The Role of Industries in Rising Inequality*

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Abstract

Using data on the universe of private sector employment we investigate the rise in earnings inequality in Italy. We find that 55% of the rise in earnings inequality between 1985 and 2018 took place between industries, while only 18% took place between firms within the same industry and 27% took place within firms. The growth in inequality between industries was very concentrated with less than 3% of industries accounting for two-thirds of the total inequality-increasing effect, while only representing around 7% of employment. The rise in inequality was predominantly driven by rising employment in low-paying industries and by increasing earnings in high-paying industries. Despite very large institutional differences, the patterns of rising inequality in Italy are remarkably similar to the ones identified for the USA which suggests that the underlying forces were likely similar.

Keywords: earnings inequality, firms, industries, technical change, wage setting institutions.

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1 Introduction and Related Literature

The increase in pay inequality in many industrialized economies since 1980s has been substantial (Atkinson et al. 2011). Many explanations focused on market-level changes in returns to different skills and on the role of technology in shaping these trends (Katz and Autor 1999, Acemoglu and Autor 2011). However, in recent years there has been a growing focus on the role of firms[1]. The traditional view is that inequality is to a large extent driven by a growing gap between the pay of top managers and workers (or high-skilled vs low-skilled workers within a firm). However, Song et al. (2019) show that two thirds of the rise in US earnings inequality since 1980s took place between firms, only one third within firms[2]. The dominant role of the between-firm component in accounting for the changes in earnings inequality has also been documented by Faggio et al. (2010) for the UK, Card et al. (2013) for West Germany and Alvarez et al. (2018) for Brazil. Increasingly, some firms pay a lot, and some pay little[3].

The focus of this paper is on the role of industries in accounting for the rise in earnings inequality. The paper answers the question, is earnings inequality growing mainly between firms in the same industry, or between firms in different industries? Are there some industries that are especially important in driving the rise in inequality? What do these key industries have in common? There is conflicting evidence on this issue for the USA. Song et al. (2019) find that vast majority of the growth in inequality took place between firms within industries. In contrast, Haltiwanger et al. (2022) find that majority of the inequality growth occurred between industries[4]. Furthermore, they find that developments in just a small number of

[1] One strand of literature focuses on estimating rent-sharing elasticity, that is elasticity of earnings of incumbent workers with respect to changes in the firm's value added (Card et al. 2018, Lamadon et al. 2019). Another set of studies use information on earnings of workers switching between firms to decompose cross-sectional variance of earnings into the contribution of worker heterogeneity, firm heterogeneity and sorting of workers into firms (Abowd et al. 1999, Card et al. 2013).

[2] Barth et al. (2016) and Haltiwanger et al. (2022) also find similar results for the US.

[3] This could be driven by increasing dispersion of firm wage premiums, by increased sorting of high-wage workers to high-wage firms or by firms becoming more homogeneous in terms of worker composition (for example due to outsourcing).

[4] Haltiwanger et al. (2022) argue that the stark difference in the contribution of industry between the

key industries (10% of total) can explain majority of the rise in US earnings inequality. The evidence for other countries is very limited despite the importance of this for understanding the causes of rising inequality. An exception is Faggio et al. (2010) who find that wage inequality in the UK was rising mostly between firms within industries.

We use a social security administrative dataset covering the universe of private-sector employment in Italy in order to decompose total variance of log annual earnings into the between-firm and the within-firm components for every year from 1985 to 2018. We apply the same sample restriction as Song et al. (2019) and Haltiwanger et al. (2022) in order to ease the comparison of results. We calculate the total variance of log annual earnings to have increased from 0.354 in 1985 to 0.450 in 2018. We find that 72.9% of the rise in earnings inequality occurred between firms, with the remaining 27.1% taking place within firms. This is very similar to the findings of Song et al. (2019) for the USA. Furthermore, just as in the US, the result that the majority of the earnings dispersion increase occurred between firms holds for all firm size categories.

Next, we further decompose the between-firm variance in two parts: the dispersion of average earnings across sectors and the dispersion of average earnings across firms within the same sector. Thus, the total variance is composed of three elements: (i) between-sector variance, (ii) between-firm-within-sector variance and (iii) within-firm variance. We show that the dominant driver of the increasing earnings inequality in Italy is the rise in the between-sector variance. 55.2% of the rise in earnings inequality in Italy between 1985 and 2018 occurred between (4-digit) sectors. The increases in between-firm-within-sector variance and within-firm variance can account for 17.7% and 27.1% of the overall growth in Italian earnings inequality, respectively. Thus our results are much closer to Haltiwanger et al. (2022) than to Song et al. (2019).

Interestingly, we find that the results are very similar when using either 2, 3 or 4 digit

two papers is due to the information on the firm's main sector of activity in the dataset used by Song et al. (2019) being of very poor quality.

industry classification. Just 88 2-digit industry categories can explain 26.7% of earnings variance in 2018 and can account for 57.3% of the rise in Italian earnings inequality between 1985 and 2018. When using 4-digit industries we have almost 600 industry categories, but the between-sector variance share[5] (between-sector variance as a share of total variance) only rises modestly to 30.2%. Therefore, it is differences in pay between broad industry categories that are very important in accounting for earnings dispersion at a point in time and its change over time.

We follow Haltiwanger et al. (2022) in calculating the contribution of each industry to the between-sector variance growth. We find that the rise in earnings inequality in Italy was similarly concentrated in terms of industries as reported by Haltiwanger et al. (2022) for the USA[6]. Less than 3% of industries account for all of the increase in between-sector variance in Italy, with the remaining industries having small and offsetting positive and negative contributions. These 3% of industries with the largest individual contributions account for around two thirds of the total between-sector inequality-increasing contributions, while representing only around 7% of employment in 1985. In Italy low-paying sectors dominate in the group of key industries. In both countries, within the set of key industries, the contribution of high-paying sectors to rising inequality was mainly driven by rising relative earnings, whereas the contribution of low-paying sectors was mainly due to their rising employment shares. Furthermore, many of the key industries are similar in Italy and in the USA. Low-paying sectors related to food and drink, accommodation, social care, cleaning and maintenance of buildings and outside spaces and employment agencies are important in both countries. High-paying sectors related to finance, pharmaceuticals and IT are also important in both countries. Overall, the patterns of rising earnings inequality are remarkably similar to the ones identified by Haltiwanger et al. (2022) for the USA.

[5]This is equivalent to R^2 from a regression of log annual earnings on industry dummy variables.

[6]We find that in Italy top 10% of industries with the largest individual contributions account for 83% of the overall positive contributions to the rise of between-sector variance. Haltiwanger et al. (2022) find that in the USA top 10% of industries represent around 82% of the sum of all positive (inequality-increasing) contributions.

There are three main contributions of the paper to the literature. First, the implication of the paper is that the underlying forces driving the rise in inequality are mainly increasing the gaps in pay across industries and that crucially, they have very uneven and concentrated impact across industries. Any theory of the rise in pay inequality must account for this. Crucially, it is just this paper and Haltiwanger et al. (2022) that question the new dominant narrative which suggests that some firms operating in the same industry are increasingly paying a lot more than others and that this is a major driver of the growth in overall earnings inequality (Faggio et al. (2010), Song et al. (2019)). This is in the context of recent literature that places the focus on firm heterogeneity within industries (Autor et al. (2020) and Freund (2022)).

Second, our dataset has certain advantages in terms of quality and coverage of data. Haltiwanger et al. (2022) suggest that the information on the industry affiliation of firms in Song et al. (2019) suffers from a substantial amount of measurement error. On the other hand, the data in Haltiwanger et al. (2022) only covers 18 out of the 50 US states and it is available for a shorter time period (1996 to 2018). An advantage of our data is very long time span (1985 to 2018) and the fact that sector of economic activity is measured very precisely at the level of each individual worker.

Third, this paper is the first to test the hypothesis in a very different institutional context to the one prevalent in the USA. In Italy industry-level country-wide collective agreements specify obligatory minimum wages for each occupation (Fanfani (2019)). These occupation and industry specific minimum wage rates are the outcome of negotiations between sector-level unions and employer organisations (Boeri et al. (2019)). Overall, over 90% of workers in Italy are covered by collective agreements (Visser (2016)). Our finding that there are many similarities in the patterns of rising inequality between Italy and the USA, especially in the specific industries that played a key role, is suggestive evidence that the underlying forces were likely similar, despite the stark differences in wage setting institutions. It is quite likely that shifts in labour demand and supply at industry level were simply reflected in the bargained wages. However, it is possible that the centralised collective bargaining system played a role in limiting the overall inequality. We find that both the level of inequality and the size of the increase in earnings inequality in Italy was about half of the level observed in the USA, when applying the same sample selection[7].

The remainder of the paper is organized as follows. Section 2 describes the data. Section 3 presents the empirical methodology. In Section 4.2 we decompose total variance of log annual earnings into between and within firm variance, whereas in Section 4.3 we instead decompose it into between-sector, between-firm-within-sector and within-firm components. In Section 4.4 we compare our results to the ones for the USA. In Section 4.5 we analyse the role of individual industries and in Section 4.6 we discuss the results and their implications. Finally, Section 5 concludes.

2 Data

We use a matched employer-employee administrative data set by the Italian Social Security Institute (INPS),[8] which contains the universe of Italian social security records of private-sector employees. The records include employment relationships between 1975 and 2018. We focus on the period 1985-2018, as it is the period of rise of wage inequality in Italy. Given that the information is collected for the purpose of paying social security contributions, the reporting is likely to be accurate. The data includes information on labour earnings (no upper limit), the number of weeks worked, unique worker and firm identifiers, location of the firm, whether the contract is full-time and demographic information of the worker (gender and year of birth). Uniquely, the database also includes information on sector of the worker. If a firm operates in multiple sectors e.g., a car company that produces cars (manufacturing) and also sells them to customers (retail), then it receives multiple identifiers from the social security

[7]Comparing to the results of Song et al. (2019) for the USA who cover a similar period to us.
[8]Istituto Nazionale della Previdenza Sociale.

institute, one for each sector that it engages in. Social security contributions of workers are registered under this sector-specific firm identifier and thus the sector of economic activity of each worker is known. In contrast administrative data from other countries typically only includes the primary sector of the firm. To ensure comparability with other studies we calculate the primary sector of a firm as the one that most of the firm's workers belong to.

The annual earnings sample is drawn to be maximally comparable to Song et al. (2019) and Haltiwanger et al. (2022). We follow their approach and sum income across all employment spells in a given year for each worker. The worker is linked with the firm that accounts for the largest share of his/her income.

Papers that study inequality with annual earnings typically impose a threshold level of annual earnings below which all observations are dropped, with the purpose of ensuring a lack of bias from individuals who are not strongly attached to the labour market (e.g., someone working only for 2 weeks in a given year and thus having extremely low annual earnings). The level of this cutoff is quite arbitrary and varies across studies. Song et al. (2019) define this threshold level of earnings as the value of working full-time for the minimum wage for one quarter of the year [9]. Italy does not have a statutory national minimum wage, but we replicate their approach as closely as possible. We take 6.77 Euro per hour as our estimate of the lowest rate of pay in Italy in 2018 (it is the pay of the lowest paid workers in one of the typical low-paying industries)[10]. Working 13 weeks (one quarter), 40 hours a week at this rate would produce 3520 Euro of annual earnings. This is our threshold level of earnings in 2018[11]. We adjust it for nominal wage growth for all the other years (1985-2018) using a series from OECD[12].

Following Song et al. (2019), we restrict the sample to only individuals between the age

[9] Their results are robust to varying the level of the threshold.

[10] 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.

[11] Our threshold level is very similar to the one in Song et al. (2019) that set it at $3,770 in 2013.

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

of 20 and 60. Additionally, we restrict the sample to only firms (and workers in firms) with at least 10 workers (at least 10 observations per firm)[13]. This is to ensure that there are enough observations to calculate the within-firm variance.

Table 1: Summary of the data

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

Table 2: Descriptive statistics

(a) Distribution of firm size

	mean	standard deviation	10%ile	50%ile	90%ile
Entire Universe in 1985	10.78	164.58	1	3	15
Earnings Sample in 1985	52.14	409.38	10	18	77
Entire Universe in 2018	10.02	213.71	1	3	14
Earnings Sample in 2018	47.84	481.85	10	17	67

(b) Distribution of annual earnings

	mean	standard deviation	10%ile	50%ile	90%ile
Entire Universe in 1985	20,320	16,518	3,425	19,983	34,407
Earnings Sample in 1985	24,806	16,830	8,901	23,124	38,095
Entire Universe in 2018	21,729	22,253	2,697	19,135	41,050
Earnings Sample in 2018	27,050	23,229	8,426	23,633	46,675

Note: Earnings are expressed in 2018 Euros, adjustment is done using national CPI index.

We can see from Table 1 that the original INPS data set (the entire universe) contains about 640.000 firms and approx 6.9 million workers in 1985 and 1.5 million firms and 14.8 million workers in 2018. The rise in the number of employed workers is mainly due to

[13] Song et al. (2019) use a higher cutoff of 20 workers per firm. However, Italy has an extremely high percentage of workers employed in small firms and thus we use a lower cutoff.

higher employment rate of women as well as population growth and immigration. The earnings sample contains approx 88,000 firms and 4.6 million workers in 1985 and approx 192,000 firms and 9.2 million workers in 2018. Hence, the sample restrictions that we make, especially the requirement of at least 10 workers per firm, imply that we only keep about 13% of the total number of firms. However, in terms of employment, our sample is still very large, keeping about two thirds of the total number of workers.

Table 2(a) presents a comparison of firm size distribution in the universe of social-security data and our sample for 1985 and 2018. Unsurprisingly, firms are on average larger in the sample due to the artificially imposed minimum level. The median number of workers per firm in 2018 is 3 in the universe and 17 in the sample. The mean firm size in 2018 is 10 in the original data and 47.8 in the sample. The mean annual earnings are higher in the sample than in the original data set (Table 2(b)). This is again unsurprising given that we impose the threshold level of annual earnings.

3 Methodology

To study the role of firms in accounting for both earnings and wage inequality in Italy between 1985 and 2018, we first perform the following variance decomposition in between-firm and within-firm variance for both annual earnings and weekly wages of full-time employees:

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

where w_{ij} denotes the log annual earnings (log weekly wage) of worker i at firm j in a given year, N denotes the total number of workers (firm-worker matches) in the data, n_j is the number of workers employed at firm j, $\bar{w}_j = \frac{1}{n_j}\sum_{\forall i|i\in j} w_{ij}$ is the value of average annual earnings (average weekly wage) at firm j and $\bar{w} = \frac{1}{N}\sum_{\forall i} w_{ij}$ is the economy-wide value of average annual earnings (average weekly wage).

Additionally, we decompose the total variance of annual earnings (weekly wages) into between-sector variance and within-sector variance:

$$\underbrace{\frac{1}{N}\sum_{\forall i}(w_{is}-\bar{w})^2}_{\text{total variance}} = \underbrace{\sum_{\forall s}\frac{n_s}{N}(\bar{w_s}-\bar{w})^2}_{\text{between-sector variance}} + \underbrace{\sum_{\forall s}\frac{n_s}{N}\frac{\sum_{\forall i|i\in s}(w_{is}-\bar{w_s})^2}{n_s}}_{\text{within-sector variance}}, \tag{2}$$

where w_{is} denotes the log annual earnings (log weekly wages) of a worker i in sector s in a given year, n_s is the number of workers employed in sector s and $\bar{w_s}$ gives the average annual earnings (weekly wage) of sector s.

Next, we separately investigate the contribution of sector and of the firms within the sector to the rise in earnings and wage inequality in Italy. We first control for the sector and then perform the between versus within firm variance decomposition. There are two equivalent ways of doing this. The first method is to regress the dependent variable (log annual earnings or log weekly wages) on sector fixed effects, including a dummy variable for every sector and dropping the constant.

$$w_{ijs} = \sum_{s=1}^{s=S}\beta_s D_s + \epsilon_{ijs}, \tag{3}$$

where w_{ijs} denotes the log annual earnings (log weekly wage) of a worker i in firm j in sector s in a given year, S is the total number of 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:

$$\underbrace{\frac{1}{N}\sum_{\forall i}(\epsilon_{ij}-\bar{\epsilon})^2}_{\text{within-sector variance}} = \underbrace{\sum_{\forall j}\frac{n_j}{N}(\bar{\epsilon_j}-\bar{\epsilon})^2}_{\text{between-firm-within-sector variance}} + \underbrace{\sum_{\forall j}\frac{n_j}{N}\frac{\sum_{\forall i|i\in j}(\epsilon_{ij}-\bar{\epsilon_j})^2}{n_j}}_{\text{within-firm variance}}, \tag{4}$$

where ϵ_{ij} is the residual from (3) 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, $\bar{\epsilon_j} = \frac{1}{n_j}\sum_{\forall i|i\in j}\epsilon_{ij}$ is the firm j's average value of either log annual earnings (log weekly wages) 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 (log weekly wages) after controlling for sector fixed effects.

The total variance of residuals from (3) 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 (3) produces between-firms-within sector variance and within-firm variance.

The second method of controlling for 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 (3). The demeaned observations are then used to calculate (4).

In addition to the two methods above it is also possible to perform the full variance decomposition directly where total variance is broken down into between-sector variance, between-firms-within-sector variance and within-firm variance. This is done by combining (1) and (2):

$$\begin{aligned}\underbrace{\frac{1}{N}\sum_{\forall i}(w_{ijs}-\bar{w})^2}_{\text{total variance}} &= \underbrace{\sum_{\forall s}\frac{n_s}{N}(\bar{w_s}-\bar{w})^2}_{\text{between-sector variance}} + \underbrace{\sum_{\forall s}\frac{n_s}{N}\sum_{\forall j|j\in s}\frac{n_j}{n_s}(\bar{w_j}-\bar{w_s})^2}_{\text{between-firm-within-sector variance}} \\ &+ \underbrace{\sum_{\forall j}\frac{n_j}{N}\frac{\sum_{\forall i|i\in j}(w_{ijs}-\bar{w_j})^2}{n_j}}_{\text{within-firm variance}}.\end{aligned} \tag{5}$$

In conclusion, all three methods above are equivalent and generate the same outcomes. As in Song et al. (2019), we use the demeaning method.

4 Results

4.1 Evolution of annual earnings in Italy

The evolution of the distribution of annual earnings in Italy is characterised by very little growth in average earnings, but a significant increase in the dispersion of earnings. Mean real annual earnings (expressed in 2018 Euros) stood at 24,806 in 1985 and they were just 27,050 in 2018 (Table 2(b)). This is even more staggering when we consider the median which saw basically no growth in the 33 year window, changing from 23,124 Euro in 1985 to 23,633 Euro in 2018.

Figure 1 shows the evolution of various percentiles of log annual earnings between 1985 and 2018. While median earnings stagnated thoroughout the period, with only very small increase in late 1980s and early 1990s, 90th percentile of earnings increased by 20 log points, with most of the growth happening between 1985 and 1995. The 10th percentile of earnings was also increasing between 1985 and the mid-1990s, but afterwards it was falling persistently, finishing 6 log points lower compared to 1985. To sum up, it seems that between 1985 and mid-1990s, dispersion was mainly growing because of fast growth in earnings at the top of the distribution, whereas between 1995 and 2018 the increase in dispersion was mainly driven by falling earnings at the bottom. This is supported by Figure 1 which shows that the 90th to 50th percentile ratio of annual earnings was growing mainly between 1985 and 2000 and the 50th to 10th percentile ratio was growing mainly in the later period, after 2005.

Total variance of log annual earnings rose from 0.354 in 1985 to 0.450 in 2018 (Table 3), representing an increase of 9.6 log points. We can see from Figure 3(b) that this increase was persistent and not episodic, the dispersion was rising throughout the period[14]. Given that we impose the same sample restrictions as Song et al. (2019) do for the US data, it is interesting to compare our results. Song et al. (2019) find that total variance of log annual earnings in their data was 0.652 in 1981 and 0.846 in 2013. Thus earnings inequality was

[14]With a brief slowdown around 2000.

much lower in Italy than in the USA throughout the period under consideration. While the increase in earnings variance in Italy is about half of the increase in the USA, it is still very significant.

Figure 1: Evolution of Log Annual Earnings by Percentile and Year.

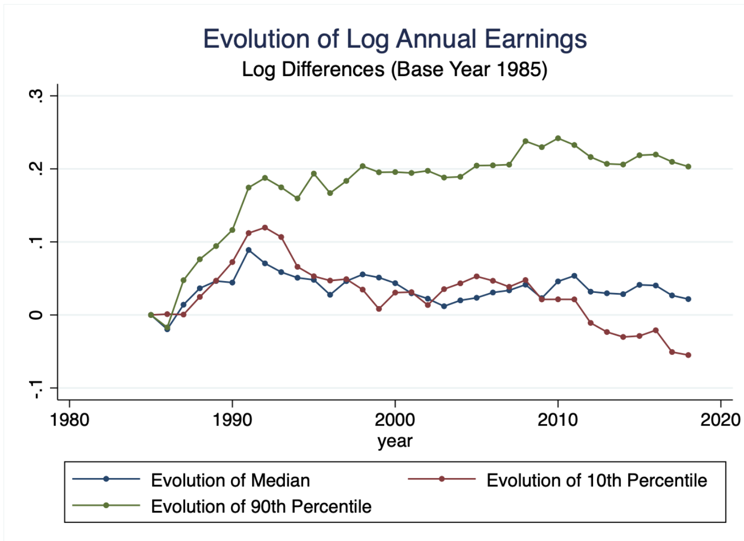
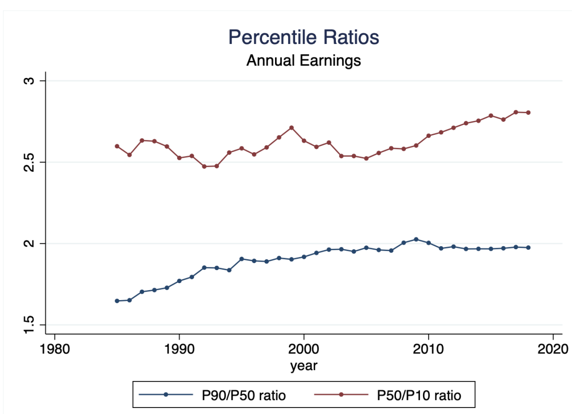
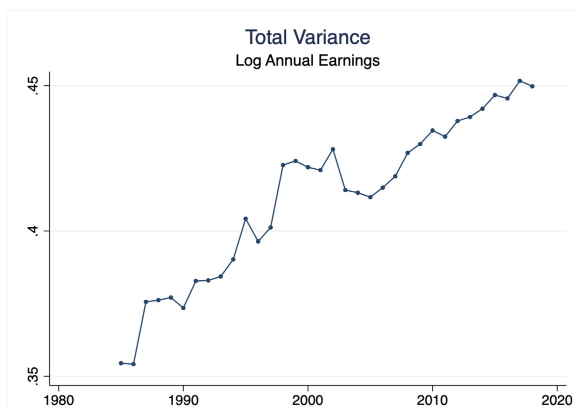


Figure 2: Growth of earnings dispersion: percentile ratios and total variance



(a) Inequality at the top and the bottom of the distribution



(b) Overall Inequality

4.2 Inequality between firms

By performing the between versus within-firm variance decomposition reported in Equation (1) using the annual earnings sample for every year from 1985 until 2018, we find that the majority of the rise in earnings inequality in Italy occurred between firms. The total variance of log annual earnings rose from 0.354 in 1985 to 0.450 in 2018 (Table 3). The rise in between-firm variance represented 72.9% of the overall increase in inequality. Within-firm pay inequality also increased, and contributed the remaining 27.1% of the total variance increase. Furthermore, the between-firm variance became a larger relative component of the total variance of log annual earnings. The dispersion in average earnings across firms represented 45.8% of the total variance in 1985, but that rose to 51.6% in 2018.

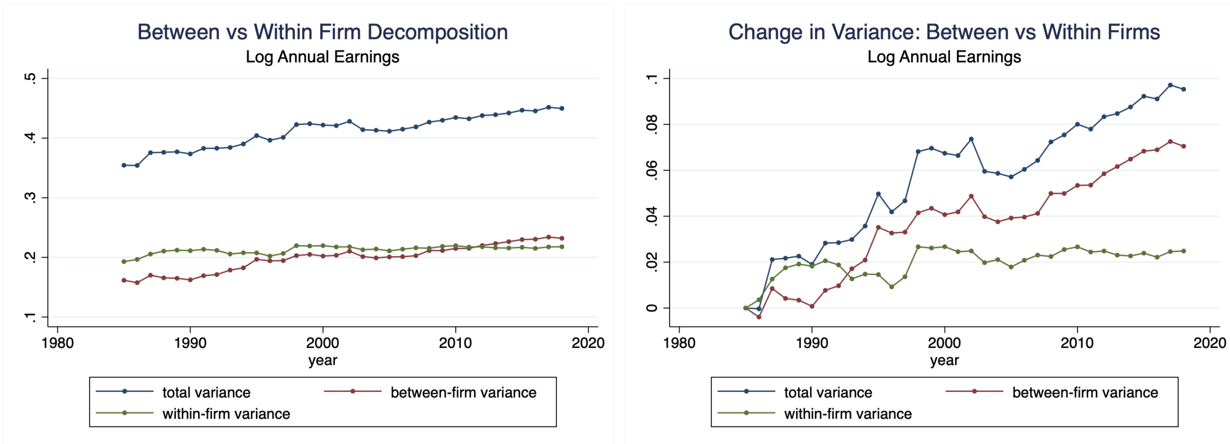
Table 3: Between versus within **firm** variance decomposition (Italy, annual earnings).

	Total	Between firm	Within firm	Between firm share	Within firm share
1985	0.354	0.162	0.192	45.8%	54.2%
2018	0.450	0.232	0.218	51.6%	48.4%
Change	0.096	0.070	0.026	-	-
% of total increase	100.0%	72.9%	27.1%	-	-

The same patterns hold up for all firm size categories. The between-firm component of variance accounts for 77.5% of the rise in total variance for small firms, 79.3% for medium firms and 73.9% for large firms (Table A1)[15]. Across firms of all sizes the between-firm variance grows at a faster rate than the within-firm component (Figure A1).

[15]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.

Figure 3: Between versus within firm variance in Italy 1985-2018 (annual earnings).



(a) Levels

(b) Change Relative to 1985

4.3 Inequality between industries

By performing the between versus within sector variance decomposition described in Equation (2) using the annual earnings sample for every year from 1985 until 2018, we find that 55.2% of the rise in earnings inequality in Italy occurred between (4-digit) sectors, while 44.8% took place within sectors (Table 4)[16]. Therefore, the rising dispersion of average earnings across industries accounts for the majority of the growth of earnings inequality in Italy. While both types of earnings dispersion were rising over time, the between-sector variance was rising faster and thus became a larger relative component of earnings inequality (Figure 4). The between-sector variance share was 23.4% in 1985 and 30.2% in 2018 (Table 4).

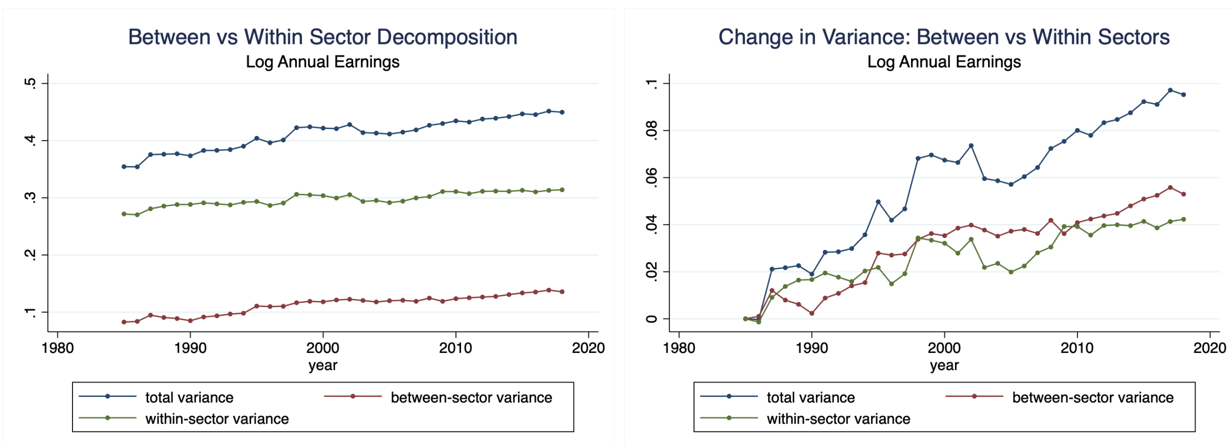
So far we have used the NACE industry classification at 4 digit level. In Table 5 we present the results of variance decomposition with 2 digit (88 industry categories), 3 digit (268 categories) and 4 digit industries (593 categories). The main conclusion is that the results are remarkably similar. The increase in between sector variance represents 57.3%, 55.2% and 55.2% of the total variance increase with 2 digit, 3 digit and 4 digit industry categories, respectively. Furthermore, the explanatory power of industry for the dispersion

[16]There are 593 sectors at 4-digit level in the data.

Table 4: Between versus within **4 digit sector** variance decomposition (593 sectors, annual earnings).

	Total	Between sector	Within sector	Between sector share	Within sector share
1985	0.354	0.083	0.271	23.4%	76.6%
2018	0.450	0.136	0.314	30.2%	69.8%
Change	0.096	0.053	0.043	-	-
% of total increase	100.0%	55.2%	44.8%	-	-

Figure 4: Between versus within **4 digit sector** variance in Italy 1985-2018 (annual earnings).



(a) Levels

(b) Change Relative to 1985

of log annual earnings in any given year also varies remarkably little whether we use broad or very detailed industry definitions. Between-sector variance share in 1985 using 2 digit, 3 digit and 4 digit sectors is 18.4%, 21.8% and 23.4% respectively. In 2018 it is 26.7%, 28.9% and 30.2%. This means that, using 2018 earnings data, having just 88 dummy variables as regressors (one for each broad 2 digit industry group) produces an r-squared value of about 27%, whereas having 593 industry dummy variables as regressors (one for each 4 digit industry) produces a very similar r-squared value of 30%.

Next, we want to investigate separately the extent to which the rise in earnings inequality

Table 5: Between versus within **2, 3 and 4 digit sectors**: variance decomposition (annual earnings).

(a) Variance change over time

	Between sector			Total
	2 digit (88 sectors)	3 digit (268 sectors)	4 digit (593 sectors)	
1985	0.065	0.077	0.083	0.354
2018	0.120	0.130	0.136	0.450
Change	0.055	0.053	0.053	0.096
% of total increase	57.3%	55.2%	55.2%	100.0%

(b) Variance shares

	Between sector		
	2 digit (88 sectors)	3 digit (268 sectors)	4 digit (593 sectors)
1985	18.4%	21.8%	23.4%
2018	26.7%	28.9%	30.2%

in Italy occurred between industries or between different firms within the same industry. We find that the majority (72.9%) of the rise in earnings inequality in Italy between 1985 and 2018 took place between firms. In Section 3 we show that the between-firm variance is actually composed of two parts: between-sector variance and between-firm-within-sector variance, while the within-firm variance is unaffected by whether we control for the sector or not[17].

Table 6(a) shows the full variance decomposition over time with 4 digit industries. While the growth of the between-sector variance accounts for 55.2% of the total variance increase, the rise of the between-firm-within-sector variance accounts for only 17.8% and the rise of the

[17] Also within-sector variance is composed of two parts: between-firm-within-sector variance and within-firm variance.

within-firm variance accounts for 27.1%. Clearly, the most important driver of the growth in earnings inequality is the rising dispersion of average earnings across sectors. Figure 5 shows that all three types of earnings dispersion were growing over this time period. However, we can see from Table 6(b) that while the between-sector component grew as a share of total variance, the shares of both the between-firm-within-sector and the within-firm components fell during the period considered.

Table 6: Sectors and firms: full variance decomposition (**4 digit sector**, annual earnings).

(a) Variance change over time

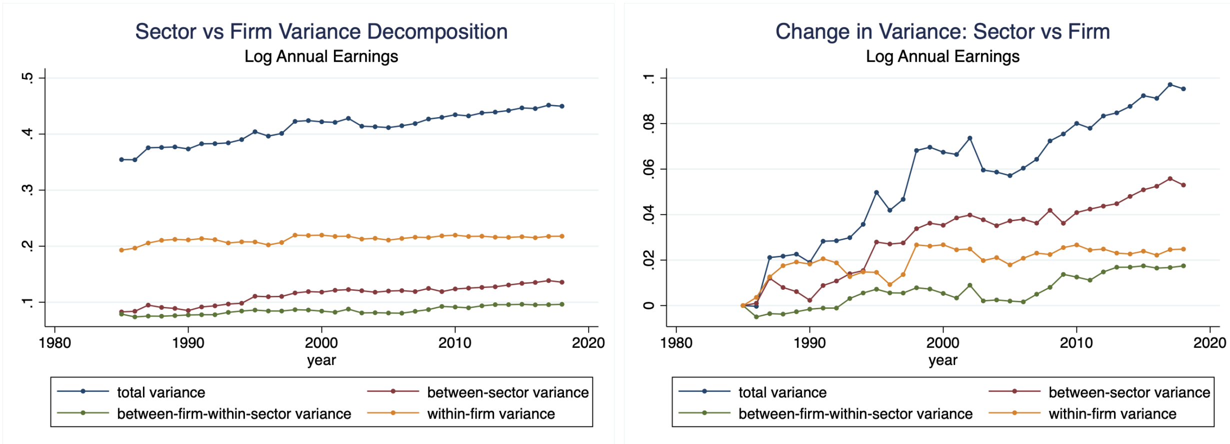
	Between sector	Between firms within sector	Within firm	Total
1985	0.083	0.079	0.192	0.354
2018	0.136	0.096	0.218	0.450
Change	0.053	0.017	0.026	0.096
% of total increase	55.2%	17.7%	27.1%	100.0%

(b) Variance shares

	Between sector	Between firms within sector	Within firm
1985	23.4%	22.3%	54.2%
2018	30.2%	21.3%	48.4%

Additionally, we also exploit a unique aspect of the Italian social-security data which is that the sector of economic activity is measured at the level of the individual worker. In the analysis above we were using the primary sector of the firm which is the economic activity that the largest group of the firm's workers are engaged in. Alternatively, we control for the sector of the worker. Thus if a firm operates in multiple sectors then for the purpose of this analysis it is effectively broken up into the different sector-specific parts. We find that this

Figure 5: Sector and firm: full variance decomposition (annual earnings).



(a) Levels

(b) Change Relative to 1985

approach produces results which are almost identical to the ones above[18].

Next, we split the earnings sample by gender and calculate variance decomposition for men only and for women only. In the male sample, total variance of log annual earnings grew from 0.255 in 1985 to 0.371 in 2018 (Table A2). This is a larger increase than for the original sample. 70.7% of the rise in earnings dispersion among men occurred between firms which is very similar to the figure when including both genders (72.9%). Between-sector variance accounts for 44.8% of the overall growth in earnings inequality which is slightly less than in the baseline earnings sample (55.2%). Between-firm-within-sector variance accounts for 25.9% of total variance increase which is slightly higher than in the baseline sample (17.7%). Within-firm variance accounts for 29.3% which is is very similar to the baseline sample figure of 27.1%. The changes in all three variances over time can be seen on Figure A2. Overall, the results for men are consistent with the baseline earnings sample.

In contrast, the patterns for women are different from the baseline sample. We find that earnings dispersion was higher among women than among men, but there was little increase in earnings dispersion among women (Table A3). Total variance of log annual earnings in the female sample was 0.424 in 1985 and 0.448 in 2018. We find that the very limited rise in

[18]The results are available by request from the authors.

earnings dispersion among women was overwhelmingly due to rising within-firm dispersion. The contribution of this component was 120.8%, meaning that between-firm variance actually fell in the female sample. This was the net outcome of an increase in between-sector variance and a much larger fall of between-firm-within-sector variance. These developments can be seen on Figure A3. However, the main characteristic of the women-only sample is that there was no significant increase in the overall dispersion. When considering either just men or both genders pooled together, we find that by far the most important driver of increasing earnings inequality was the growing between-sector variance.

4.4 Comparison with the USA

In this section we compare our findings for Italy using the annual earnings sample with the results of Song et al. (2019) and Haltiwanger et al. (2022) who perform similar variance decomposition of log annual earnings for the USA. Song et al. (2019) use a longitudinal data set covering workers and firms for the entire U.S. labor market from 1981 to 2013. Their data, provided by the U.S. Social Security Administration (SSA), is the only dataset that covers the universe of US private sector employment. Haltiwanger et al. (2022) use Longitudinal Employer-Household Dynamics (LEHD) linked employer-employee data, which is created by the U.S. Census Bureau for period 1996 to 2018. The main disadvantage of their data is that for the period under consideration, it only covers 18 out of the 50 US states. However, their database offers much better quality information on the industry that the firm belongs to than is the case for Song et al. (2019). Haltiwanger et al. (2022) also focus on private sector earnings only and use the same sample restrictions as Song et al. (2019) (which we also adopt to ease comparisons, as explained in the Data section). Both Song et al. (2019) and Haltiwanger et al. (2022) use 4 digit NAICS industries and we contrast their results to our estimates with 4 digit NACE industry classification[19].

[19]It could be argued that 3 digit NACE industry codes are a closer comparison to 4 digit NAICS industries. This is because 4 digit NAICS classification only contains 301 different industries while NACE industry

Table 7 and Table 8 show the results of the decomposition of the total variance of log annual earnings into the between-sector, between-firm-within-sector and within-firm components calculated by Song et al. (2019) and Haltiwanger et al. (2022), respectively. We compare these results to ours in Table 6. We find that 72.9% of the rise in earnings inequality in Italy between 1985 and 2018 occurred between firms. This is in line with the US results of both Song et al. (2019) and Haltiwanger et al. (2022) who find that the between firm component accounted for 69.6% and 84.3% of the total variance increase, respectively.

Table 7: Song et al. (2019): **Sectors and firms**: full variance decomposition (**4 digit sector**, USA, annual earnings).

(a) Variance change over time

	Between sector	Between firms within sector	Within firm	Total
1981	0.135	0.088	0.429	0.652
2013	0.141	0.216	0.489	0.846
Change	0.006	0.128	0.060	0.194
% increase	3.09	65.98	30.93	100.00

(b) Variance shares

	Between sector	Between firms within sector	Within firm	Total
1981	20.71	13.50	65.80	100.00
2013	16.67	25.53	57.80	100.00

Note: Figures in this table are derived from Table 2 in Song et al. (2019).

However, some really interesting differences emerge once we account for separate contributions of industry and firms within the same industry. Song et al. (2019) find that of

classification contains 273 industry categories at the 3 digit and approx 600 unique industries at the 4 digit level of aggregation. However, we show in Table 5 that using either 3 digit or 4 digit NACE industry codes results in very similar results.

Table 8: Haltiwanger et al. (2022): **Sectors and firms**: full variance decomposition (**4 digit sector**, USA, annual earnings).

(a) Variance change over time

	Between sector	Between firms within sector	Within firm	Total
1996-2002	0.170	0.112	0.512	0.794
2012-2018	0.245	0.140	0.531	0.915
Change	0.075	0.028	0.018	0.121
% increase	61.9	23.1	14.9	100.00

(b) Variance shares

	Between sector	Between firms within sector	Within firm	Total
1996-2002	21.4	14.0	64.6	100.00
2012-2018	26.8	15.3	58.0	100.00

Note: Figures in this table are derived from Table 1 in Haltiwanger et al. (2022).

the increase in total variance of earnings between 1981 and 2013 in the US only 3.1% is accounted for by the between-sector component, while 66% is accounted for by the between-firms-within-sector component and the remaining 30.9% is accounted for by the within-firm variance component (Table 7(a)). Thus Song et al. (2019) argue that the dominant driver of rising earnings inequality in the US has been rising heterogeneity in pay between firms in the same industry. However, Haltiwanger et al. (2022) reach completely different conclusion. They find that of the rise in the US earnings inequality between 1996 and 2018, 61.9% occurred between industries, only 23.1% occurred between firms in the same industry and 14.9% occurred within firms (Table 8(a)). Hence, Haltiwanger et al. (2022) suggest that the majority of the rise in US earnings dispersion has been driven by increasing heterogeneity of pay across industries and that rising pay heterogeneity across firms in the same industry and within firms played only a small role. Haltiwanger et al. (2022) argue that the much larger role played by rising dispersion of average earnings across industries in their analysis is the result of measuring industry affiliation of the firm correctly. They argue that the information on industry in Song et al. (2019) suffers from a substantial amount of measurement errors.

How do our results for Italy fit in this picture? We find that the between-sector component accounts for about 55% of the rise in total variance of earnings which is obviously much closer to the 62% found by Haltiwanger et al. (2022) than to the 3% found by Song et al. (2019). Additionally, we find that the between-firm-within-sector component accounts for about 18% of the rise in Italian earnings inequality which is again much closer to the 23% figure found by Haltiwanger et al. (2022) than to the 66% figure of Song et al. (2019). Additionally, Kleinman (2022) uses the same data as Haltiwanger et al. (2022) and shows that when one considers a longer time window, the importance of between-sector component in the US inequality growth declines slightly. Kleinman (2022) finds that in the USA between 1980 and 2017, just under half of the rise in earnings inequality took place between 4-digit industries. This is very similar to our results for Italy.

It is important to distinguish between cross-sectional variance decomposition and the decomposition of the growth in inequality. According to both Song et al. (2019) and Haltiwanger et al. (2022), in any given year majority of the earnings inequality in the USA takes place within firms. According to Song et al. (2019) within-firm variance as a share of total variance in the USA is 65.8% in 1981 and 57.8% in 2013 (Table 7(b)). According to Haltiwanger et al. (2022) it is 64.6% in the 1996-2002 period and 58.0% in the 2012-2018 period (Table 8(b)). The within-firm variance share is lower in Italy, it starts at 54.2% in 1985 and ends up at 48.4% in 2018 (Table 6(b)). On the other hand, 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.

To sum up, there are two conclusions that we can draw from the comparison of our results for Italy to the ones for the USA: i) the finding that growing heterogeneity in pay between industries rather than between firms in the same industry is the dominant driver of the growth in earnings inequality is in line with the results of Haltiwanger et al. (2022) for the US and is in direct contrast to the findings of Song et al. (2019); ii) either the firm or the industry that the individual is employed in is a better predictor of his/her annual earnings in Italy than it is in the USA.

4.5 The industries that drive growth in inequality

We have seen that the growing between-sector variance accounts for more than half of the increase in total variance of annual earnings in Italy between 1985 and 2018. In this section we follow the approach in Haltiwanger et al. (2022) to analyse which specific sectors are responsible for this growth in inequality. We calculate the contribution of individual sectors to the between-sector variance growth using the following expression:

$$\underbrace{\Delta var(\bar{w}_{s,p} - \bar{w}_p)}_{\substack{\text{between-sector} \\ \text{variance growth}}} = \sum_{s=1}^{523} \underbrace{\Delta \underbrace{\left(\frac{n_{s,p}}{N_p}\right)}_{\substack{\text{employment} \\ \text{share}}} (\underbrace{\bar{w}_{s,p} - \bar{w}_p}_{\substack{\text{relative} \\ \text{earnings}}})^2}_{\substack{\text{sector s's contribution} \\ \text{to between sector} \\ \text{variance growth}}} \tag{6}$$

where N_p is total employment in period p, $n_{s,p}$ is employment in sector s in period p, $\bar{w}_p$ denotes economy-wide average earnings in period p and $\bar{w}_{s,p}$ are average earnings in sector s in period p. We define the contribution of sector s to between-sector variance increase as $\Delta\left(\frac{n_{s,p}}{N_p}\right)(\bar{w}_{s,p} - \bar{w}_p)^2$.

When does an industry contribute towards an increase or decrease in inequality? We can see from equation 6 that contribution of a sector to between-sector variance growth consists of two parts: changes in relative earnings and changes in employment share. Let's consider first changes in relative earnings. When the average earnings in a high-paying industry increase over time, or in a low-paying industry decrease over time, this increases between sector variance. On the contrary, if average earnings move closer towards the economy average, then inequality falls. That is when average earnings in a high-paying industry decline or when average earnings in a low-paying industry increase. Now let's consider the role of changes in employment. Inequality will grow when there is an increase in employment shares of industries which have average earnings far away from the economy average, either paying very high or very low annual 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 industry represents a larger share of employment.

Table 9: 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 (6) for definition of the contribution of a particular sector to between sector variance growth.

We start the analysis by focusing on the broad 2-digit industries. There are a total of 85 2-digit industries in our data (industry classification is NACE)[20]. We follow Haltiwanger et al. (2022) in grouping industries by the size of their individual contributions to between sector variance growth. We can see from Table 9 that there are 3 industries which each account

[20]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 and thus their omission does not have an important effect on the results.

for more than 10% of the increase in the between-sector variance. Together these three industries account for 61.2% of the between-sector variance growth, while only representing 2.5% of total employment in 1985. It is worth noting how large the contribution of these top 3 industries really is. Given that the rise of between-sector variance accounts for 55% of the overall increase in earnings inequality, just these three industries account for a third of the rise in earnings inequality in Italy.

There are further 7 (2-digit) industries which each have a contribution between 3.4% and 10% and together represent 38.7% of the between-sector variance growth, while only accounting for 13.5% of total employment in 1985. This means that just 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 initially only representing 16% of employment in Italy.

We provide detail on these top 10 (2-digit) industries in Table 10. The industry with the largest contribution is Food and beverage service activities (56) which on its own accounts for 26.2% of the between-sector variance growth. The second most important sector is Employment activities (78) which accounts for 17.5%. The third is Services to buildings and landscape activities (81), also with 17.5% contribution. In fourth and fifth place are Social work activities without accommodation (88) and Accommodation industry (55) which account for 9.5% and 6.6% respectively.

We can see from Table 10 that all of the top five industries experienced a decline in their average annual earnings relative to the economy average. Even more importantly, they all experienced massive increases in their employment as a share of total employment in the economy between 1985 and 2018. Food and drink sector increased its employment share from 1.0% to 4.4%. Employment activities (covering employment agencies), went from almost non-existent in 1985 to representing 4.9% of total employment in 2018. 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 sector incorporating hotels and other types of accommodation also experienced a significant growth in its employment share, from 1.4% to 2.5%.

However, not all the industries in the top 10 are low-paying. There are four industries which were already paying more than the economy average in 1985 (their relative earnings were positive) and their relative earnings increased. In terms of changes in the employment share the pattern is mixed, with some growing and some shrinking as a share of total employment.

Table 10: Top 10 (2-digit) sectors in terms of increasing between-sector variance

2 digit ATECO code	Industry title	Employment share 1985	Employment share 2018	Relative earnings 1985	Relative earnings 2018	Share of between sector variance growth
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	4.4%	3.0%	0.15	0.38	5.9%
33	Repair and installation of machinery	5.6%	5.3%	0.06	0.24	5.3%
35	Electricity, gas, steam and air con. 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 (6) for definitions.

Let's now consider the remaining 75 (2-digit) NACE industries. These industries have offsetting contributions in such a way that their net effect on between-sector variance growth is essentially zero. We can see from Table 9 that there are 35 industries with individual contributions to the rise of between-sector variance between 0.05% and 3.4%. Together they account for 40.0% of the rise in between-sector variance. There are additional 17 industries that each contribute roughly 0% (precisely between -0.05% and 0.05%) to the rise in between sector variance. Their joint contribution is almost zero. Finally, there are 23 industries with negative contribution, meaning that they were actually reducing inequality. Together their contribution is -39.8% which when combined with the contribution of the previous two groups results in net zero contribution of the bottom 75 (2-digit) industries.

It is interesting to also consider which are the industries with the largest inequality-reducing effect. The top 10 industries with the largest (in absolute value) negative contributions are presented in Table A4. Two industries stand out. These are Education (85) and Construction (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).

So far we looked at broad (2-digit) industries. In order to more precisely identify the industries that are responsible for the growth in between-sector variance and thus for a large part of the rise in overall earnings inequality, we repeat the analysis with narrow 4-digit industries. The contribution of a 2-digit industry might actually be driven by just a small subset of the 4-digit industries that it incorporates. Additionally, this will allow us to contrast our results to the results of Haltiwanger et al. (2022) for the USA who also use information on industry at 4-digit level[21].

There are in total 523 industries at 4-digit level of aggregation[22]. We can see from Table 11 that there are 5 (4-digit) sectors with individual relative contribution of more than 5% that jointly account for 65.5% of the increase in between-sector variance (and thus about a third of the overall earnings inequality increase), while only representing 2.8% of employment in 1985. There are additional 9 sectors with individual contributions between 2.6% and 5% that together account for 33.0% of the rise in between-sector variance, while collectively only having an employment share of 4.9% at the beginning of the period under consideration. Thus just 14 out of the total of 523 (4-digit) industries together account for 98.5% of the growth in between-sector variance (roughly 55% of the overall rise in inequality),

[21] Haltiwanger et al. (2022) use NAICS classification at 4-digit level

[22] We restrict 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.

while representing only 7.7% of total employment in 1985.

The remaining 509 (4-digit) industries have offsetting contributions in a way that jointly their impact is close to zero. This consists of 188 industries with positive impact on between-sector variance growth (with the size of individual contributions between 0.05% and 2.6% of the increase in between-sector variance) that jointly represents 67.3% of the total increase. There were further 246 industries with roughly zero impact on the change in between-sector variance, and finally there were 75 industries with negative (inequality-reducing) impact on between-sector variance with joint contribution of -67.4%.

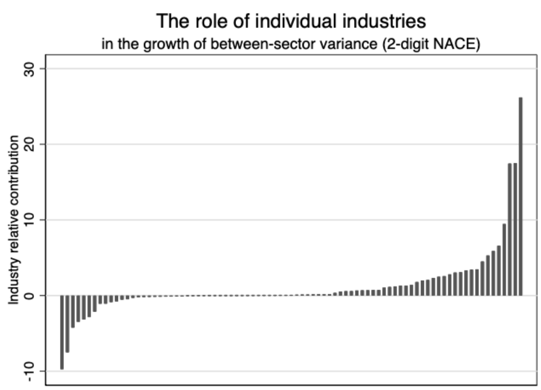
Table 11: Contribution of **4-digit** sector groups to between sector variance growth (grouped based on individual sector share)

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%

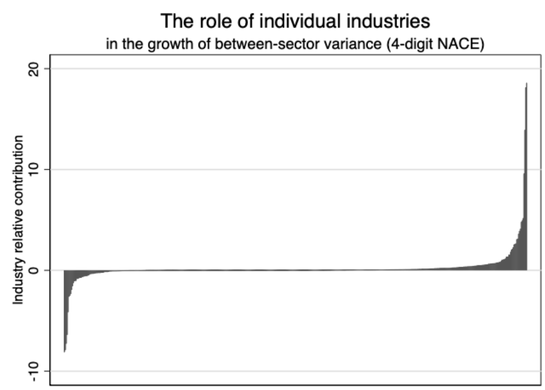
Note: See Equation (6) for definition of the contribution of a particular sector to between sector variance growth.

Thus we find that the growth in earnings inequality was extremely concentrated. We find that less than 3% of industries (14 out of 523) account for around two thirds of all of the positive contributions to the rise of between-sector variance, while representing only 7.7% of total employment in 1985. This is shown graphically on Figure 6 where we can see a small number of industries with large negative contributions, vast majority of industries with contribution close to zero and a small number of industries with very large positive contributions to the rise in between-sector variance. Hence we find that changes in relative earnings and employment shares of just a handful of industries have disproportionate impact on the overall earnings inequality. This is in line with the findings of Haltiwanger et al. (2022) who show that just 30 out of 301 4-digit NAICS industries (top 10% of industries) account for 98.1% of the between-industry variance growth in the USA between 1996 and 2018, with the remaining industries having offsetting contributions (small positive and negative contributions). Their top 10% of industries represent around 82% of the overall positive contributions to the rise of between-sector variance. We find that the degree of concentration in Italy is remarkably similar. In our data top 10% of industries with the largest individual contributions account for 83% of the overall positive contributions.

Figure 6: The relative role of individual industries in the growth of between-sector variance (in percentage points)



(a) 2-digit NACE industries



(b) 4-digit NACE industries

We provide detail on the top 14 (4-digit) industries in Italy in Table 12. Most of these 4-digit industries belong to one of the top 2-digit industries displayed in Table 10, this is especially true among the low-paying sectors. However, there are a few 4-digit industries with large contributions that do not belong to any of the broad industries listed in Table 10, so it is useful to undertake analysis with the narrow industries[23].

[23] These are Passenger rail transport (4910) and Servicing of personal computers (8790).

Table 12: Top 14 (4-digit) sectors in terms of increasing between-sector variance

4 digit ATECO 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	0.1%	0.7%	-0.11	0.54	3.6%
6209	Servicing of personal computers	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	Pharmaceutical manufacturing	0.5%	0.4%	0.34	0.69	2.6%

Note: Relative earnings is the gap between average log earnings of a particular industry and the economy average. See Equation (6) for definitions.

To what extent are the key industries driving the growth in inequality in Italy similar to the key industries in the USA[24]? Haltiwanger et al. (2022) list all industries with larger than 1% contribution to the rise of between-sector variance, we do the same in Table A5. We compare the two lists. Because the US NAICS and the European NACE classification of industries are different and to the best of our knowledge, there exists no one-to-one mapping between them, we cannot simply compare the industry codes. However, we can see patterns between the two countries in what parts of the economy the key industries are capturing.

In both countries, industries related to food and drink feature most prominently in the list of key industries. Employment Services is another low-paying sector with large contribution in both Italy and the USA. Other low-paying sectors which are important in both the USA and Italy are sectors related to social care (both reisdential and non-residential), sectors related to cleaning and maintenance of buildings and sectors related to hotels and other types of accommodation. High-paying industries which feature in both country lists are

[24]As reported in Table 3 in Haltiwanger et al. (2022).

pharmaceutical manufacturing and sectors related to financial services and insurance. Sectors related to IT appear on both lists, but whereas in Italy it is Servicing of Personal Computers, in the USA the IT sectors feature more prominently and cover software publishing, computer system design and semiconductor manufacturing. Among the low-paying sectors, the main difference seems to be that retail industries appear to be much more important in accounting for the rise in inequality in the USA than in Italy. Another difference is that there seem to be more high-paying sectors with large relative contributions to the rise of inequality in the USA relative to Italy. However, among the low-paying sectors in particular, the patterns are remarkably similar.

Table 13: Sector contributions to between sector variance growth, by average earnings (4-digit sectors)

Sector relative earnings	Number of sectors	Total employment share	Total contribution to between sector variance growth	Total share of between sector variance growth	Shift-share: employment	earnings
			Top 14 sectors			
High paying	5	4.8%	0.008	16.0%	43.6%	57.5%
Low paying	9	11.4%	0.042	82.5%	68.8%	32.3%
			The remaining 509 sectors			
High paying	316	54.6%	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: Employment shares are calculated as the average of 1985 and 2018 employment shares. See Equation (6) 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 7. 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.

As shown in Table 13, among the top 14 (4-digit) industries in Italy with the largest contributions to the rise of between-sector variance, there are 5 high-paying industries which account for 16.0% of between-sector variance growth and 9 low-paying industries which account for 82.5% of the growth in between-sector variance. Thus we find that among the top (4-digit) sectors, low-paying sectors play the dominant role in Italy. In contrast, in the USA the contributions of high and low paying sectors among the top 10% of sectors were quite similar. For the remaining 509 sectors we find that high-paying and low-paying sectors have roughly offsetting impact. High paying sectors were contributing towards the rise in inequality, while low-paying sectors were reducing inequality. These same patterns hold when using broad 2-digit industries, as shown in Table A6. Finally, all of the patterns identified in this section hold when we restrict the sample only to males[25].

We follow Haltiwanger et al. (2022) in using the standard shift-share decomposition to disentangle the role of changes in employment shares and in relative earnings. The contribution of sector s to between-sector variance growth (which is defined in (6)) is decomposed into the employment and earnings components in the following way:

$$\underbrace{\Delta\left(\frac{n_{s,p}}{N_p}\right)(\bar{w}_{s,p}-\bar{w}_p)^2}_{\substack{\text{sector s's contribution}\\ \text{to between sector}\\ \text{variance growth}}} = \underbrace{\overline{(\bar{w}_{s,p}-\bar{w}_p)^2}\Delta\left(\frac{n_{s,p}}{N_p}\right)}_{\text{employment contribution}} + \underbrace{\overline{\left(\frac{n_{s,p}}{N_p}\right)}\Delta(\bar{w}_{s,p}-\bar{w}_p)^2}_{\text{earnings contribution}} \tag{7}$$

where $\overline{(\bar{w}_{s,p}-\bar{w}_p)^2}$ and $\overline{\left(\frac{n_{s,p}}{N_p}\right)}$ denote averages of 1985 and 2018 values of relative earnings and employment share respectively. Thus the employment component of a contribution of a given sector represents the effect of a change in the employment share of the industry on the between-sector variance, while keeping the relative earnings of the industry fixed, whereas the earnings component allows for changes in relative earnings of the industry, while keeping the employment share of the industry constant. Employment and earnings components can both be positive or negative.

The results of this decomposition are displayed in Table 13. Let's focus on the top 14 sectors that we defined earlier. We find that the contribution of the high-paying industries in this group was mainly driven by changes in relative earnings. In contrast, the contribution

[25]Results are available upon request.

to rising inequality of the low-paying sectors in this group was mainly driven by changes in employment shares. Both patterns are the same as identified by Haltiwanger et al. (2022) for the USA. Thus the reasons why between sector variance increased are different at the opposite ends of the distribution. At the top of the earnings distribution, the growth in inequality was driven by rising earnings in high-paying sectors. At the bottom of the distribution, it was mainly driven by increasing employment in low-paying sectors, and to a lesser extent by falling relative earnings in these industries. We find the same pattern when performing the analysis with 2-digit industries, focusing on the top 10 industries, as shown in Table A6.

$$\underbrace{\Delta var(\bar{w}_{s,p} - \bar{w}_p)}_{\substack{\text{between-sector} \\ \text{variance growth}}} = \underbrace{\sum_{s=1}^{523} \overline{(\bar{w}_{s,p} - \bar{w}_p)^2} \Delta \left(\frac{n_{s,p}}{N_p} \right)}_{\text{total employment contribution}} + \underbrace{\sum_{s=1}^{523} \overline{\left(\frac{n_{s,p}}{N_p} \right)} \Delta (\bar{w}_{s,p} - \bar{w}_p)^2}_{\text{total earnings contribution}} \tag{8}$$

However, when applying the shift-share decomposition of (7) to every industry, and then summing employment and earnings components separately across all the industries (as shown in (8)), we find that majority of the rise in earnings inequality is accounted for by changes in relative earnings, rather than by changes in employment shares of industries. We can see from Table 13 that shifts in employment, holding relative earnings of industries constant, account in total for 17% of the rise in between-sector variance[26]. In Haltiwanger et al. (2022) the figure is very similar at 14%. This is the net effect of changes in employment shares across all the industries (for growing industries the employment component is positive, for shrinking industries it is negative). Thus employment shifted generally more towards the industries with annual earnings far from the economy average which made inequality larger. However, growing dispersion of relative earnings across industries was the primary source of the growth of between-sector variance which itself accounts for more than half of the overall earnings inequality increase.

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

4.6 Discussion of the results

To sum up the results of the paper, we find that majority, specifically 55%, of the rise in earnings inequality in Italy between 1985 and 2018 took place between industries. Thus the between-sector variance was the main driver of the rise in overall inequality. Furthermore, we find that the growth in earnings dispersion across industries was very concentrated, with a small fraction of industries playing disproportionate role. Furthermore, we find that the degree of concentration was very similar to the results found by Haltiwanger et al. (2022) for the USA. Additionally, we find that the increase in earnings inequality across industries in Italy was mainly driven by rising employment shares of low-paying industries and by increasing earnings of high-paying industries which is also the pattern found for the USA. Among these key industries were low-paying sectors related to food and drink, accommodation, social care, cleaning of buildings and employment services sector, and high-paying sectors related to finance, pharmaceuticals and servicing of personal computers. Furthermore, there are many similarities in the key industries between the USA and Italy, especially among the low-paying sectors.

It is interesting to explore what the key industries, the industries with the largest contribution to the growth of the between-sector earnings dispersion, have in common, as we might learn something about the potential drivers of the growth in overall earnings inequality in Italy. Among the key industries low-paying sectors (those paying below the economy average) dominate and they have two things in common: i) within the context of the theory of routine-biased technical change, jobs in these industries would be categories as manual non-routine jobs, ii) they all experienced very large increases in employment shares which could be partially driven by outsourcing or more broadly by changes in the way that workers are allocated to firms and industries.

The theory of routine-biased technical change suggests that new technology such as computers, software and automation is a substitute for skilled, but repetitive tasks (Acemoglu and Autor (2011)). What cannot be automated is both unskilled manual labour and high skilled creative work (Autor et al. (2003)). Therefore demand for both lowest and highest paid occupations should increase, whereas demand should fall for those occupations with medium level of pay which mainly involve skilled, but repetitive tasks (Autor et al. (2006), Autor and Dorn (2013)). A prediction of the theory is employment polarisation, where employment share of low-skilled jobs and very high skilled jobs rises, while share of employment in middle-skill occupations falls (Goos and Manning (2007),Goos et al. (2014)). There is of course a lot of overlap between occupations and industries with low-paying industries employing mainly low-paying occupations. Hence if these technological forces have been operating in Italy, we might find employment polarisation in terms of industries.

We investigate the issue of polarisation in our data. Figure 7 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, the fifth quantile those with the highest earnings.

The main pattern that stands out from Figure 7 is that there was very large decline in employment share of the 4th quantile and a very large increase in employment share of the second quantile. The third (middle) quantile also experienced a decline in employment share, while the 1st and the 5th quantiles saw similarly large increases in employment share. This plot could be interpreted as evidence of job polarisation, employment declining in industries that are roughly in the middle of the distribution, and rising in those at the top and particularly in those at the bottom. We can see that employment share of industries between 40th and 80th percentile fell, while employment share of industries below 40th percentile and also those above 80th percentile increased.

An increase in relative labour demand in low-paid and high-paid industries, (and a decrease for industries in the middle) in combination with an increase in labour supply for the

Figure 7: Changes in employment shares by industry quantiles (ranked by mean earnings in 1985)

low-paid industries could generate the patterns that we observe, which are rising employment share, but falling relative earnings in low-paying industries and rising relative earnings in the high-paying industries. The increase in labour supply in the low-paid industries can be explained by the fact that there are very low barriers of entry to employment in these industries in terms of required formal qualifications. You do not need a specialist university degree to work in the cleaning industry or the food and drink sector, whereas you would need it to work in the financial services or the pharmaceutical industry.

However, changes in employment shares of industries are not necessarily driven just by changes in employment of different occupations in the overall economy. A large role was most likely played by changes in the allocation of workers to firms and industries. Perhaps it is not that there are more cleaners in Italy in 2018 than in 1985, but that they have different employers. You might be doing the same job (e.g. cleaning) and perhaps even at the same workplace (e.g. a manufacturing firm), but instead of being hired by the firm that benefits from your work directly, you are hired by a cleaning company that is a subcontractor to the manufacturing company. We can see from Table 10 that "Services to buildings and landscape activities" grew from 1.5% to 3.7% as a share of total employment. Even more strikingly, "Employment activities" sector (covers employment agencies) went from being less than 0.01% of total employment in 1985 to being almost 5% of total employment in 2018.

Domestic outsourcing can have implications for the pay of the affected workers. Goldschmidt and Schmieder (2017) find that in Germany wages in outsourced jobs fall by approximately 10–15% relative to equivalent jobs that are not outsourced. This wage penalty seems to be coming mainly from the loss of firm-specific rents. This is supported by Drenik et al. (2023) who use a unique Argentinian administrative dataset that links temporary work agencies with the final user firms and find that an agency worker will receive on average around 49% of the firm wage premium of a regular worker in the same firm. Finally, Goldschmidt and Schmieder (2017) find that 9% of the increase in German wage inequality since the 1980s can be accounted for by increasing outsourcing of cleaning, security, and logistics services alone. From our results it looks quite likely that outsourcing also played a large role in the rise of Italian earnings inequality.

It is really striking that we find so many similarities in the patterns of rising earnings inequality between our results for Italy and the Haltiwanger et al. (2022) results for the USA, given that there are enormous differences between the two countries in the way that wages are set. In Italy industry-level country-wide collective agreements specify obligatory minimum wages for each occupation or job title ("livelli di inquadramento")[27]. Job titles are defined by collective bargaining agreements on the basis of the complexity of the employee's tasks, qualifications and seniority levels (Fanfani 2019). Each collective agreement specifies minimum wages for 5-10 different job titles. The minimum wages for each job title in each industry are the outcome of negotiations between sector-level unions and employer organisations (Boeri et al. 2019). However, the mapping of collective agreements to industries

[27] There are hundreds of collective agreements, but approx 150 of the largest ones cover over 90% of workers in the INPS social-security data set.

is not simple, some industries have multiple collective agreements and sometime a single collective agreement covers multiple industries (Fanfani 2019). Collective agreements apply to all workers in the covered firms irrespective of the union membership status (Devicienti et al. 2019). Overall, over 90% of workers in Italy are covered by collective agreements (Visser 2016).

Additionally, there are no opting-out clauses in the Italian system of industrial relations (Devicienti et al. 2019). A firm facing low demand or reduced profitability cannot reach a firm-level agreement with its workforce that would undercut the centrally negotiated terms. Furthermore, firms cannot downgrade workers to lower paid job titles, as workers can only move up in the firms' hierarchy (Fanfani 2019). While firms in Italy cannot pay below the wages set at sector level, they are free to pay above the minimum levels specified for each occupation. Still, the relationship between wages and either firm productivity or local labour market conditions is much weaker in Italy than in Germany or the USA (Boeri et al. 2019).

Devicienti et al. (2019) use a dataset containing information on worker wages as well as collective bargaining agreements for the region of Veneto to show that from the mid-1980s until the early 2000s the growth in wage dispersion occurred entirely between the "livelli di inquadramento". There was no growth in wage dispersion within job titles[28]. Devicienti et al. (2019) suggest that the growth in wage inequality in Italy has been mainly the result of the rising dispersion of industry and occupation-specific minimum wages.

However, this does not rule out explanations of rising earnings inequality based on technological change. Devicienti et al. (2019) acknowledge that there are underlying market forces determining wage inequality and that these were most likely reflected in the growing dispersion of industry and occupation specific minimum wages. Shifts in labour demand and supply at industry level were likely reflected in the bargained wages. However, Devicienti et al. (2019) suggest that the system of collective bargaining was still in control of how

[28]While it seems reasonable to assume that similar patterns would emerge at national level, as far as we are aware the literature has not investigated this yet due to data limitations.

much overall wage inequality it was going to allow. This is consistent with us finding that both the level of inequality and the size of the increase in earnings inequality in Italy was about half of the level observed in the USA, when using the same sample selection[29]. Our finding that there are many similarities in the pattern of rising inequality between Italy and the USA, especially in the specific industries that played a key role, is suggestive evidence that the underlying forces were likely similar, despite the stark differences in wage setting institutions.

5 Conclusion

We use data covering the universe of private sector employment in Italy in order to investigate the main drivers of rising earnings inequality, specifically whether inequality is mainly rising between firms in different industries, between firms within the same industry or within firms. We compare our results to the findings of Haltiwanger et al. (2022) for the USA. In both countries, earnings inequality was mainly driven by increasing dispersion of earnings across industries. We find that 55% of the rise in earnings inequality in Italy between 1985 and 2018 took place between industries, while only 18% took place between firms within the same industry and 27% took place within firms. This is in contrast to the findings of Song et al. (2019) for the USA and Faggio et al. (2010) for the UK who find that the between-firm-within-industry variance was the dominant driver of the growth of total pay inequality. Furthermore, we find that the explanatory role of industry does not increase much when moving from broad 2-digit industries (88 categories) to narrow 4-digit industries (around 600 categories).

Furthermore, the rise in between-sector variance was highly concentrated. 3% of industries with the largest individual contributions account for around two thirds of the total between-sector inequality-increasing contributions, while representing only around 7% of

[29]Comparing to the results of Song et al. (2019) for the USA who cover a similar period to us.

employment in 1985. The degree of concentration is similar to that reported by Haltiwanger et al. (2022) for the USA. In both countries, the growth in inequality was driven predominantly by rising relative earnings in high-paying industries and rising employment in low-paying industries. Additionally, there are many similarities in the list of industries with the largest contribution to inequality growth, with sectors related to food and drink, accommodation, social care, cleaning and maintenance of buildings, employment agencies, finance, pharmaceuticals and IT being important in both countries.

We find that despite enormous differences in institutions between the two countries, in particular Italy having sector-level collective bargaining that covers around 90% of workers and the USA having little collective bargaining, the patterns of rising earnings inequality are remarkably similar between the two countries. This suggests that the underlying forces driving the rise in inequality are likely similar. The implication is that these forces are mainly increasing the gaps in pay across industries and that crucially, they have very uneven and concentrated impact across industries. Any theory of the rise in pay inequality must account for this.

6 Appendix

6.1 Tables

Table A1: Between versus within firm variance decomposition for different firm sizes (annual earnings).

(a) Small firms

	Between firm	Within firm	Total
1985	0.154	0.181	0.335
2018	0.209	0.197	0.406
Change	0.055	0.016	0.071
% of total increase	77.5%	22.5%	100.0%

(b) Medium firms

	Between firm	Within firm	Total
1985	0.142	0.198	0.340
2018	0.215	0.217	0.432
Change	0.073	0.019	0.092
% of total increase	79.3%	20.7%	100.0%

(c) Large firms

	Between firm	Within firm	Total
1985	0.122	0.198	0.320
2018	0.227	0.235	0.462
Change	0.105	0.037	0.142
% of total increase	73.9%	26.1%	100.0%

Note: Small firm: 10-49 employees; medium firm: 50-249 employees; large firm: over 250 employees.

Table A2: Sectors and firms: full variance decomposition (**only men**, 4 digit sector, annual earnings).

(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	0.034	0.116
% of total increase	44.8%	25.9%	29.3%	100.0%

(b) Variance shares

	Between sector	Between firms within sector	Within firm
1985	24.3%	22.0%	53.7%
2018	30.7%	23.2%	46.1%

Table A3: Sectors and firms: full variance decomposition (**only women**, 4 digit sector, annual earnings).

(a) Variance change over time

	Between sector	Between firms within sector	Within firm	Total
1985	0.075	0.129	0.220	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%	30.4%	51.9%
2018	18.1%	26.3%	55.6%

Table A4: Top 10 (2-digit) sectors in terms of decreasing between-sector variance

2 digit ATECO code	Industry title	Employment share 1985	Employment share 2018	Relative earnings 1985	Relative earnings 2018	Share of between sector variance growth
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 (6) for definitions.

Table A5: Sectors with larger than 1% contribution to the growth of between-sector variance (29 sectors, 4-digit)

4 digit ATECO 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 care	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	0.1%	0.7%	-0.11	0.54	3.6%
6209	Servicing of personal computers	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	Pharmaceutical manufacturing	0.5%	0.4%	0.34	0.69	2.6%
3316	Maintenance of of aircraft and spacecraft	0.5%	0.4%	0.17	0.61	2.6%
8430	Compulsory social securitiy	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 service activities	0.3%	2.8%	0.27	-0.22	2.1%
9609	Other personal service activities	0.0%	0.7%	-0.47	-0.39	1.8%
6499	Other financial service activities	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	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 (6) for definitions.

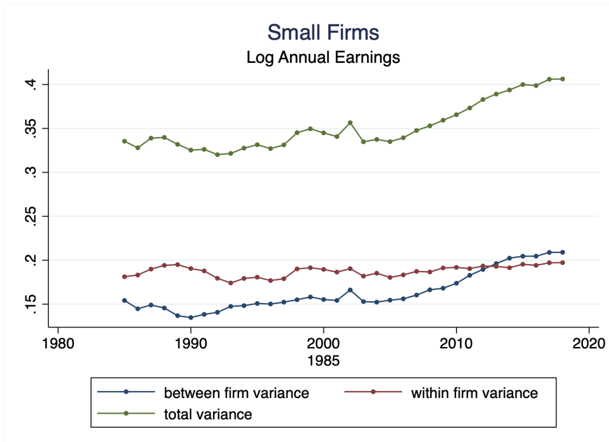
Table A6: Sector contributions to between sector variance growth, by average earnings (2-digit sectors)

Sector relative earnings	Number of sectors	Total employment share	Total contribution to between sector variance growth	Total share of between sector variance growth	Shift-share: employment	Shift-share: earnings
			Top 10 sectors			
High paying	4	10.6%	0.011	19.2%	-9.1%	109.2%
Low paying	6	11.9%	0.045	80.7%	65.3%	34.8%
			The remaining 75 sectors			
High paying	47	44.5%	0.013	23.0%		
Low paying	28	33.0%	-0.013	-22.9%		
Total	85	100.0%	0.055	100.0%	24.3%	75.9%

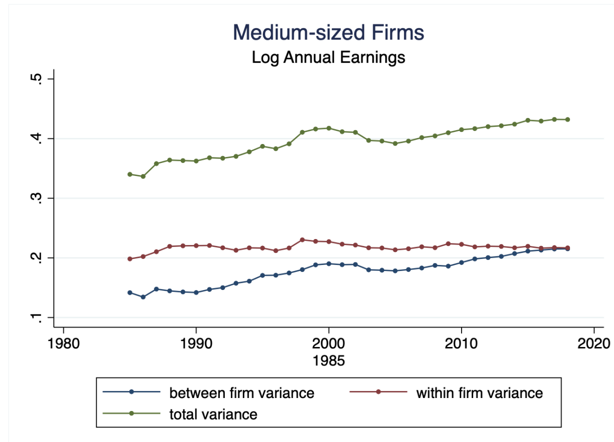
Note: Employment shares are calculated as the average of 1985 and 2018 employment shares. See Equation (6) for definitions of relative earnings and of the contribution of a particular sector to between sector variance growth. Sector is high paying (low paying) if its average relative earnings are positive (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 7. 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.

6.2 Figures

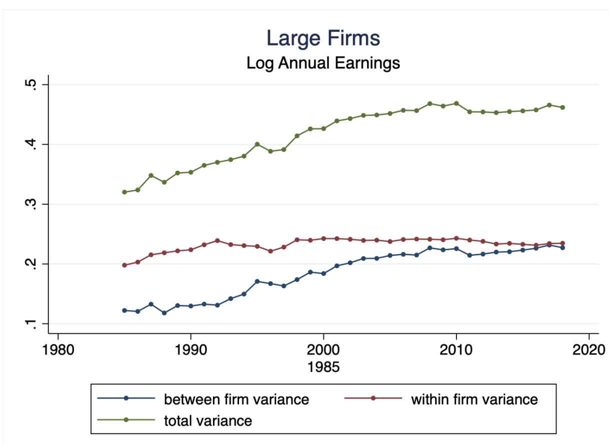
Figure A1: Different firm sizes: between versus within firm variance in Italy 1985-2018 (annual earnings).



(a) Small firms



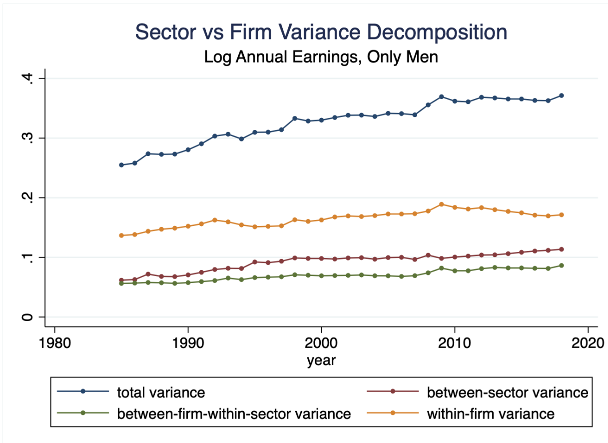
(b) Medium firms



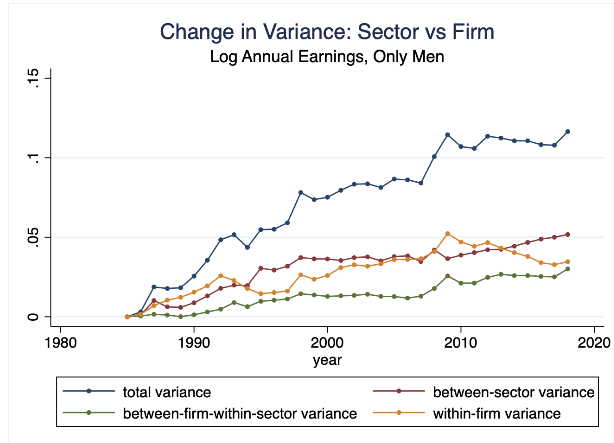
(c) Large firms

Note: Small firm: 10-49 employees; medium firm: 50-249; large firm: over 250 employees.

Figure A2: Sector and firm: full variance decomposition. (annual earnings, only men).

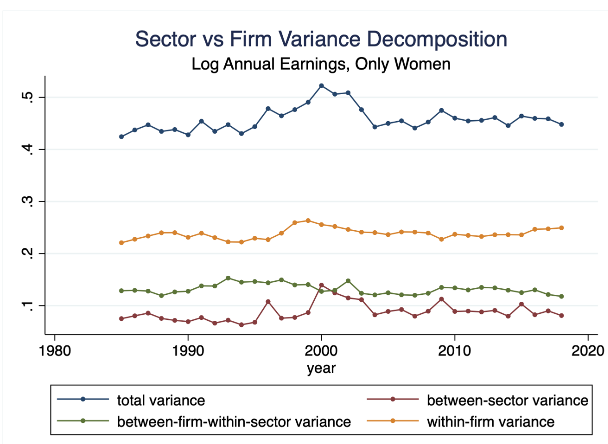


(a) Levels

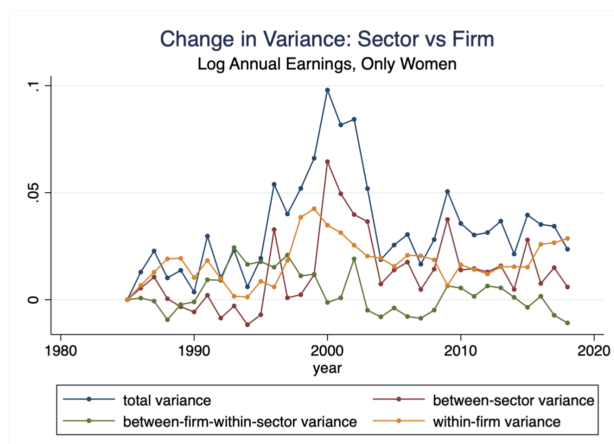


(b) Change Relative to 1985

Figure A3: Sector and firm: full variance decomposition. (annual earnings, only women).



(a) Levels



(b) Change Relative to 1985

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