other human resources provision	0.34	-0.23	0.09	-0.21	0.41	-0.44
5610	Restaurants and mobile food service activities	-0.05	-0.35	-0.23	-0.26	-0.28	-0.61
8129	Other cleaning activities	-0.50	-0.39	-0.04	-0.21	-0.54	-0.60
8899	Other non-residential social work	-0.21	-0.33	-0.01	-0.11	-0.22	-0.44
5629	Other food service activities	-0.16	-0.33	-0.11	-0.22	-0.27	-0.55
5510	Hotels and similar accommodation	-0.11	-0.19	-0.31	-0.28	-0.42	-0.47
5630	Beverage serving activities	-0.13	-0.31	-0.15	-0.25	-0.28	-0.56
8121	General cleaning of buildings	-0.51	-0.45	-0.00	-0.35	-0.51	-0.80
3514	Trade of electricity	0.67	0.54	0.08	0.18	0.75	0.72
4910	Passenger rail transport, interurban	-0.14	0.37	0.03	0.17	-0.11	0.54
6209	Computer service activities	0.12	0.20	0.01	0.09	0.13	0.29
8790	Other residential care activities	-0.33	-0.34	-0.01	-0.09	-0.34	-0.43
3312	Repair of machinery	0.02	0.12	0.05	0.13	0.06	0.25
2120	Manufacture of pharmaceutical preparations	0.26	0.54	0.09	0.15	0.34	0.69

Note: Industries are disaggregated at 4-digit level.

Finally, we investigate whether the large falls in relative annual earnings of the key inequality-increasing industries (Section 3.4) were mainly due to falling relative rate of pay or falling relative labour supply quantities in those industries. Table 9 displays relative (log) weekly earnings, relative (log) weeks worked and relative (log) annual earnings for both 1985 and 2018 for the top 4-digit sectors. We can see that falls in relative weekly earnings played a much more important role than falls in relative weeks worked.

[40] These components sum approximately to the increase in between-sector variance of annual earnings.

[41] We also perform the analysis splitting the sample between 1985-2000 and 2000-2018, as the surge of temporary contracts happened mainly after 2000. Results are similar for the two subperiods.

6 Discussion of the results

The rise in earnings inequality between 1985 and 2018 in Italy took place mainly between industries and was very concentrated in a small number of industries. These were mainly low-paying service sectors which were contributing towards greater inequality both by becoming much larger as a share of total employment, and by their average earnings falling relative to the economy average. These changes reflected a re-allocation of workers across industries, with workers with low earnings ability being more likely to work with other low-income workers in the same industry (between-sector segregation), and being more likely to work in industries with particularly low average firm premium (between-sector sorting). The growth in the inequality of annual earnings was due mainly to the rising variance of wage rates and by the rising positive association between the rate of pay and how much individuals work, while changes in labour supply appeared to be minimal.

6.1 Italy versus US

When comparing our findings for Italy with the results of Haltiwanger et al. (2022) for the US, we find similar results.[42] Specifically, they find that 61.9% of the rise in the US earnings inequality between 1996 and 2018 occurred between industries, while 23.1% between firms in the same industry and 14.9% within firms (Table 1 in Haltiwanger et al. (2022)). Our numbers (55%, 18% and 27%) are not too far away. Using the same data source as Haltiwanger et al. (2022), Kleinman (2022) shows that when considering a longer time period, the importance of the between-sector component declines slightly: just under half of the rise in earnings inequality took place between 4-digit industries in the US between 1980 and 2017. Comparing (Haltiwanger et al. 2022, Table 3)'s list of all industries with larger than 1% contribution to the rise of between-sector variance with our list (Table A3) we observe that

[42] Haltiwanger et al. (2022) use Longitudinal Employer-Household Dynamics (LEHD) linked employer-employee data, covering only 18 out of the 50 US states for the period 1996-2018 and containing comprehensive information on the industry that the firm belongs to.

industries related to “Food and Drink” and “Employment Services” feature most prominently in both countries.[43] Other low-paying industries which are important in both countries are sectors related to social care (both residential and non-residential), cleaning and maintenance of buildings and sectors related to hotels and other types of accommodation. High-paying industries which feature in both countries are pharmaceutical manufacturing and sectors related to financial services and insurance. Sectors related to IT appear on both lists, but whereas in Italy it is listed as “Servicing of Personal Computers” and contributes marginally to inequality, in the US IT sectors feature more prominently and cover software publishing, computer system design and semiconductor manufacturing. While among low-paying sectors the patterns are very similar, with the only difference being that retail industries are more important in the US, the number of high-paying sectors with large relative contributions to the rise of inequality in the US is much larger compared to Italy. In both countries, the dispersion of firm pay premiums did not play a significant role and instead the growth in earnings inequality was driven by the rising dispersion of the worker-specific component of pay and by an increase in sorting. Our results regarding the increasing industry-level sorting and segregation accounting for more than half of the total rise in earnings inequality is also in line with the findings of Haltiwanger et al. (2022). Finally, regarding the cross-sectional variance decomposition, according to Haltiwanger et al. (2022), in any given year the majority of the earnings inequality in the US takes place within firms: the within-firm variance as a share of total variance is about 65% in 1996-2002 and 58% in 2012-2018 intervals. We find that the between-sector share in Italy not only increased from 23.4% in 1985 to 30.2% in 2018, but that at the end of the period it is slightly higher than any of the US estimates. Thus, either the firm or the industry that the individual is employed in is a better predictor of his/her annual earnings in Italy than in the US.

[43]Since there is no one-to-one mapping of the US NAICS and the European NACE classification of industries, we cannot directly compare industry codes. However, we can identify patterns between the two countries.

6.2 Potential drivers

Our findings prompt the question of what is behind this significant thirty-year increase in inequality between industries. Our analysis does not aim to offer a conclusive answer to this question; nevertheless, it provides a basis for discussion of potential non-excludable significant factors. We learnt that to explain the increasing earnings inequality over the past three decades, it is essential to understand the changes in the organisation of production within a relatively small number of industries. Several driving forces are consistent with the patterns we have documented. In what follows we discuss three potential candidates and the supporting evidence for the case of Italy: technological change, trade and domestic outsourcing.

One of the central predictions stemming from the Theory of Routine-Biased Technical Change (RBTC) is that the advancement of technology leads to shifts in labour demand. Specifically, this theory posits that technological progress increases the demand for workers in both the lowest and highest-paid occupations, while it diminishes the demand for those in routine jobs characterized by moderate pay levels. These observations have been corroborated in studies such as Autor (2006), Autor (2003), Goos (2007), and Goos (2014).

In line with this notion, Faia et al. (2022) provide compelling evidence of these technological forces at work in Italy. In our research, we expand this evidence by presenting descriptive statistics that highlight the phenomenon of employment polarization across industries. Figure 4 depicts changes in employment shares across industry quantiles, based on annual earnings in 1985. Our findings reveal a decline in the employment share of the 3rd and 4th quantiles, in contrast to an increase in the employment share of the 1st, 2nd, and 5th quantiles. These results are notably consistent with the predictions of the RBTC theory, further underscoring the impact of technological advancement on employment patterns in various industries.[44]

[44]In Italy industry-level country-wide collective agreements specify obligatory minimum wages for each occupation or job title. There are hundreds of collective agreements, but around 150 of the largest ones cover

Figure 4: Changes in employment shares by industry quantiles (1985-2018).

Note: The graph displays changes in employment shares by industry quantiles. Industries are first ranked based on their average annual earnings in 1985, then they are put into 5 bins, each containing industries with the same joint employment share in 1985 (approximately 20%). The first quantile represents industries with the lowest annual earnings in 1985, and the fifth quantile those with the highest earnings.

Our finding of declining wages and increasing employment in few low-skill service industries could potentially result from import substitution or international outsourcing. These phenomena might have diminished the demand for specific tradable goods (such as manufacturing) in favor of non-tradable service sectors. While there is limited evidence available for Italy, research by Citino and Linarello (2022) and Basso (2020) indicates that the overall impact of increased trade with China on total manufacturing employment has been relatively small, thus suggesting that this particular channel may not have been the primary driving force behind these trends.

Finally, it is important to acknowledge the potential influence of domestic outsourcing on the earnings of the workforce. Employees with specific skills may find themselves concentrated within industries that rely more heavily on outsourcing. This sorting effect would lead to an increased clustering of workers with similar income levels or skills in specific industries, contributing to increased earnings disparities, in line with our results (Goldschmidt and Schmieder 2017, Drenik et al. 2023).

over 90% of workers in the INPS social-security data set. Each collective agreement specifies minimum wages for 5-10 different job titles. However, the mapping of collective agreements to industries is not one-to-one, some industries have multiple collective agreements and a single collective agreement might cover multiple industries (Fanfani 2019).

7 Conclusion

Our analysis provides a comprehensive explanation for the thirty-year rise in earnings inequality in Italy and uncovers the role of shifts in the organization of production across firms, particularly across different industries. The majority of the rise in earnings inequality in Italy happened between industries. A few low-paying service sectors contributed towards greater inequality both by growing their employment share and by their average rate of pay falling relative to the economy average. The rise in between-sector inequality was not due to rising dispersion of average firm premiums across industries. Instead it was due to industries becoming more different in the average earnings ability of their workers and due to an increase in sorting. Workers with low earnings ability are more likely to work with other low-income workers in the same industry (between-sector segregation), and they are more likely to work in industries with particularly low average firm premium (between-sector sorting).

The patterns that characterize the growth in the Italian earnings inequality are remarkably similar to the ones found by Haltiwanger et al. (2022) for the US. This is despite very large differences in institutions between the two countries. This suggests the presence of similar underlying forces. The patterns we find are consistent with shifts in industry-level labour demand, driven by trade or technological change, and subsequent reallocation of workers across sectors, likely complemented by domestic outsourcing. Further research will be devoted to disentangling these potential underlying mechanisms.

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8 Appendix A

8.1 Tables

Table A1: Sectors and firms: full variance decomposition - only men.

(a) Variance change over time

	Between sector	Between firms within sector	Within firm	Total
1985	0.062	0.056	0.137	0.255
2018	0.114	0.086	0.171	0.371
Change	0.052	0.030	0.035	0.116
% of total increase	44.8%	25.9%	30.2%	100.0%

(b) Variance shares

	Between sector	Between firms within sector	Within firm
1985	24.2%	22.1%	53.6%
2018	30.6%	23.3%	46.2%

Note: The sample includes only men. See Equation (2) for definitions. Industries are disaggregated at 4-digit level.

Table A2: Sectors and firms: full variance decomposition - only women.

(a) Variance change over time

	Between sector	Between firms within sector	Within firm	Total
1985	0.075	0.129	0.221	0.424
2018	0.081	0.118	0.249	0.448
Change	0.006	-0.011	0.029	0.024
% of total increase	25.0%	-45.8%	120.8%	100.0%

(b) Variance shares

	Between sector	Between firms within sector	Within firm
1985	17.7%	30.3%	52.0%
2018	18.1%	26.3%	55.7%

Note: The sample includes only women. See Equation (2) for definitions. Industries are disaggregated at 4-digit level.

Table A3: Sectors with larger than 1% contribution to the growth of between-sector variance (29 sectors, 4-digit).

NACE code	Industry title	Employment share		Relative earnings		Share of between sector variance growth
		1985	2018	1985	2018	
7830	Other human resources provision	0.0%	4.9%	0.41	-0.44	18.6%
5610	Restaurants and mobile food service activities	0.4%	2.6%	-0.28	-0.61	18.2%
8129	Other cleaning activities	1.5%	3.2%	-0.54	-0.60	13.9%
8899	Other non-residential social work	0.5%	2.6%	-0.22	-0.44	9.6%
5629	Other food service activities	0.5%	1.0%	-0.27	-0.55	5.2%
5510	Hotels and similar accommodation	1.1%	2.1%	-0.42	-0.47	5.0%
5630	Beverage serving activities	0.2%	0.8%	-0.28	-0.56	4.8%
8121	General cleaning of buildings	0.0%	0.3%	-0.51	-0.80	4.1%
3514	Trade of electricity	0.1%	0.5%	0.75	0.72	3.9%
4910	Passenger rail transport, interurban	0.1%	0.7%	-0.11	0.54	3.6%
6209	Computer service activities	0.2%	2.0%	0.13	0.29	3.2%
8790	Other residential care activities	0.1%	0.9%	-0.34	-0.43	3.1%
3312	Repair of machinery	2.6%	2.5%	0.06	0.25	2.7%
2120	Manufacture of pharmaceutical preparations	0.5%	0.4%	0.34	0.69	2.6%
3316	Repair and maintenance of aircraft and spacecraft	0.5%	0.4%	0.17	0.61	2.6%
8430	Compulsory social security activities	0.4%	0.3%	0.18	0.65	2.3%
910	Support activities for oil and gas extraction	0.1%	0.1%	0.34	0.93	2.1%
8299	Other business support activities n.e.c.	0.3%	2.8%	0.27	-0.22	2.1%
9609	Other personal service activities n.e.c.	0.0%	0.7%	-0.47	-0.39	1.8%
6499	Other financial service activities n.e.c.	0.7%	0.3%	0.14	0.62	1.6%
2910	Manufacture of motor vehicles	2.7%	0.4%	0.07	0.46	1.6%
4771	Retail sale of clothing in specialised stores	0.2%	1.1%	-0.11	-0.26	1.4%
5520	Holiday and other short-stay accommodation	0.1%	0.3%	-0.57	-0.62	1.4%
6520	Reinsurance	0.8%	0.6%	0.43	0.63	1.3%
3320	Installation of industrial machinery and equipment	0.9%	1.0%	0.09	0.26	1.2%
2110	Manufacture of basic pharmaceutical products	0.6%	0.3%	0.36	0.64	1.1%
9602	Hairdressing and other beauty treatment	0.0%	0.2%	-0.53	-0.64	1.1%
9329	Other amusement and recreation activities	0.0%	0.2%	-0.65	-0.66	1.1%
4711	Grocery stores	0.8%	3.6%	-0.03	-0.12	1.0%

Note: Relative earnings is the gap between average log earnings of a particular industry and the economy average. See Equation (3) for definitions.

Table A4: Contribution of 4-digit sector groups to between sector variance growth (grouped based on individual sector share) - only men.

Individual sector share of between sector variance growth	Number of sectors	Total employment share in 1985	Total contribution to between sector variance growth	Total share of between sector variance growth
> 5%	5	2.7%	0.031	61.0%
1.6% to 5%	15	7.0%	0.019	38.1%
0.05% to 1.6%	166	37.4%	0.022	44.1%
-0.05% to 0.05%	263	18.6%	0.001	1.1%
< -0.05%	72	34.4%	-0.022	-44.3%
Total	521	100.0%	0.050	100.0%

Note: The sample includes only men. See Equation (3) for definition of the contribution of a particular sector to between sector variance growth. Industries are disaggregated at 4-digit level.

Table A5: Top 20 4-digit sectors contributing to increasing between-sector variance - only men.

NACE code	Industry title	Employment share		Relative earnings		Share of between sector variance growth
		1985	2018	1985	2018	
8129	Other cleaning activities	1.4%	3.2%	-0.56	-0.67	19.4%
8899	Other non-residential social work	0.5%	2.7%	-0.20	-0.51	13.5%
5610	Restaurants and mobile food service activities	0.3%	2.0%	-0.13	-0.58	13.4%
5629	Other food service activities	0.4%	1.1%	-0.29	-0.64	8.1%
7830	Other human resources provision	0.0%	3.2%	0.40	-0.32	6.6%
8790	Other residential care activities	0.1%	0.9%	-0.33	-0.48	4.0%
8121	General cleaning of buildings	0.0%	0.3%	-0.56	-0.82	3.5%
3514	Trade of electricity	0.1%	0.6%	0.71	0.64	3.3%
5630	Beverage serving activities	0.1%	0.6%	-0.19	-0.52	3.3%
4910	Passenger rail transport, interurban	0.1%	0.7%	-0.16	0.46	3.0%
6209	Computer service activities	0.2%	2.1%	0.16	0.25	2.5%
2120	Manufacture of pharmaceutical preparations	0.5%	0.5%	0.29	0.61	2.5%
3316	Repair and maintenance of aircraft and spacecraft	0.6%	0.5%	0.08	0.52	2.4%
4711	Grocery stores	0.8%	3.8%	0.00	-0.18	2.3%
8299	Other business support activities n.e.c.	0.3%	2.7%	0.28	-0.22	2.1%
9609	Other personal service activities n.e.c.	0.0%	0.7%	-0.45	-0.41	2.0%
8430	Compulsory social security activities	0.5%	0.4%	0.17	0.55	2.0%
910	Support activities for oil and gas extraction	0.1%	0.2%	0.39	0.83	1.9%
3312	Repair of machinery	2.7%	2.7%	0.04	0.19	1.8%
6499	Other financial service activities n.e.c.	0.8%	0.3%	0.09	0.56	1.6%

Note: The sample includes only men. Relative earnings is the gap between the average log earnings of a particular industry and the economy average. See Equation 3 for definitions. Industries are disaggregated at 4-digit level.

Table A6: Industry-enhanced AKM variance decomposition - 4-digit industry - only men.

	Interval 1		Interval 5		Growth	
	1985-1991		2013-2019		1 to 5	
	Var.	Share	Var.	Share	Change	% of total var. change
	(1)	(2)	(3)	(4)	(5)	(6)
Total variance	0.250	-	0.347	-	0.097	-
Between-sector	**0.060**	**24.0%**	**0.104**	**30.0%**	**0.044**	**45.4%**
Sector pay premium	0.018	7.0%	0.014	3.9%	-0.004	-4.1%
Sector sorting	0.023	9.1%	0.042	12.2%	0.020	20.3%
Sector segregation	0.020	8.0%	0.048	13.8%	0.028	28.5%
Between-firm-within-sector	**0.045**	**18.0%**	**0.071**	**20.5%**	**0.026**	**26.8%**
Firm pay premium	0.052	20.7%	0.041	11.9%	-0.010	-10.8%
Firm sorting	-0.053	-21.4%	-0.025	-7.2%	0.028	29.2%
Firm segregation	0.047	18.7%	0.055	15.8%	0.008	8.3%
Within-firm	**0.144**	**57.6%**	**0.172**	**49.6%**	**0.028**	**28.9%**
Person effect	0.111	44.3%	0.141	40.5%	0.030	30.7%
Time-variant characteristics	0.009	3.8%	0.003	1.0%	-0.006	-6.1%
Covariance of the above two	-0.018	-7.2%	-0.009	-2.7%	0.008	8.7%
Residuals	0.042	16.8%	0.037	10.7%	-0.005	-5.2%

Note: See Equation (7) for definitions. Industries are disaggregated at 4-digit level.

Table A7: Average worker and firm fixed effects of the top 14 (4-digit) sectors contributing to the increased between-sector variance.

4dig NACE code	Industry title	Relative firm FE 1985-1991	Relative firm FE 2013-2019	Relative worker FE 1985-1991	Relative worker FE 2013-2019
7830	Other human resources provision	0.06	-0.17	0.21	-0.30
5610	Restaurants and mobile food service activities	-0.21	-0.26	-0.08	-0.32
8129	Other cleaning activities	-0.27	-0.22	-0.33	-0.41
8899	Other non-residential social work	-0.28	-0.18	-0.05	-0.27
5629	Other food service activities	-0.20	-0.20	-0.14	-0.38
5510	Hotels and similar accommodation	-0.23	-0.22	-0.17	-0.26
5630	Beverage serving activities	-0.16	-0.24	-0.12	-0.31
8121	General cleaning of buildings	-0.27	-0.31	-0.58	-0.47
3514	Trade of electricity	0.10	0.29	0.76	0.40
4910	Passenger rail transport, interurban	-0.07	0.31	-0.03	0.20
6209	Computer service activities	0.08	0.06	0.05	0.22
8790	Other residential care activities	-0.20	-0.15	-0.27	-0.27
3312	Repair of machinery	0.03	0.08	0.03	0.14
2120	Manufacture of pharmaceutical preparations	0.20	0.21	0.15	0.45

Note: Relative firm FE is the gap between the average industry firm fixed effect, given by $\bar{\psi}^s$, and the economy average, $\bar{\psi}$. Relative worker FE is the gap between the average industry worker fixed effect (including the effects of observable characteristics), given by $\bar{\theta}^s + \bar{X}^s\beta$, and the economy average, $\bar{\theta} + \bar{X}\beta$. See Equation 6 for definitions. Industries are disaggregated at 4-digit level.

Table A8: Decomposition of log weekly earnings.

(a) Variance change over time

	Between sector	Between firms within sector	Within firm	Total
1985	0.045	0.038	0.076	0.159
2018	0.062	0.048	0.094	0.203
Change	0.017	0.010	0.017	0.045
% of total increase	37.8%	22.2%	37.8%	100.0%

(b) Variance shares

	Between sector	Between firms within sector	Within firm
1985	28.1%	23.9%	48.0%
2018	30.5%	23.5%	46.0%

Note: Industries are disaggregated at 4-digit level.

Table A9: Decomposition of log weeks worked (FTE).

(a) Variance change over time

	Between sector	Between firms within sector	Within firm	Total
1985	0.019	0.035	0.114	0.167
2018	0.020	0.027	0.108	0.155
Change	0.001	-0.008	-0.005	-0.012
% of total decrease	-8.3%	66.7%	41.7%	100.0%

(b) Variance shares

	Between sector	Between firms within sector	Within firm
1985	11.1%	21.1%	67.8%
2018	12.6%	17.5%	69.9%

Note: Industries are disaggregated at 4-digit level.

Table A10: Decomposition of covariance of log weekly earnings and log weeks worked (FTE).

(a) Covariance change over time

	Between sector	Between firms within sector	Within firm	Total
1985	0.010	0.003	0.001	0.014
2018	0.027	0.011	0.007	0.045
Change	0.017	0.008	0.006	0.032
% of total increase	53.1%	25.0%	18.8%	100.0%

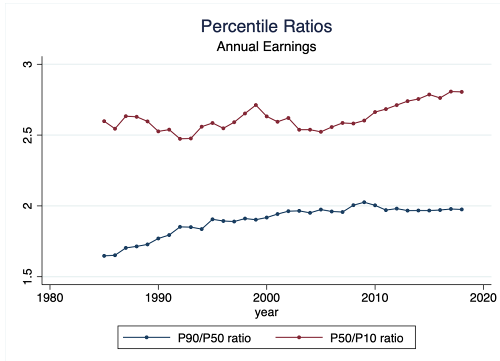
(b) Covariance shares

	Between sector	Between firms within sector	Within firm
1985	72.4%	20.7%	6.9%
2018	60.1%	23.7%	16.2%

Note: Industries are disaggregated at 4-digit level.

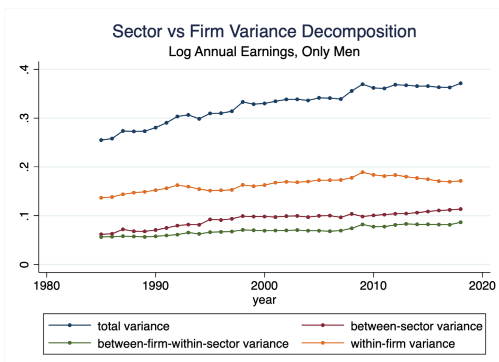
8.2 Figures

Figure A1: Growth of earnings dispersion: percentile ratios and total variance.

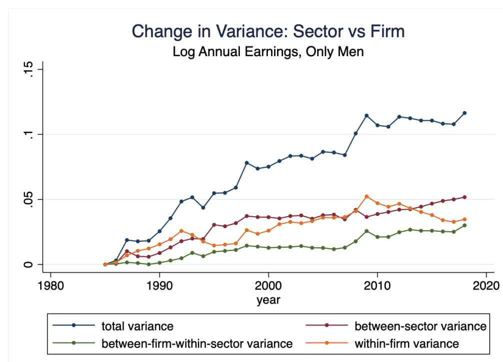


Note: P90, P50 and P10 refer to the 90th, 50th and 10th percentiles of annual earnings.

Figure A2: Sector and firm: full variance decomposition - only men.



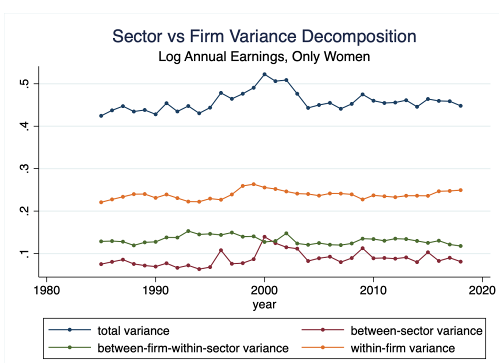
(a) Levels



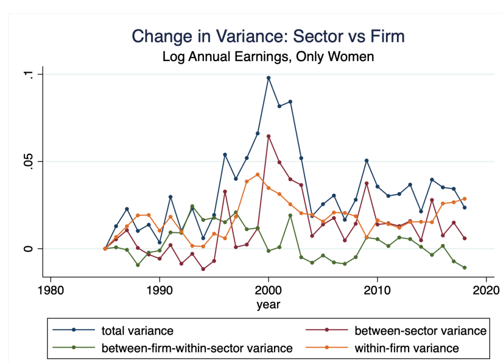
(b) Change Relative to 1985

Note: The sample includes only men. See Equation (2) for definitions. Industries are disaggregated at 4-digit level.

Figure A3: Sector and firm: full variance decomposition - only women.



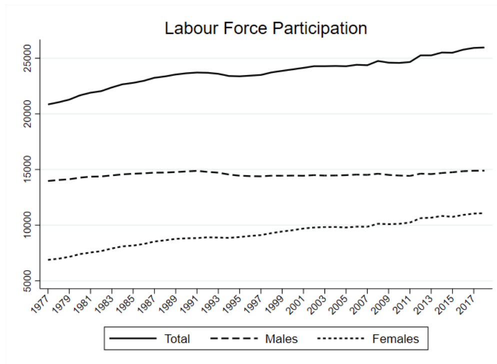
(a) Levels



(b) Change Relative to 1985

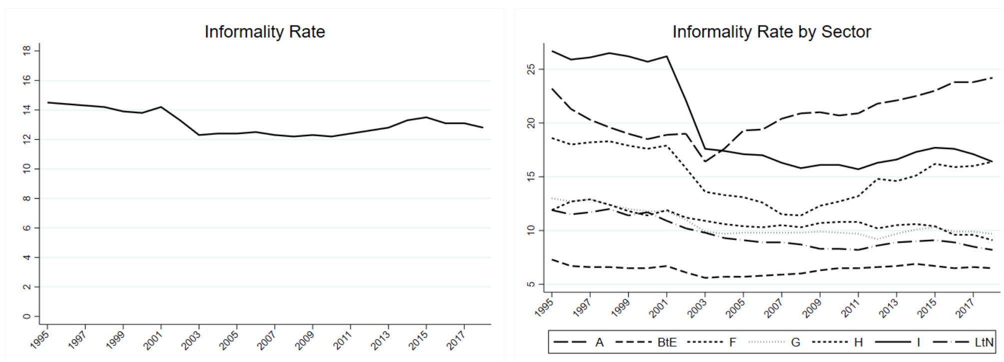
Note: The sample includes only women. See Equation (2) for definitions. Industries are disaggregated at 4-digit level.

Figure A4: Labour force participation by gender (in thousands).



Note: number of individuals who are in the labour force (employed and unemployed) by gender.
Source: Italian Institute of Statistics.

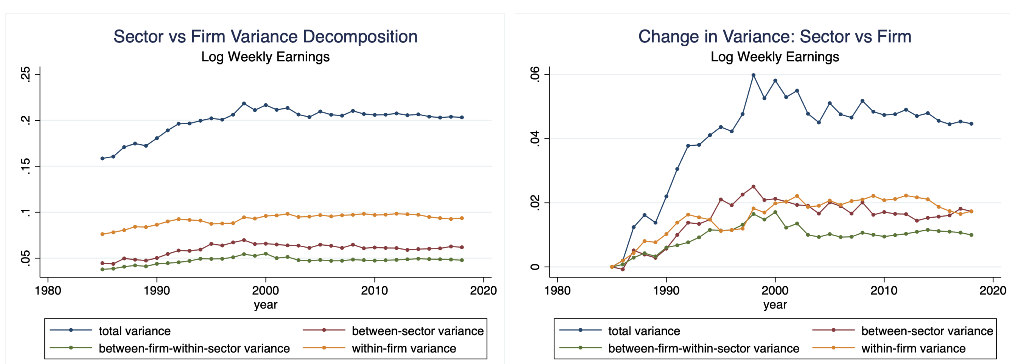
Figure A5: Informality rate.



(a) Informality Rate (b) Informality Rate by Sector

Note: The informality rate is computed as the ratio between employment in the informal sector and total employment. Sectors are classified (NACE Level 1 Codes) as: A (agriculture, forestry and fishing), BtE (mining and quarrying, manufacturing, electricity, gas, steam and air conditioning supply, water supply, sewerage, waste management and remediation activities), F (construction), G (Wholesale and retail trade; repair of motor), H (Transporting and storage), I (Accommodation and food service activities), LtN (Real estate activities; professional, scientific and technical activities; administrative and support service activities).
Source: Italian Institute of Statistics.

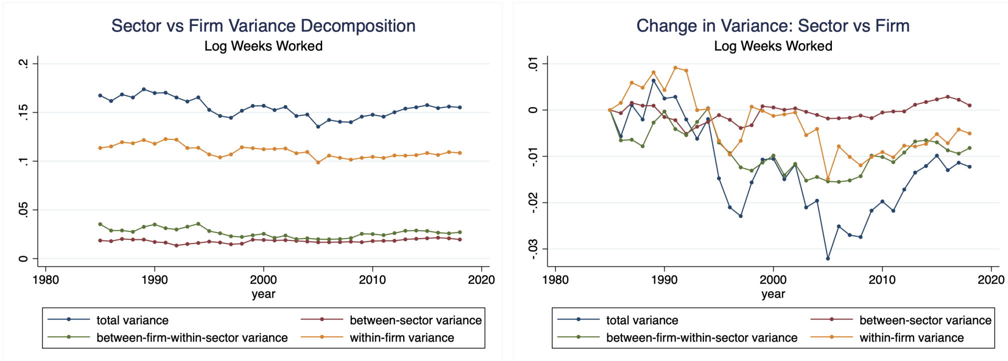
Figure A6: Decomposition of log weekly earnings.



(a) Levels (b) Change Relative to 1985

Note: See Equation (2) for definitions. Industries are disaggregated at 4-digit level.

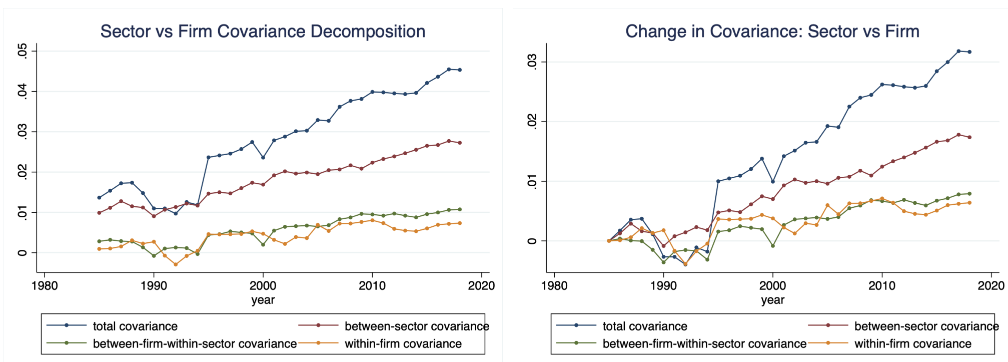
Figure A7: Decomposition of log weeks worked (FTE).



(a) Levels (b) Change Relative to 1985

Note: See Equation (2) for definitions. Industries are disaggregated at 4-digit level.

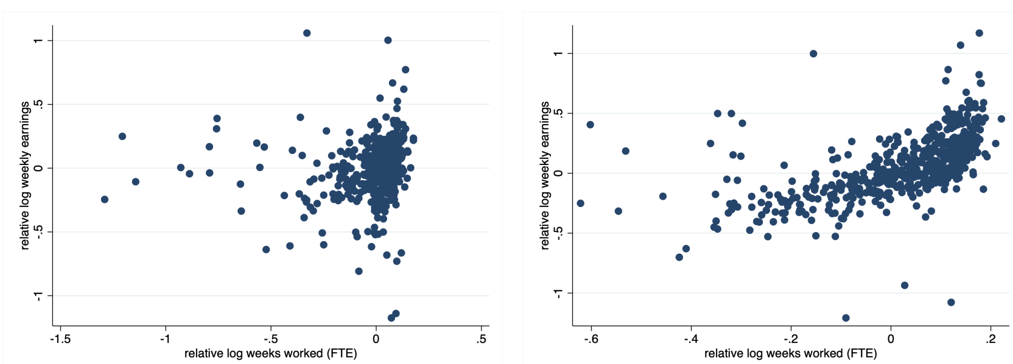
Figure A8: Decomposition of covariance of log weekly earnings and log weeks worked (FTE).



(a) Levels (b) Change Relative to 1985

Note: Industries are disaggregated at 4-digit level.

Figure A9: Relative weekly earnings vs relative weeks worked (FTE).



(a) 1985 (b) 2018

Note: log weekly earnings and log weeks worked (FTE) are expressed here relative to the economy average. NACE industries are at 4-digit level.

9 Appendix B: Online Appendix

9.1 How we control for the sector of the firm

There are two equivalent ways of controlling for the sector of the firm and obtaining between-firm within-sector variance. The first method is to regress log annual earnings on sector fixed effects, thus including a dummy variable for every sector and dropping the constant.

$$w_{ijs} = \sum_{s=1}^{s=S} \beta_s D_s + \epsilon_{ijs}, \tag{10}$$

where w_{ijs} denotes the log annual earnings of a worker i in firm j in sector s in a given year, S is the total number of sectors in the data, D_s is a dummy variable that takes value 1 if the observation is for sector s and 0 otherwise, β_s is the OLS coefficient on the fixed effect for sector s, and ϵ_{ijs} is the residual.

Next, we take the residuals from the above regression and perform the between versus within firm variance decomposition with them, as follows:

$$\underbrace{\frac{1}{N}\sum_{\forall i}(\epsilon_{ij} - \bar{\epsilon})^2}_{\text{within-sector variance}} = \underbrace{\sum_{\forall j}\frac{n_j}{N}(\bar{\epsilon_j} - \bar{\epsilon})^2}_{\text{between-firm-within-sector variance}} + \underbrace{\sum_{\forall j}\frac{n_j}{N}\frac{\sum_{\forall i|i\in j}(\epsilon_{ij} - \bar{\epsilon_j})^2}{n_j}}_{\text{within-firm variance}}, \tag{11}$$

where ϵ_{ij} is the residual from (Equation (10)) for worker i in firm j, N still denotes the total number of workers (firm-worker matches) in the data, n_j is the number of workers employed at firm j, $\bar{\epsilon_j} = \frac{1}{n_j}\sum_{\forall i|i\in j}\epsilon_{ij}$ are the firm j's average log annual earnings after controlling for sector fixed effects and $\bar{\epsilon} = \frac{1}{N}\sum_{\forall i}\epsilon_{ij}$ is the economy-wide average of log annual earnings after controlling for sector fixed effects.

The total variance of residuals from (Equation (10)) is equal to the within-sector variance given that controlling for sector fixed effects removes the between-sector variance. Performing between versus within-firm variance decomposition on the residuals from Equation (10) produces between-firms-within-sector variance and within-firm variance.

The second method of controlling for the sector is to demean each observation by the sector of the worker i.e., for every observation subtract the average of the sector that the observation belongs to. This method also removes the between-sector variance and it is equivalent to Equation (10). The demeaned observations are then used to calculate Equation (11).

9.2 Sub-periods analysis

We split our time period into two sub-periods: 1985 to 2003 and 2003 until 2018. There are two reasons for this. First, there was a legislative change and short-term employment contracts became increasingly common since 2003.[45] Second, we saw earlier that the patterns of rising inequality are markedly different in the two sub-periods (Section 3.1). Between 1985 and 2003 inequality in the upper half of the distribution (p90/p50 ratio) was steadily rising, while inequality in the bottom half was roughly constant (Figure A1). In contrast, since 2003 inequality in the bottom of the distribution (p50/p10 ratio) has been steadily increasing, while inequality in the upper half has been stable.

Table B1: Sectors and firms: full variance decomposition.

(a) Variance change 1985-2003

	Between sector	Between firms within sector	Within firm	Total
1985	0.083	0.079	0.193	0.355
2003	0.120	0.081	0.213	0.414
Change	0.038	0.002	0.020	0.060
% of total increase	63.3%	3.3%	33.3%	100.0%

(b) Variance change 2003-2018

	Between sector	Between firms within sector	Within firm	Total
2003	0.120	0.081	0.213	0.414
2018	0.136	0.096	0.218	0.450
Change	0.016	0.015	0.005	0.036
% of total increase	44.4%	41.7%	13.9%	100.0%

Note: See Equation (2) for definitions. Industries are disaggregated at 4-digit level.

Table B1 shows our variance decomposition results separately for each sub-period. Firstly, we can see that industry plays an important role in both periods, explaining 63.3% of the total rise in earnings inequality between 1985 and 2003 and 44.4% between 2003 and 2018. Secondly, within-firm inequality only plays important role in the earlier period, its contribution is 33.3% and 13.9% in the two periods respectively. Thirdly, while between-firm-within-sector variance plays almost no role in the earlier period (just 3.3%) it plays a very large

[45] Short-term contracts were first introduced in 1998 and they were fully implemented into law by 2003.

role in the latter period, accounting for 41.7% of the rise in earnings inequality between 2003 and 2018. We can see from Figure 2 that between-firm-within-sector variance was growing sharply in the 2007-2009 period which may be linked to the financial crisis. In contrast, between-sector variance was growing strongly between 1990 and 2002 and again between 2010 and 2017.

9.3 Contribution to inequality (2-digit sectors)

We group (2-digit) industries by the size of their individual contributions to between sector variance growth. In our data three industries account individually for more than 10% of the increase in the between-sector variance (Table B2), while together account for 61.2% of the between-sector variance growth, although they only represent 2.5% of total employment in 1985.[46]. Since the rise of between-sector variance accounts for 55% of the overall increase in earnings inequality, these three industries account for a third of the rise in earnings inequality in Italy.

There are further seven industries contributing between 3.4% and 10% of the increase in the between-sector variance and together representing 38.7% of the between-sector variance growth, while only accounting for 13.5% of total employment in 1985. Thus, 10 out of the 85 (2-digit) industries account for 99.9% of the between sector variance growth (and thus 55% of the overall earnings inequality increase), while representing 16% of employment in 1985.

Table B2: Contribution of 2 digit sector groups to between sector variance growth (grouped based on individual sector share)

Individual sector share of between sector variance growth	Number of sectors	Total employment share in 1985	Total contribution to between sector variance growth	Total share of between sector variance growth
$>$ 10%	3	2.5%	0.034	61.2%
3.4% to 10%	7	13.5%	0.021	38.7%
0.05% to 3.4%	35	46.8%	0.022	40.0%
-0.05% to 0.05%	17	6.6%	-0.000	-0.1%
$<$ -0.05%	23	30.6%	-0.022	-39.8%
Total	85	100.0%	0.055	100.0%

Note: See Equation (3) for definition of the contribution of a particular sector to between sector variance growth.

[46]There 85 2-digit industries in our data. We only include industries which exist in the dataset in both 1985 and 2018. The omitted sectors together account for only 3% of the increase in between-sector variance.

The industry with the largest contribution is Food and beverage service activities (NACE code 56) which on its own accounts for 26.2% of the between-sector variance growth (Table B3). The second most important sector is Employment activities (NACE code 78) which accounts for 17.5%, followed by Services to buildings and landscape activities (NACE code 81), also with 17.5% contribution. In fourth and fifth place are Non-residential social care (NACE code 88) and Accommodation industry (NACE code 55) which account for 9.5% and 6.6%, respectively. These top five industries experienced a decline in their average annual earnings relative to the economy average and massive increases in their employment as a share of total employment in the economy between 1985 and 2018 (Table B3). The Food and beverage sector increased its employment share from 1.0% to 4.4%, while the Employment activities (covering employment agencies) sector went from almost zero in 1985 to representing 4.9% of total employment in 2018. The sector Services to buildings and landscape activities which mainly represents cleaning of buildings, grew from 1.5% to 3.7%; Non-residential social care grew massively from 0.5% to 2.7%. The Accommodation sector also experienced a significant growth in its employment share, from 1.4% to 2.5%.

Not all the industries in the top 10 are low-paying: four industries already paying more than the economy average in 1985 (their relative earnings were positive) experienced an increase in relative earnings. Regarding employment share, the pattern is mixed, with some growing and some shrinking as a share of total employment.

Table B3: Top 10 sectors contributing to increasing between-sector variance.

NACE code	Industry title	Employment share		Relative earnings		Share of between sector variance growth
		1985	2018	1985	2018	
56	Food and beverage service activities	1.0%	4.4%	-0.27	-0.59	26.2%
78	Employment activities	0.0%	4.9%	0.41	-0.44	17.5%
81	Services to buildings and landscape activities	1.5%	3.7%	-0.52	-0.61	17.5%
88	Social work activities without accommodation	0.5%	2.7%	-0.21	-0.45	9.5%
55	Accommodation	1.4%	2.5%	-0.42	-0.49	6.6%
28	Manufacture of machinery and equipment n.e.c.	4.4%	3.0%	0.15	0.38	5.9%
33	Repair and installation of machinery and equipment	5.6%	5.3%	0.06	0.24	5.3%
35	Electricity, gas, steam and air conditioning supply	0.3%	0.7%	0.50	0.69	4.5%
21	Pharmaceutical manufacturing	1.2%	0.8%	0.35	0.67	3.5%
87	Residential care activities	0.2%	1.0%	-0.07	-0.43	3.4%

Note: Relative earnings is the gap between average log earnings of a particular industry and the economy average. See Equation (3) for definitions. Indutries are disaggregated at 2-digit level.

The remaining 75 (2-digit) NACE industries have offsetting contributions to the between-sector variance growth in such a way that their net effect is essentially zero. Thirty-five indus-

Table B4: Top 10 2-digit sectors contributing to decreasing between-sector variance.

NACE code	Industry title	Employment share		Relative earnings		Share of between sector variance growth
		1985	2018	1985	2018	
85	Education	2.4%	1.3%	-0.55	-0.36	-9.8%
41	Construction of buildings	5.1%	1.0%	-0.29	-0.11	-7.5%
14	Manufacture of wearing apparel	3.5%	1.3%	-0.29	-0.22	-4.2%
53	Postal and courier activities	0.2%	1.4%	-1.12	0.16	-3.5%
84	Public administration	2.8%	0.5%	-0.28	0.31	-3.2%
3	Fishing and aquaculture	0.2%	0.1%	-1.07	-0.90	-2.8%
15	Manufacture of leather and rel. prod.	2.0%	1.1%	-0.25	-0.05	-2.1%
58	Publishing activities	0.4%	0.1%	0.46	0.42	-1.1%
10	Manufacture of food products	3.5%	2.6%	-0.13	0.02	-1.1%
19	Manufacture of coke and refined petrol. prod.	0.6%	0.2%	0.46	0.72	-0.9%

Note: Relative earnings is the gap between average log earnings of a particular industry and the economy average. See Equation (3) for definitions.

tries with individual contributions to the rise of between-sector variance between 0.05% and 3.4% account for 40.0% of the rise in between-sector variance (Table B2). Additional seventeen industries contribute roughly 0% individually (precisely between -0.05% and 0.05%) to the rise in between sector variance. Their joint contribution is almost zero. Finally, twenty-three industries with negative contribution, i.e., they reduced inequality, together account for -39.8%, which when combined with the contribution of the previous two groups results in a net zero contribution of the bottom 75 (2-digit) industries. The top 10 industries with the largest (in absolute value) negative contributions are presented in Table B4. Two industries stand out: Education (NACE code 85) and Construction (NACE code 41). They both experienced significant declines in their employment share and also a fall in the absolute value of their relative earnings, i.e. their average annual earnings moved closer to the economy average (from below).

Table B5: Sector contributions to between sector variance growth - 2-digit industries.

Sector relative earnings	Number of sectors	Total employment share in 1985	Total contribution to between sector variance growth	Total share of between sector variance growth	Shift-share: employment	earnings
			Top 10 sectors			
High paying	4	11.5%	0.011	19.2%	-9.1%	109.2%
Low paying	6	4.5%	0.045	80.7%	65.3%	34.8%
			The remaining 75 sectors			
High paying	47	54.3%	0.013	23.0%		
Low paying	28	29.7%	-0.013	-22.9%		
Total	85	100.0%	0.055	100.0%	17.0%	85.4%

Note: See Equation (3) for definitions of relative earnings and of the contribution of a particular sector to between sector variance growth. Sector is high paying (low paying) if its average relative earnings are positive (negative) where the average is taken over the 1985 and 2018 values. Total contribution of a particular sector to between sector variance growth is decomposed into the role of employment and earnings changes as defined in Equation (4). To calculate the shares we sum the employment and earnings components across sectors and divide each by the corresponding sum of the total contribution to between sector variance growth. Industries are disaggregated at 2-digit level.

Table B6: Contribution of 2-digit sector groups to between sector variance growth (grouped based on individual sector share) - only men.

Individual sector share of between sector variance growth	Number of sectors	Total employment share in 1985	Total contribution to between sector variance growth	Total share of between sector variance growth
> 10%	3	2.8%	0.031	64.3%
3.8% to 10%	7	14.0%	0.016	33.5%
0.05% to 3.8%	34	48.1%	0.016	33.2%
-0.05% to 0.05%	16	3.4%	0.000	0.0%
< -0.05%	25	31.6%	-0.015	-31.0%
Total	85	100.0%	0.049	100.0%

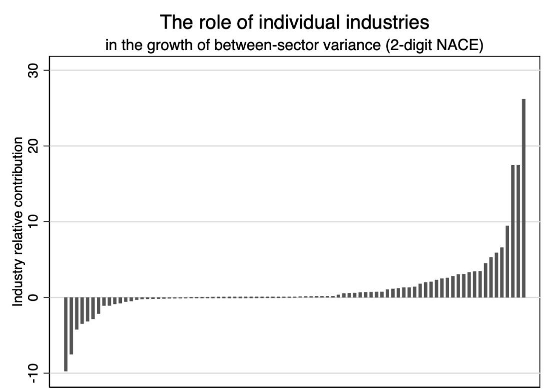
Note: The sample includes only men. See Equation (3) for definition of the contribution of a particular sector to between sector variance growth. Industries are disaggregated at 2-digit level.

Table B7: Top 10 2-digit sectors contributing to increasing between-sector variance - only men.

NACE code	Industry title	Employment share		Relative earnings		Share of between sector variance growth
		1985	2018	1985	2018	
56	Food and beverage service activities	0.9%	3.7%	-0.22	-0.59	25.5%
81	Services to buildings and landscape activities	1.5%	3.6%	-0.54	-0.67	24.1%
88	Social work activities without accommodation	0.5%	2.7%	-0.19	-0.52	14.6%
78	Employment activities	0.0%	3.2%	0.40	-0.32	6.9%
28	Manufacture of machinery and equipment n.e.c.	4.6%	3.3%	0.10	0.30	5.2%
87	Residential care activities	0.2%	1.0%	-0.11	-0.48	4.8%
47	Retail trade, except of motor vehicles and motorcycles	2.8%	8.5%	-0.03	-0.16	4.4%
35	Electricity, gas, steam and air conditioning supply	0.3%	0.8%	0.46	0.60	4.3%
33	Repair and installation of machinery and equipment	5.7%	5.7%	0.03	0.19	4.2%
82	Business support activities	0.4%	3.2%	0.26	-0.25	3.8%

Note: The sample includes only men. Relative earnings is the gap between average log earnings of a particular industry and the economy average. See Equation (3) for definitions. Industries are disaggregated at 2-digit level.

Figure B1: The relative role of individual industries in the growth of between-sector variance (in percentage points) - 2 digit industries.



Note: the graph depicts the contribution of each sector to the growth of the between-sector variance. A small number of industries provide large negative contributions, the vast majority of industries have contribution close to zero and a small number of industries provide very large positive contributions to the rise in the between-sector variance.

9.4 Standard AKM decomposition

Table B8 shows results of the simple AKM variance decomposition based on Equation (6) for the first (1985-1991) and the last (2013-2019) interval and the change in variance between the two periods. Total variance of log annual earnings rises from 0.341 in the 1st interval to 0.422 in the final seven-year interval which represents an increase of 8.1 log points. We can see that variance of worker effects represents more than half of variance of annual earnings, 55.1% and 59.7% in the two intervals respectively. On the other hand, variance of firm effects is much smaller and declines over time, accounts for only 20.8% and 13.5% of total variance. Variance of time-variant characteristics also shrinks, from 5.9% of total variance to 3.6%. Residual variance also declines, from 21.1% to 13.7% of total variance. Covariance between worker and firm effects which represents the extent of sorting is small and negative in the first interval, but it is much larger and positive in the final interval.

Table B8: AKM variance decomposition

	Interval 1		Interval 5		Growth	
	1985-1991		2013-2019		1 to 5	
	Var.	Share	Var.	Share	Change	% of total var. change
	(1)	(2)	(3)	(4)	(5)	(6)
Total variance						
Var(y)	0.341	-	0.422	-	0.081	-
Components						
Var(WFE)	0.188	55.1%	0.252	59.7%	0.064	79.0%
Var(FFE)	0.071	20.8%	0.057	13.5%	-0.014	-17.3%
Var(Xb)	0.020	5.9%	0.015	3.6%	-0.005	-6.2%
Var(ϵ)	0.072	21.1%	0.058	13.7%	-0.014	-17.3%
$2 * Cov(WFE, FFE)$	-0.013	-3.8%	0.045	10.7%	0.058	71.6%
$2 * Cov(WFE, Xb)$	-0.002	-0.6%	-0.009	-2.1%	-0.007	-8.6%
$2 * Cov(FFE, Xb)$	0.005	1.5%	0.004	0.9%	-0.001	-1.2%
Sample size (millions)	33.9		59.0			
Workers (millions)	6.9		11.4			
Firms (thousands)	162		300			

Note: See equation (6). Var(y): variance of annual earnings, Var(WFE): variance of worker fixed effects, Var(FFE): variance of firm fixed effects, Var(Xb): variance of time-variant characteristics, Var(ϵ): variance of residuals.

Moving on to our main interest, explaining change in earnings dispersion over time, we can see that two channels dominate. These are growing variance of worker effects and increasing sorting of highly paid workers into high-paying firms. Increase in variance of worker effects accounts for 79.0% of the total growth in earnings dispersion, while increasing sorting accounts for 71.6%. The other components all had negative, inequality-reducing contribution, the most important being shrinking variance of firm effects and of residual variance. Variance of time-variant characteristics and their covariance with worker and firm effects also all declined in size. Furthermore, we find very similar results when restricting our sample to just men (Table B9). Based on this we can conclude that earnings dispersion in Italy between 1985 and 2019 grew not because of changes in firm wage premiums, but because of growing heterogeneity in worker personal component of pay (their earnings ability that is mobile between firms) and due to an increase in sorting where workers with high earnings ability are increasingly working at firms with high pay premiums.[47] This is the same as the finding of Song et al. (2019) for the US.[48] However, our findings are very different from the results of Card et al. (2013) for West Germany where rising variance of firm fixed effects is an important component of the overall rise in inequality. The different patterns between Germany and Italy can potentially be explained by very significant decentralisation of collective bargaining in Germany where in many cases wage bargaining shifted from industry to the level of the firm. This could explain the growing dispersion in firm pay premiums. No such decentralisation of wage bargaining took place in Italy.

[47] This is in line with the findings of Devicienti et al. (2019) for Italian male wage inequality, comparing 1982–1987 and 1996–2001 periods.

[48] Song et al. (2019) also find growing variance of worker fixed effects and of the covariance between worker and firm effects and a small fall in the variance of firm fixed effects.

Table B9: AKM variance decomposition - only men.

	Interval 1 1985-1991 Var. (1)	Interval 1 1985-1991 Share (2)	Interval 5 2013-2019 Var. (3)	Interval 5 2013-2019 Share (4)	Growth 1 to 5 Change (5)	Growth 1 to 5 % of total var. change (6)
Total variance						
Var(y)	0.250	-	0.347	-	0.097	-
Components						
Var(WFE)	0.182	72.8%	0.245	70.6%	0.063	64.9%
Var(FFE)	0.069	27.6%	0.055	15.9%	-0.014	-14.4%
Var(Xb)	0.011	4.4%	0.004	1.2%	-0.007	-7.2%
Var(ϵ)	0.042	16.8%	0.037	10.7%	-0.005	-5.2%
$2 * Cov(WFE, FFE)$	-0.032	-12.8%	0.018	5.2%	0.050	51.5%
$2 * Cov(WFE, Xb)$	-0.023	-9.2%	-0.012	-3.5%	0.011	11.3%
$2 * Cov(FFE, Xb)$	0.001	0.4%	-0.001	-0.3%	-0.002	-2.1%
Sample size (millions)	28.7		47.6			
Workers (millions)	5.9		9.5			
Firms (thousands)	141		260			

Note: See equation (6). Var(y): variance of annual earnings, Var(WFE): variance of worker fixed effects, Var(FFE): variance of firm fixed effects, Var(Xb): variance of time-variant characteristics, Var(ϵ): variance of residuals.

Table B10: Average worker and firm fixed effects of the top 10 (2-digit) sectors contributing to the increased between-sector variance.

2dig NACE code	Industry title	Relative firm FE 1985-1991	Relative firm FE 2013-2019	Relative worker FE 1985-1991	Relative worker FE 2013-2019
56	Food and beverage service activities	-0.20	-0.24	-0.11	-0.34
78	Employment activities	0.06	-0.17	0.21	-0.30
81	Services to buildings and landscape activities	-0.27	-0.23	-0.32	-0.40
88	Social work activities without accommodation	-0.28	-0.18	-0.05	-0.28
55	Accommodation	-0.24	-0.23	-0.17	-0.27
28	Manufacture of machinery and equipment n.e.c.	0.07	0.13	0.07	0.21
33	Repair and installation of machinery and equipment	0.03	0.07	0.03	0.14
35	Electricity, gas, steam and air conditioning supply	0.16	0.28	0.31	0.38
21	Pharmaceutical manufacturing	0.21	0.20	0.15	0.43
87	Residential care activities	-0.06	-0.15	-0.13	-0.26

Note: Relative firm FE is the gap between the average industry firm fixed effect, given by $\bar{\psi}^s$, and the economy average, $\bar{\psi}$. Relative worker FE is the gap between the average industry worker fixed effect (including the effects of observable characteristics), given by $\bar{\theta}^s + \bar{X}^s\beta$, and the economy average, $\bar{\theta} + \bar{X}\beta$. See Equation 6 for definitions. Industries are aggregated at 2-digit level.

Table B11: Industry-enhanced AKM variance decomposition - 2-digit industry.

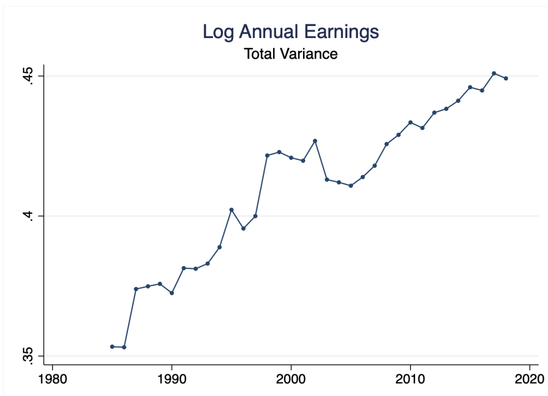
	Interval 1 1985-1991		Interval 5 2013-2019		Growth 1 to 5	
	Var.	Share	Var.	Share	Change	% of total var. change
	(1)	(2)	(3)	(4)	(5)	(6)
Total variance	0.341	-	0.422	-	0.081	-
Between-sector	**0.062**	**18.2%**	**0.112**	**26.5%**	**0.050**	**61.7%**
Sector pay premium	0.019	5.5%	0.017	3.9%	-0.002	-2.8%
Sector sorting	0.025	7.2%	0.049	11.6%	0.024	30.1%
Sector segregation	0.018	5.4%	0.046	10.9%	0.028	34.1%
Between-firm-within-sector	**0.072**	**21.1%**	**0.098**	**23.2%**	**0.026**	**32.1%**
Firm pay premium	0.052	15.3%	0.041	9.7%	-0.011	-14.0%
Firm sorting	-0.032	-9.5%	-0.000	-0.1%	0.032	39.6%
Firm segregation	0.052	15.3%	0.057	13.5%	0.005	6.0%
Within-firm	**0.207**	**60.7%**	**0.213**	**50.5%**	**0.006**	**7.4%**
Person effect	0.123	36.0%	0.154	36.5%	0.031	38.8%
Time-variant characteristics	0.017	5.1%	0.013	3.2%	-0.004	-5.1%
Covariance of the above two	-0.005	-1.5%	-0.013	-3.0%	-0.008	-9.4%
Residuals	0.072	21.1%	0.058	13.7%	-0.014	-17.3%

Note: See Equation (7) for definitions. Industries are aggregated at 2-digit level.

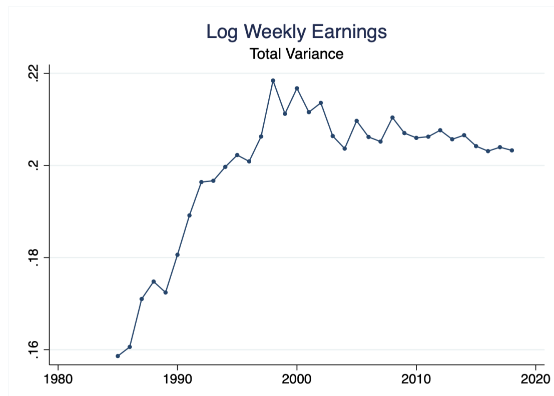
9.5 Weekly earnings vs weeks worked

In section 5 we decompose variance of annual earnings into the variance of weeks worked, variance of weekly earnings (wage rates) and their covariance. We find that the growth of annual earnings inequality was driven by rising wage inequality and rising positive association between the rate of pay and how much individuals work. In contrast, the variance of weeks actually declined slightly. In this section we investigate the change in each component of Equation 9 over time and we check robustness of the main finding by splitting the sample by gender and age.

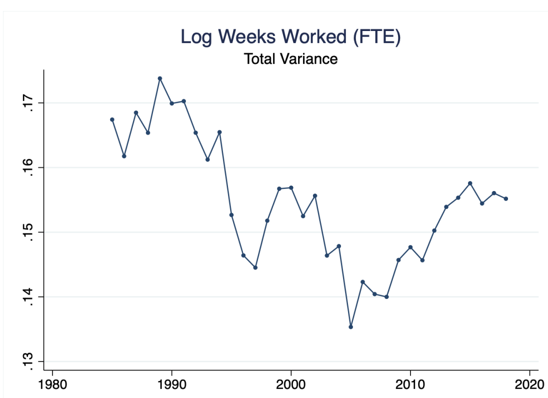
Figure B2: Decomposing annual earnings into weeks worked (FTE) and average weekly earnings.



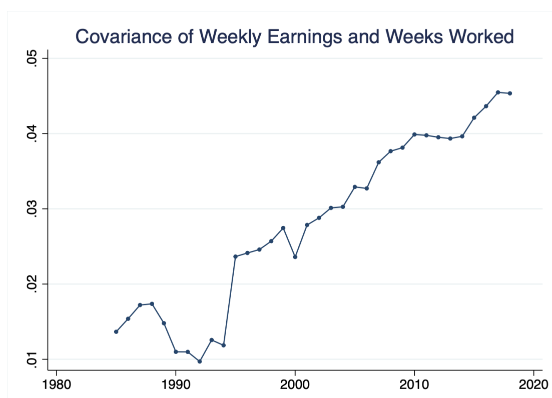
(a) Variance of log annual earnings



(b) Variance of log of average weekly earnings in a year



(c) Variance of log of full-time equivalent (FTE) weeks in a year



(d) Covariance between log of weeks worked (FTE) and log average weekly wages

Note: See Equation (9) for definitions.

Figure B2 displays the evolution of the individual components of the decomposition in Equation (9) over time. The variance of log annual earnings is rising throughout the 1985-

2018 period, with the exception of a brief slowdown around the year 2000; the variance of log weekly earnings was rising sharply from 1985 until around 2000 and it has plateaued since. This is in line with the findings of Devicienti et al. (2019) who suggest that the Italian wage inequality was growing fast in the second half of 1980s and in 1990s and has been flat since 2000. However, inequality of annual earnings has continued to increase at a fast pace in the last two decades. Our decomposition can explain why. The variance of log of (FTE) weeks worked in a year decreased slightly over the 1985-2018 period. However, it reached the lowest point around 2005 and has been growing since then, reversing some of the decline in previous years. However, changes in the dispersion of labour supply quantities are quite small relative to the other components and this variance is approximately flat over the period considered. Finally, the steep rise in the covariance between weekly earnings and weeks worked is particularly pronounced in the period after 2000 (Figure B2).

Thus, the main driver of rising inequality of annual earnings in the 1985-2000 period is rising inequality in the rate of pay, while in the 2000-2018 period the main driver is rising positive association between the rate of pay and labour supply quantities. This explains why the variance of log annual earnings continued to grow in the last two decades, despite wage inequality being flat in that period.

Table B12: Decomposing annual earnings into full-time equivalent weeks worked and average weekly earnings - only men.

(a) Variance change over time

	Weekly earnings variance	Weeks worked variance	2*Covariance of weeks and earnings	Annual earnings variance
1985	0.159	0.080	0.016	0.255
2018	0.204	0.108	0.059	0.371
Change	0.045	0.028	0.043	0.116
% of total increase	38.8%	24.1%	37.1%	100.0%

(b) Variance shares

	Weekly earnings	Weeks worked	2*Covariance of weeks and earnings
1985	62.4%	31.4%	6.3%
2018	55.0%	29.1%	15.9%

Note: The sample includes only men. Industries are disaggregated at 4-digit level.

We repeat the analysis restricting the sample to only men and find that the results are consistent with findings for the whole population (Table B12). The variance of weeks worked increased and accounted for 24.1% of the rise in annual earnings variance. However, the dominant role is played by the growing wage rate inequality and the growing positive association between wage rates and weeks worked, with contributions of 38.8% and 37.1% respectively.

We then investigate the role of age by splitting the sample further into young men (aged 20-40) and older men (aged 41-60). We find that the rise in the dispersion of weeks worked was 6 times higher among young men than older men (Tables B14 and B15). This is the expected outcome of a dual labour market where by 2018 some young workers are in permanent jobs, while others are on temporary contracts, leading to a greater variance of weeks worked. In contrast, we would expect that older workers and young workers in 1985 would overwhelmingly be in permanent jobs. Our results are therefore in line with the findings of Bianchi and Paradisi (2023) who highlight the age aspect of the Italian pay inequality.

We have seen earlier that there was only a small rise in annual earnings variance among women (Table A2). However, this hides very large shifts in the components of Equation (9). There was a massive decline in the variance of weeks worked, from 0.351 in 1985 to 0.250 in 2018 (Table B13). This has been roughly offset by the steep rise in the covariance between wage rates and weeks worked, rising from a very large negative to a very large positive value. The patterns for women are most likely driven by factors specific to women, such as compositional changes due to the large increase in the female labour market participation during this period, as shown in Figure A4.

Table B13: Decomposing annual earnings into full-time equivalent weeks worked and average weekly earnings - only women.

(a) Variance change over time

	Weekly earnings variance	Weeks worked variance	2*Covariance of weeks and earnings	Annual earnings variance
1985	0.140	0.351	-0.068	0.423
2018	0.137	0.250	0.061	0.447
Change	-0.003	-0.101	0.129	0.024
% of total increase	-12.5%	-420.8%	537.5%	100.0%

(b) Variance shares

	Weekly earnings	Weeks worked	2*Covariance of weeks and earnings
1985	33.1%	83.0%	-16.1%
2018	30.6%	55.9%	13.6%

Note: The sample includes only women. Industries are disaggregated at 4-digit level.

Table B14: Decomposing annual earnings into full-time equivalent weeks worked and average weekly earnings - only young men.

(a) Variance change over time

	Weekly earnings variance	Weeks worked variance	2*Covariance of weeks and earnings	Annual earnings variance
1985	0.122	0.079	0.021	0.222
2018	0.140	0.133	0.044	0.317
Change	0.018	0.054	0.023	0.095
% of total increase	18.9%	56.8%	24.2%	100.0%

(b) Variance shares

	Weekly earnings	Weeks worked	2*Covariance of weeks and earnings
1985	55.0%	35.6%	9.5%
2018	44.2%	42.0%	13.9%

Note: The sample includes only men under the age of 40. Industries are disaggregated at 4-digit level.

Table B15: Decomposing annual earnings into full-time equivalent weeks worked and average weekly earnings - only older men.

(a) Variance change over time

	Weekly earnings variance	Weeks worked variance	2*Covariance of weeks and earnings	Annual earnings variance
1985	0.201	0.082	0.007	0.290
2018	0.229	0.091	0.059	0.380
Change	0.028	0.009	0.052	0.090
% of total increase	31.1%	10.0%	57.8%	100.0%

(b) Variance shares

	Weekly earnings	Weeks worked	2*Covariance of weeks and earnings
1985	69.3%	28.3%	2.4%
2018	60.3%	23.9%	15.5%

Note: The sample includes only men above the age of 40. Industries are disaggregated at 4-digit level.

9.6 Firm size cutoff: 5 employees

Table B16: Sectors and firms: full variance decomposition (4-digit sectors).

(a) Variance change over time

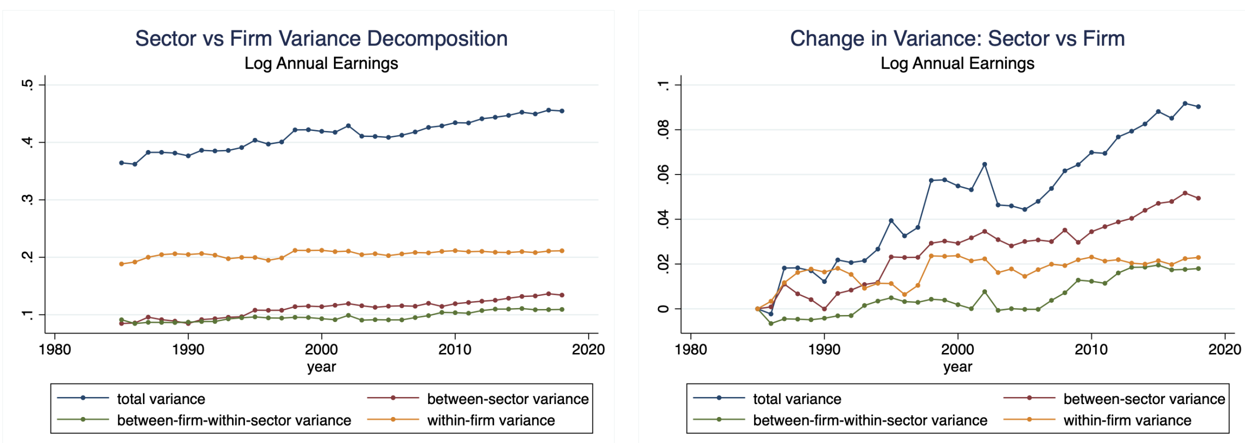
	Between sector	Between firms within sector	Within firm	Total
1985	0.085	0.091	0.188	0.364
2018	0.134	0.109	0.211	0.455
Change	0.049	0.018	0.023	0.090
% of total increase	54.4%	20.0%	25.6%	100.0%

(b) Variance shares

	Between sector	Between firms within sector	Within firm
1985	23.3%	25.0%	51.7%
2018	29.5%	24.0%	46.5%

Note: See Equation (2) for definitions. Industries are disaggregated at 4-digit level.

Figure B3: Sector and firm: full variance decomposition.



(a) Levels (b) Change Relative to 1985

Note: See Equation (2) for definitions. Industries are disaggregated at 4-digit level.

Table B17: Contribution of 4-digit sector groups to between sector variance growth (grouped based on individual sector share).

Individual sector share of between sector variance growth	Number of sectors	Total employment share in 1985	Total contribution to between sector variance growth	Total share of between sector variance growth
> 5%	5	2.7%	0.032	67.6%
2.6% to 5%	9	5.3%	0.015	32.2%
0.05% to 2.6%	193	39.6%	0.034	70.3%
-0.05% to 0.05%	254	17.2%	0.001	1.1%
< -0.05%	79	35.2%	-0.034	-71.2%
Total	540	100.0%	0.048	100.0%

Note: See Equation (3) for definition of the contribution of a particular sector to between sector variance growth. Industries are disaggregated at 4-digit level.

Table B18: Top 4-digit sectors contributing to increasing between-sector variance.

NACE code	Industry title	Employment share		Relative earnings		Share of between sector
		1985	2018	1985	2018	variance growth
5610	Restaurants and mobile food service activities	0.5%	3.5%	-0.35	-0.62	26.0%
7830	Other human resources provision	0.0%	4.3%	0.38	-0.39	13.9%
8129	Other cleaning activities	1.5%	2.9%	-0.51	-0.56	11.3%
5630	Beverage serving activities	0.2%	1.3%	-0.35	-0.60	8.9%
8899	Other non-residential social work	0.5%	2.4%	-0.22	-0.40	7.5%
5629	Other food service activities	0.4%	0.9%	-0.23	-0.51	4.3%
8121	General cleaning of buildings	0.0%	0.3%	-0.52	-0.77	4.1%
3514	Trade of electricity	0.1%	0.5%	0.78	0.76	4.1%
4910	Passenger rail transport, interurban	0.1%	0.6%	-0.07	0.58	4.0%
6209	Computer service activities	0.2%	1.9%	0.12	0.31	3.7%
5510	Hotels and similar accommodation	1.3%	2.1%	-0.47	-0.47	3.5%
3312	Repair of machinery	2.7%	2.4%	0.07	0.26	3.1%
3316	Repair and maintenance of aircraft and spacecraft	0.5%	0.3%	0.21	0.65	2.6%
9602	Hairdressing and other beauty treatment	0.1%	0.3%	-0.55	-0.65	2.6%

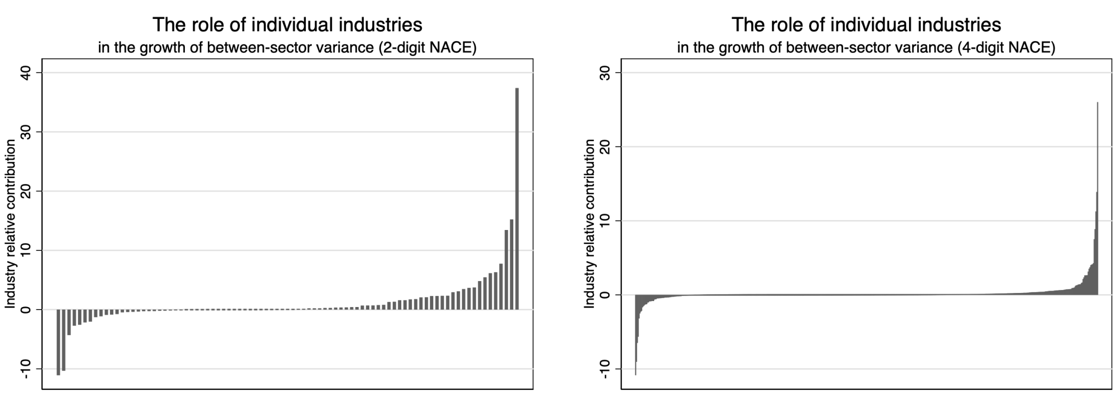
Note: Relative earnings is the gap between the average log earnings of a particular industry and the economy average. See Equation 3 for definitions. Industries are disaggregated at 4-digit level.

Table B19: Sector contributions to between sector variance growth (4-digit sectors).

Sector relative earnings	Number of sectors	Total employment share in 1985	Total contribution to between sector variance growth	Total share of between sector variance growth	Shift-share: employment	earnings
			Top 14 sectors			
High paying	5	3.6%	0.008	17.6%	41.6%	59.2%
Low paying	9	4.5%	0.039	82.2%	70.1%	30.7%
			The remaining 526 sectors			
High paying	322	59.5%	0.019	39.1%		
Low paying	204	32.5%	-0.019	-38.9%		
Total	540	100.0%	0.048	100.0%	17.0%	85.4%

Note: Employment shares are calculated as the average of 1985 and 2018 employment shares. See Equation (3) for definitions of relative earnings and of the contribution of a particular sector to between-sector variance growth. The sector is high paying (low paying) if its average relative earnings are positive (negative) where the average is taken over the 1985 and 2018 values. The total contribution of a particular sector to between-sector variance growth is decomposed into the role of employment and earnings changes as defined in Equation (4). To calculate the shares we sum the employment and earnings components across sectors and divide each by the corresponding sum of the total contribution to between sector variance growth. Industries are disaggregated at 4-digit level.

Figure B4: The relative role of individual industries in the growth of between-sector variance (in percentage points): 2 digits vs 4 digits.



(a) 2-digit NACE industries (b) 4-digit NACE industries

Note: in the graph it is reported the contribution of each 4-digit sector to the growth of the between-sector variance. A small number of industries provide large negative contributions, the vast majority of industries have contribution close to zero and a small number of industries provide very large positive contributions to the rise in the between-sector variance.

9.7 No firm size cutoff

Table B20: Sectors and firms: full variance decomposition (4-digit sectors).

(a) Variance change over time

	Between sector	Between firms within sector	Within firm	Total
1985	0.090	0.116	0.176	0.381
2018	0.137	0.136	0.193	0.467
Change	0.048	0.020	0.018	0.086
% of total increase	55.8%	23.3%	20.9%	100.0%

(b) Variance shares

	Between sector	Between firms within sector	Within firm
1985	23.6%	30.4%	46.0%
2018	29.4%	29.2%	41.4%

Note: See Equation (2) for definitions. Industries are disaggregated at 4-digit level.

Table B21: Contribution of 4-digit sector groups to between sector variance growth (grouped based on individual sector share).

Individual sector share of between sector variance growth	Number of sectors	Total employment share in 1985	Total contribution to between sector variance growth	Total share of between sector variance growth
> 5%	5	2.8%	0.030	65.8%
2.6% to 5%	9	4.7%	0.016	33.9%
0.05% to 2.6%	207	38.7%	0.034	73.1%
-0.05% to 0.05%	246	12.7%	0.001	1.4%
< -0.05%	97	41.1%	-0.034	-74.2%
Total	564	100.0%	0.046	100.0%

Note: See Equation (3) for definition of the contribution of a particular sector to between sector variance growth. Industries are disaggregated at 4-digit level.

Table B22: Top 4-digit sectors in terms of increasing between-sector variance.

NACE code	Industry title	Employment share 1985	Employment share 2018	Relative earnings 1985	Relative earnings 2018	Share of between sector variance growth
5610	Restaurants and mobile food service activities	0.7%	3.9%	-0.41	-0.60	28.0%
5630	Beverage serving activities	0.4%	1.9%	-0.43	-0.62	14.4%
7830	Other human resources provision	0.0%	3.7%	0.35	-0.33	8.5%
8129	Other cleaning activities	1.4%	2.6%	-0.48	-0.51	7.7%
9602	Hairdressing and other beauty treatment	0.3%	0.9%	-0.63	-0.69	7.1%
8899	Other non-residential social work	0.5%	2.1%	-0.22	-0.34	4.7%
6209	Computer service activities	0.2%	1.8%	0.11	0.35	4.5%
4910	Passenger rail transport, interurban	0.1%	0.5%	-0.02	0.65	4.5%
3514	Trade of electricity	0.1%	0.4%	0.82	0.81	4.2%
3312	Repair of machinery	2.6%	2.2%	0.09	0.30	3.9%
8121	General cleaning of buildings	0.0%	0.3%	-0.46	-0.72	3.7%
5629	Other food service activities	0.4%	0.8%	-0.19	-0.45	3.1%
3316	Repair and maintenance of aircraft and spacecraft	0.4%	0.3%	0.26	0.72	2.7%
2120	Manufacture of pharmaceutical preparations	0.4%	0.3%	0.44	0.80	2.6%

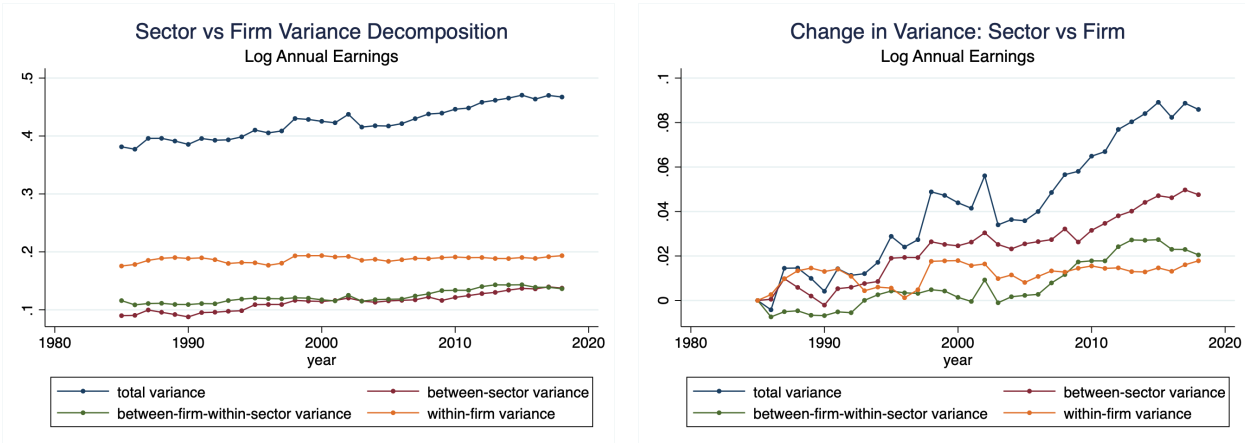
Note: Relative earnings is the gap between the average log earnings of a particular industry and the economy average. See Equation 3 for definitions. Industries are disaggregated at 4-digit level

Table B23: Sector contributions to between sector variance growth, by average earnings (4-digit sectors).

Sector relative earnings	Number of sectors	Total employment share in 1985	Total contribution to between sector variance growth	Total share of between sector variance growth	Shift-share: employment	Shift-share: earnings
Top 14 sectors						
High paying	7	3.8%	0.014	31.0%	51.2%	49.3%
Low paying	7	3.6%	0.032	68.7%	68.1%	32.5%
The remaining 550 sectors						
High paying	324	55.8%	0.016	35.2%		
Low paying	226	36.7%	-0.016	-34.8%		
Total	564	100.0%	0.046	100.0%	17.0%	85.4%

Note: Employment shares are calculated as the average of 1985 and 2018 employment shares. See Equation (3) for definitions of relative earnings and of the contribution of a particular sector to between-sector variance growth. The sector is high paying (low paying) if its average relative earnings are positive (negative) where the average is taken over the 1985 and 2018 values. The total contribution of a particular sector to between-sector variance growth is decomposed into the role of employment and earnings changes as defined in Equation (4). To calculate the shares we sum the employment and earnings components across sectors and divide each by the corresponding sum of the total contribution to between sector variance growth.

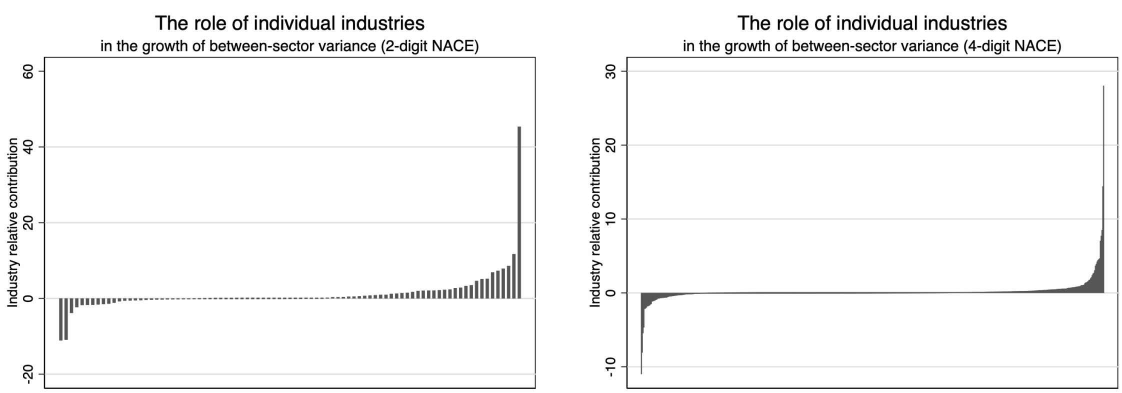
Figure B5: Sector and firm: full variance decomposition.



(a) Levels (b) Change Relative to 1985

Note: See Equation (2) for definitions. Industries are disaggregated at 4-digit level.

Figure B6: The relative role of individual industries in the growth of between-sector variance (in percentage points): 2 digits vs 4 digits.



(a) 2-digit NACE industries (b) 4-digit NACE industries

Note: See Equation (3) for the definition of the contribution of a particular sector to between-sector variance growth. We keep all sectors which are present across the years considered.

9.8 Only sectors with no change in coverage of INPS data: NACE code from 10 to 84

Table B24: Sectors and firms: full variance decomposition (4-digit sectors).

(a) Variance change over time

	Between sector	Between firms within sector	Within firm	Total
1985	0.076	0.077	0.190	0.343
2018	0.133	0.097	0.219	0.449
Change	0.057	0.020	0.029	0.105
% of total increase	54.3%	19.0%	27.6%	100.0%

(b) Variance shares

	Between sector	Between firms within sector	Within firm
1985	22.2%	22.5%	55.3%
2018	29.6%	21.6%	48.8%

Note: See Equation (2) for definitions. Industries are disaggregated at 4-digit level.

Table B25: Contribution of 4-digit sector groups to between sector variance growth (grouped based on individual sector share).

Individual sector share of between sector variance growth	Number of sectors	Total employment share in 1985	Total contribution to between sector variance growth	Total share of between sector variance growth
$> 5\%$	6	3.9%	0.042	76.8%
2.5% to 5%	7	1.9%	0.012	22.5%
0.05% to 2.5%	164	46.4%	0.030	54.1%
-0.05% to 0.05%	197	15.6%	0.001	1.2%
$< -0.05\%$	60	32.0%	-0.030	-54.6%
Total	434	100.0%	0.055	100.0%

Note: See Equation (3) for definition of the contribution of a particular sector to between sector variance growth. Industries are disaggregated at 4-digit level.

Table B26: Top 4-digit sectors contributing to increasing between-sector variance.

NACE code	Industry title	Employment share 1985	Employment share 2018	Relative earnings 1985	Relative earnings 2018	Share of between sector variance growth
7830	Other human resources provision	0.0%	5.5%	0.39	-0.47	22.0%
5610	Restaurants and mobile food service activities	0.4%	2.9%	-0.30	-0.63	20.7%
8129	Other cleaning activities	1.6%	3.6%	-0.55	-0.63	16.5%
5510	Hotels and similar accommodation	1.2%	2.3%	-0.44	-0.50	6.1%
5629	Other food service activities	0.5%	1.1%	-0.29	-0.58	6.0%
5630	Beverage serving activities	0.2%	0.9%	-0.30	-0.59	5.5%
8121	General cleaning of buildings	0.0%	0.4%	-0.53	-0.83	4.6%
3514	Trade of electricity	0.1%	0.6%	0.73	0.69	3.8%
4910	Passenger rail transport, interurban	0.1%	0.7%	-0.13	0.51	3.4%
8299	Other business support activities n.e.c.	0.4%	3.1%	0.25	-0.24	2.9%
6209	Computer service activities	0.3%	2.3%	0.11	0.26	2.7%
2120	Manufacture of pharmaceutical preparations	0.6%	0.5%	0.33	0.66	2.6%
3316	Repair and maintenance of aircraft and spacecraft	0.6%	0.4%	0.15	0.58	2.5%

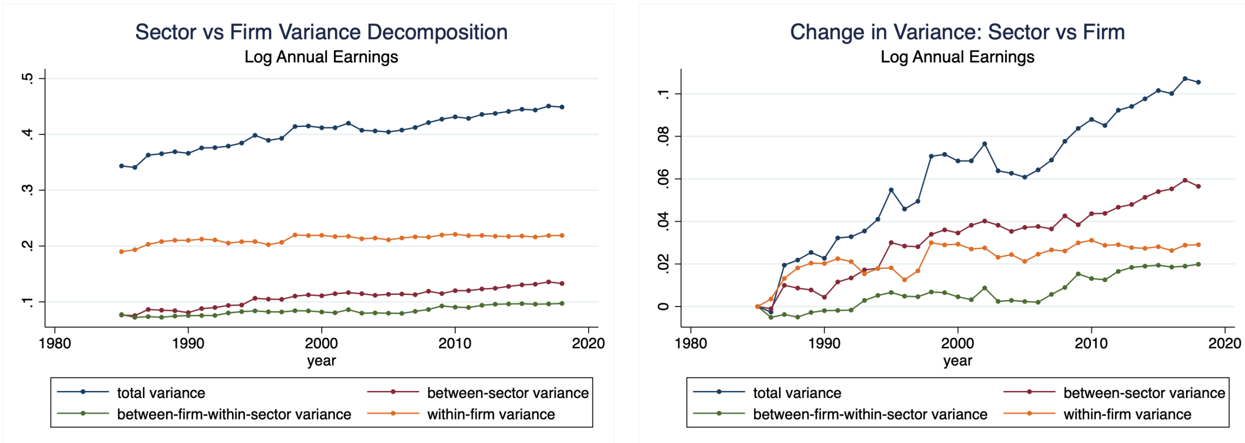
Note: Relative earnings is the gap between the average log earnings of a particular industry and the economy average. See Equation (3) for definitions.

Table B27: Sector contributions to between sector variance growth, by average earnings (4-digit sectors).

Sector relative earnings	Number of sectors	Total employment share in 1985	Total contribution to between sector variance growth	Total share of between sector variance growth	Shift-share: employment	Shift-share: earnings
Top 13 sectors						
High paying	6	1.9%	0.010	17.9%	53.1%	48.1%
Low paying	7	3.9%	0.045	81.4%	68.2%	33.0%
The remaining 421 sectors						
High paying	259	61.4%	0.017	31.5%		
Low paying	162	32.7%	-0.017	-30.8%		
Total	434	100.0%	0.055	100.0%	17.0%	85.4%

Note: Employment shares are calculated as the average of 1985 and 2018 employment shares. See Equation (3) for definitions of relative earnings and of the contribution of a particular sector to between-sector variance growth. The sector is high paying (low paying) if its average relative earnings are positive (negative) where the average is taken over the 1985 and 2018 values. The total contribution of a particular sector to between-sector variance growth is decomposed into the role of employment and earnings changes as defined in Equation (4). To calculate the shares we sum the employment and earnings components across sectors and divide each by the corresponding sum of the total contribution to between sector variance growth.

Figure B7: Sector and firm: full variance decomposition.

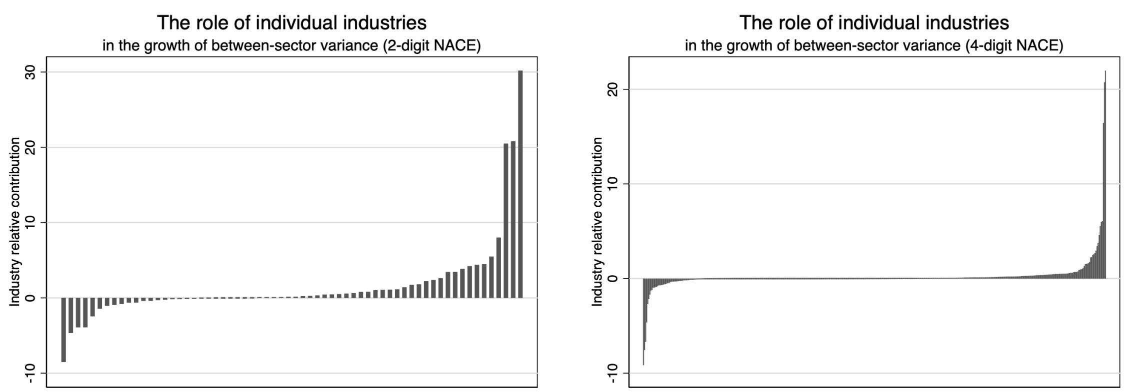


(a) Levels

(b) Change Relative to 1985

Note: See Equation (2) for definitions. Industries are disaggregated at 4-digit level.

Figure B8: The relative role of individual industries in the growth of between-sector variance (in percentage points): 2 digits vs 4 digits.



(a) 2-digit NACE industries

(b) 4-digit NACE industries

Note: in the graph it is reported the contribution of each 4-digit sector to the growth of the between-sector variance. A small number of industries provide large negative contributions, the vast majority of industries have contribution close to zero and a small number of industries provide very large positive contributions to the rise in the between-sector variance.

9.9 Analysis without sectors "Accommodation" (NACE code 55) and "Food and beverage service activities" (NACE code 56)

Table B28: Sectors and firms: full variance decomposition (4-digit sectors).

(a) Variance change over time

	Between sector	Between firms within sector	Within firm	Total
1985	0.081	0.077	0.192	0.351
2018	0.121	0.096	0.215	0.433
Change	0.040	0.019	0.023	0.082
% of total increase	48.8%	23.2%	28.0%	100.0%

(b) Variance shares

	Between sector	Between firms within sector	Within firm
1985	23.2%	22.1%	54.7%
2018	28.0%	22.2%	49.8%

Note: See Equation 2 for definitions. Industries are disaggregated at 4-digit level.

Table B29: Contribution of 4-digit sector groups to between sector variance growth (grouped based on individual sector share).

Individual sector share of between sector variance growth	Number of sectors	Total employment share in 1985	Total contribution to between sector variance growth	Total share of between sector variance growth
> 5%	5	2.1%	0.033	85.3%
4.5% to 5%	3	0.5%	0.005	13.9%
0.05% to 4.5%	194	46.3%	0.036	94.7%
-0.05% to 0.05%	235	17.4%	0.000	1.2%
< -0.05%	79	33.7%	-0.036	-95.1%
Total	516	100.0%	0.038	100.0%

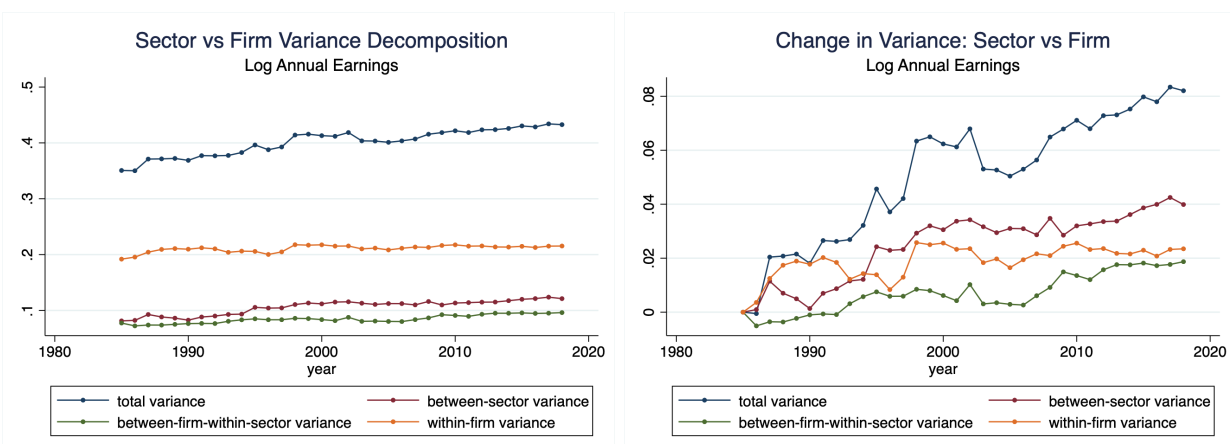
Note: See Equation (3) for definition of the contribution of a particular sector to between sector variance growth. Industries are disaggregated at 4-digit level.

Table B30: Top 4-digit sectors in terms of increasing between-sector variance.

NACE code	Industry title	Employment share 1985	Employment share 2018	Relative earnings 1985	Relative earnings 2018	Share of between sector variance growth
7830	Other human resources provision	0.0%	5.3%	0.40	-0.48	32.0%
8129	Other cleaning activities	1.5%	3.4%	-0.54	-0.64	24.8%
8899	Other non-residential social work	0.5%	2.8%	-0.22	-0.49	16.6%
8121	General cleaning of buildings	0.0%	0.4%	-0.52	-0.84	6.6%
8790	Other residential care activities	0.1%	1.0%	-0.35	-0.47	5.4%
3514	Trade of electricity	0.1%	0.6%	0.74	0.68	4.9%
8299	Other business support activities n.e.c.	0.3%	3.0%	0.26	-0.26	4.5%
4910	Passenger rail transport, interurban	0.1%	0.7%	-0.12	0.50	4.5%

Note: Relative earnings is the gap between the average log earnings of a particular industry and the economy average. See Equation (3) for definitions.

Figure B9: Sector and firm: full variance decomposition.



(a) Levels

(b) Change Relative to 1985

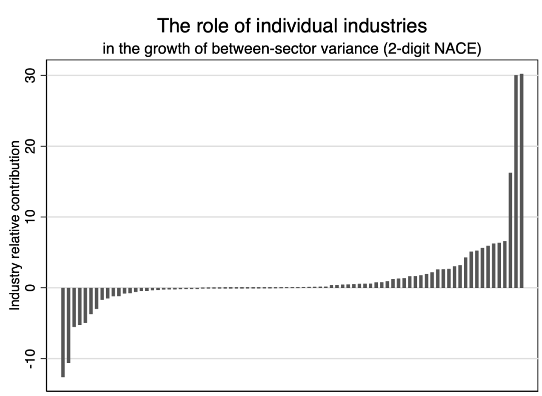
Note: See Equation 2 for definitions. Industries are disaggregated at 4-digit level.

Table B31: Sector contributions to between sector variance growth, by average earnings (4-digit sectors).

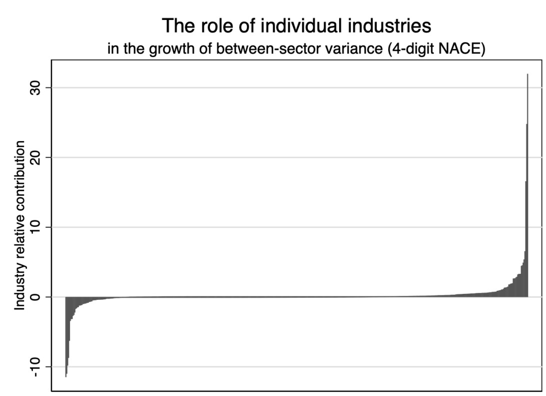
Sector relative earnings	Number of sectors	Total employment share in 1985	Total contribution to between sector variance growth	Total share of between sector variance growth	Shift-share: employment	Shift-share: earnings
Top 8 sectors						
High paying	2	0.2%	0.004	9.4%	84.1%	17.1%
Low paying	6	2.5%	0.034	89.9%	74.3%	26.8%
The remaining 508 sectors						
High paying	297	61.6%	0.018	48.1%		
Low paying	211	35.7%	-0.018	-47.3%		
Total	516	100.0%	0.038	100.0%	17.0%	85.4%

Note: Employment shares are calculated as the average of 1985 and 2018 employment shares. See Equation (3) for definitions of relative earnings and of the contribution of a particular sector to between-sector variance growth. The sector is high paying (low paying) if its average relative earnings are positive (negative) where the average is taken over the 1985 and 2018 values. The total contribution of a particular sector to between-sector variance growth is decomposed into the role of employment and earnings changes as defined in Equation (4). To calculate the shares we sum the employment and earnings components across sectors and divide each by the corresponding sum of the total contribution to between sector variance growth.

Figure B10: The relative role of individual industries in the growth of between-sector variance (in percentage points): 2 digits vs 4 digits.



(a) 2-digit NACE industries



(b) 4-digit NACE industries

Note: in the graph it is reported the contribution of each 4-digit sector to the growth of the between-sector variance. A small number of industries provide large negative contributions, the vast majority of industries have contribution close to zero and a small number of industries provide very large positive contributions to the rise in the between-sector variance.

9.10 Analysis without sector "Employment activities" (NACE code 78)

Table B32: Sectors and firms: full variance decomposition (4-digit sectors).

(a) Variance change over time

	Between sector	Between firms within sector	Within firm	Total
1985	0.083	0.079	0.193	0.354
2018	0.132	0.101	0.211	0.444
Change	0.049	0.022	0.018	0.089
% of total increase	55.1%	24.7%	20.2%	100.0%

(b) Variance shares

	Between sector	Between firms within sector	Within firm
1985	23.3%	22.2%	54.4%
2018	29.8%	22.7%	47.6%

Note: See Equation (2) for definitions. Industries are disaggregated at 4-digit level.

Table B33: Contribution of 4-digit sector groups to between sector variance growth (grouped based on individual sector share).

Individual sector share of between sector variance growth	Number of sectors	Total employment share in 1985	Total contribution to between sector variance growth	Total share of between sector variance growth
$> 5\%$	6	4.1%	0.034	71.6%
2.7% to 5%	8	1.8%	0.013	28.2%
0.05% to 2.7%	184	43.0%	0.034	70.4%
-0.05% to 0.05%	252	18.6%	0.001	1.4%
$<$ -0.05%	72	32.5%	-0.034	-71.5%
Total	522	100.0%	0.048	100.0%

Note: See Equation (3) for definition of the contribution of a particular sector to between sector variance growth. Industries are disaggregated at 4-digit level

Table B34: Top 4-digit sectors in terms of increasing between-sector variance.

NACE code	Industry title	Employment share 1985	Employment share 2018	Relative earnings 1985	Relative earnings 2018	Share of between sector variance growth
5610	Restaurants and mobile food service activities	0.4%	2.8%	-0.28	-0.63	22.1%
8129	Other cleaning activities	1.5%	3.4%	-0.54	-0.63	18.2%
8899	Other non-residential social work	0.5%	2.8%	-0.22	-0.47	12.1%
5510	Hotels and similar accommodation	1.1%	2.2%	-0.42	-0.50	6.8%
5629	Other food service activities	0.5%	1.1%	-0.27	-0.57	6.5%
5630	Beverage serving activities	0.2%	0.9%	-0.28	-0.58	5.9%
8121	General cleaning of buildings	0.0%	0.3%	-0.51	-0.83	4.9%
3514	Trade of electricity	0.1%	0.5%	0.75	0.70	4.1%
8790	Other residential care activities	0.1%	1.0%	-0.34	-0.45	3.9%
4910	Passenger rail transport, interurban	0.1%	0.7%	-0.11	0.51	3.8%
6209	Computer service activities	0.2%	2.1%	0.13	0.26	3.0%
8299	Other business support activities n.e.c.	0.3%	2.9%	0.27	-0.24	3.0%
2120	Manufacture of pharmaceutical preparations	0.5%	0.4%	0.34	0.67	2.8%
3316	Repair and maintenance of aircraft and spacecraft	0.5%	0.4%	0.17	0.59	2.7%

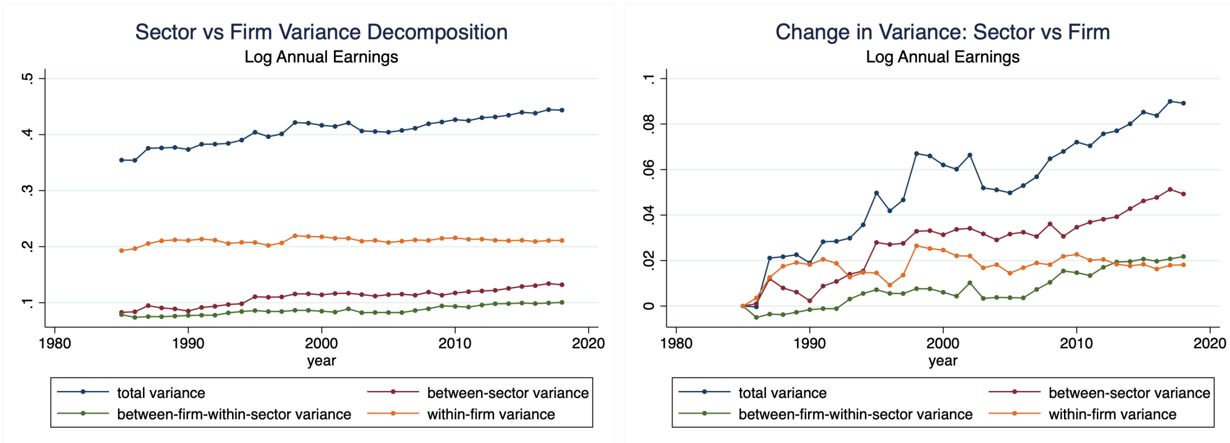
Note: Relative earnings is the gap between the average log earnings of a particular industry and the economy average. See Equation (3) for definitions.

Table B35: Sector contributions to between sector variance growth, by average earnings (4-digit sectors).

Sector relative earnings	Number of sectors	Total employment share in 1985	Total contribution to between sector variance growth	Total share of between sector variance growth	Shift-share: employment	Shift-share: earnings
Top 14 sectors						
High paying	6	1.8%	0.009	19.3%	56.2%	44.9%
Low paying	8	4.2%	0.038	80.5%	59.8%	41.3%
The remaining 508 sectors						
High paying	308	64.1%	0.017	35.6%		
Low paying	200	30.0%	-0.017	-35.4%		
Total	522	100.0%	0.048	100.0%	17.0%	85.4%

Note: Employment shares are calculated as the average of 1985 and 2018 employment shares. See Equation (3) for definitions of relative earnings and of the contribution of a particular sector to between-sector variance growth. The sector is high paying (low paying) if its average relative earnings are positive (negative) where the average is taken over the 1985 and 2018 values. The total contribution of a particular sector to between-sector variance growth is decomposed into the role of employment and earnings changes as defined in Equation (4). To calculate the shares we sum the employment and earnings components across sectors and divide each by the corresponding sum of the total contribution to between sector variance growth.

Figure B11: Sector and firm: full variance decomposition.

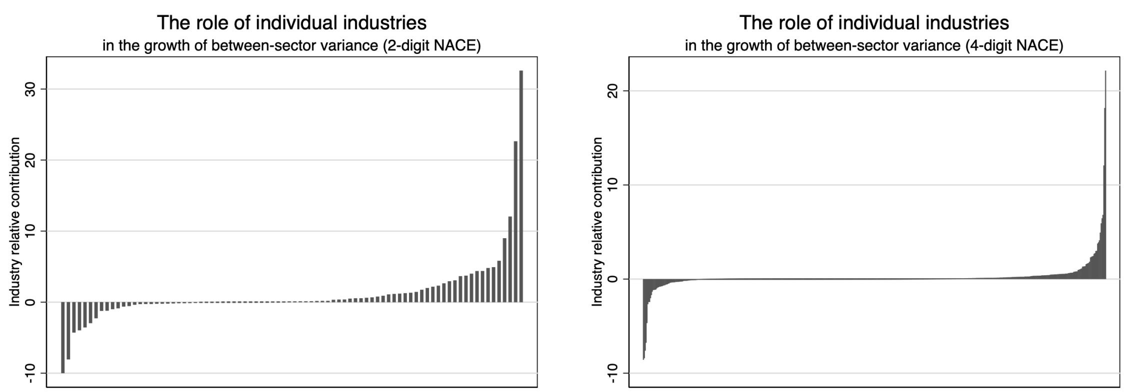


(a) Levels

(b) Change Relative to 1985

Note: See Equation (2) for definitions. Industries are disaggregated at 4-digit level.

Figure B12: The relative role of individual industries in the growth of between-sector variance (in percentage points): 2 digits vs 4 digits.



(a) 2-digit NACE industries

(b) 4-digit NACE industries

Note: in the graph it is reported the contribution of each 4-digit sector to the growth of the between-sector variance. A small number of industries provide large negative contributions, the vast majority of industries have contribution close to zero and a small number of industries provide very large positive contributions to the rise in the between-sector variance.