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The Role of Industries in Rising Inequality

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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 a small number of low-paid service sectors accounting for most of the increase. Workers with low earnings ability have become more likely to work in the same industries than other low-income workers, and they are more likely to work in industries with particularly low average firm premia. The growth in inequality of annual earnings has been driven by rising variance of wage rates and by rising positive association between the rate of pay and how much individuals work. Despite very large institutional differences, the patterns of rising earnings 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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Il ruolo dei settori nella crescita della disuguaglianza

Abstract

Utilizzando i dati dell'universo dei lavoratori italiani nel settore privato in questo articolo studiamo l'aumento della disuguaglianza di reddito in Italia. I nostri risultati mostrano che il 55% dell'aumento della disuguaglianza di reddito tra il 1985 e il 2018 e' avvenuta tra settori, il 18% tra imprese nello stesso settore e il 27% all' interno delle imprese. La crescita della disuguaglianza tra settori e' stata concentrata in un numero limitato di settori che pagano salari relativamente bassi. I lavoratori con scarsa capacità di guadagno lavorano piu' spesso con altri lavoratori come loro in settori che pagano in media di meno. La crescita della disuguaglianza di reddito e' stata trainata dalla crescita della varianza dei salari e dall'associazione positiva dei salari e delle settimane lavorate. Nonostante grandi differenze a livello istituzionale, i tratti individuati in Italia sono molto simili a quelli trovati per gli USA; questa evidenza suggerisce la presenza di forze determinanti comuni.

Keywords: disuguaglianza di reddito, imprese, settori, cambiamento tecnologico, istituzioni del mercato del lavoro.

1 Introduction

Since at least the 1980's there has been a very well documented[1] and substantial increase in pay inequality in many industrialized economies. 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). More recently, there has been a growing focus on the role of firms. In an influential paper, Song et al. (2019) show that two thirds of the rise in US earnings inequality since the 1980s took place between firms, only one third within firms[2]. This pattern where most of the change in earnings inequality takes place between firms seems to be widespread, as it has also been shown 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. Furthermore, Song et al. (2019) show that the increase in between-firm earnings variance was not driven by rising dispersion of firm wage premiums, but instead by changes in the allocation of workers across firms, where highly-paid workers are more likely to work with each other and to work in firms with high pay premiums.

A question that remains unanswered is whether earnings inequality is growing mainly between firms in the same industry, or between firms in different industries. While Faggio et al. (2010) find the former using UK data, Haltiwanger et al. (2022a) use US Census data with precise information on the industry of the firm and find that the majority of the inequality growth occurred between industries. Additionally, they find that developments in just a small number of key industries (10% of total) can explain the majority of the rise in US earnings inequality. The evidence for other countries remains very limited, in particular for Continental European countries with very different institutions from the US. This question is important for understanding drivers of inequality, whether these forces operate at the level of industries, or they are related to firm heterogeneity within industries, such as the

[1] See (Atkinson et al. 2011), for instance

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

phenomenon of "superstar firms" (Autor et al. (2020)).

In this paper we use a social security administrative dataset covering the universe of private-sector employment in Italy in order to investigate the role of industries in the rise of earnings inequality. In addition to simple variance decompositions, we investigate the role of industry average pay premiums and sorting of workers across industries. We adopt the sample restrictions of Song et al. (2019) and Haltiwanger et al. (2022a) in order to ease comparison of results. We find that the development of real annual earnings in Italy is characterised by absence of growth (stagnant mean and median) and by rising dispersion. Variance of log annual earnings in our data has increased from 0.354 in 1985 to 0.450 in 2018.

Our first major result is that between-sector variance has been the dominant source of earnings inequality growth in Italy, just as Haltiwanger et al. (2022a) find for the USA. Specifically, of the total increase in log annual earnings variance in Italy between 1985 and 2018: 55% took place between industries, 18% between firms within the same industry and 27% within firms. Furthermore, this increase in between-sector variance was similarly concentrated as in the USA, with a small number of industries playing disproportionate role. Less than 3% of (4-digit NACE) industries account for two-thirds of the total inequality-increasing effect (between industries), while only initially representing around 7% of employment.

We find that the key industries in Italy in terms of their role in rising inequality are low-paying service sectors related to food and drink, accommodation, social care, cleaning of buildings and work agencies. This is in contrast to Haltiwanger et al. (2022a) results for the USA where low and high-paying industries play approximately equal role. However, there is a lot of overlap among the important low-paying sectors in the two countries. The key low-paying industries in Italy were contributing towards greater inequality both by becoming much larger as a share of total employment, as well as by their average earnings falling relative to the economy average. Interestingly, we find that the results are very similar when using either 2, 3 or 4 digit 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[3] 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.

Our second key finding is that earnings inequality in Italy grew because of rising dispersion in worker-specific component of pay and an increase in assortative sorting of workers into firms and industries, while the variance of industry and firm pay premiums actually declined. We estimate regression model of worker and firm fixed effects (Abowd et al. (1999)) for five 7-year panels. Comparing AKM-based variance decomposition for the first (1985-1991) and the last (2013-2019) interval, we find that variance of firm fixed effects declined slightly, while variance of worker fixed effects and covariance between worker and firm fixed effects both increased substantially. This is in line with results of Song et al. (2019) for the USA.

Next, we calculate industry-enhanced AKM variance decomposition proposed by Haltiwanger et al. (2022a) where variances and covariances are additionally split into their between-sector, between-firm-within-sector and within-firm components. We find that the majority of the rise in Italian earnings inequality is accounted for by growing between-sector sorting and segregation (the same as found by Haltiwanger et al. (2022a) for the USA). Workers with low earnings ability are more likely to work with other low-income workers in the same industry (segregation), and they are more likely to work in industries with particularly low average firm premia (sorting).

Our third major finding is that the dispersion in labour supply quantities across workers has remained broadly constant in Italy, and the growth in inequality of annual earnings has been driven by rising variance of wage rates and in particular, by rising positive association

[3] Between-sector variance as a share of total variance. This is equivalent to R^2 from a regression of log annual earnings on industry dummy variables.

between the rate of pay and how much individuals work. Unlike Song et al. (2019) and Haltiwanger et al. (2022a), in addition to earnings, we have information on how much individuals work over the year (measured as full-time equivalent weeks). From this we calculate the average rate of pay of an individual in a given year. Variance of log annual earnings is then composed of variance of log weeks worked, variance of log wage rates and a term containing covariance of weeks and wage rates. Relative contributions to the rise of annual earnings inequality of the three terms above are respectively -10%, 48% and 62%. Of the rise in covariance between weeks worked and wage rates, more than half is accounted for by the between-sector component. The fact that sectors with low rates of pay also increasingly employ workers part-time or for only a part of the year amplifies the effect of wage dispersion on inequality of annual earnings.

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. Furthermore, this is driven by changes in the allocation of workers across industries. Any theory of the rise in pay inequality must account for these facts. This is in the context of recent literature that instead places the focus on firm heterogeneity within industries (Autor et al. (2020) and Freund (2022)).

The patterns that we find are consistent with shifts in industry-level labour demand, driven by structural transformation, Routine-Biased Technical Change or trade (Acemoglu and Autor (2011), Autor and Dorn (2013)). The falling pay and rising employment in the key low-skill service sectors can be explained as a combination of an increase in labour demand and an even larger increase in labour supply in these sectors, as workers move there from declining sectors and there are relatively few barriers to entry. Our findings could also be partially accounted for by the rise of domestic outsourcing.

Second, 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)). Overall, over 90% of workers in Italy are covered by collective agreements (Visser (2016)). Our finding that despite stark differences in institutions there are many similarities in the patterns of rising inequality between Italy and the USA is suggestive evidence that the underlying forces are likely similar. It seems reasonable that collectively bargained wages simply reflected shifts in labour demand at industry level. 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 is about half of the level observed in the USA[4].

Third, we have information on how much individuals work which allows us to contribute to the small and emerging literature examining the contribution of dispersion of hours worked, hourly wage rates and their covariance to the annual earnings inequality (Checchi et al. (2016), Checchi et al. (2022)). We show that in Italy inequality of annual earnings grew much more than inequality of wage rates, despite no persistent change in the dispersion of labour supply quantities. This was due to the rising positive association between how much individuals work and their rate of pay. This is related to the literature on dual labour markets in Europe that studies the role of temporary contracts (Saint-Paul (1996), Bentolila et al. (2020)). Some have argued that similar dualism with workers in the second-tier jobs facing lower wages and much higher unemployment risk also applies to the USA (Ahn et al. (2023)). In any case, this highlights the importance of studying separately the dispersion in wage rates and in labour supply.

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

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

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 data set by the Italian Social Security Institute (INPS),[5] 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 the 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, the 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 the 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 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. (2022a). 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.

[5]Istituto Nazionale della Previdenza Sociale.

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[6]. 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)[7]. 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[8]. We adjust it for nominal wage growth for all the other years (1985-2018) using a series from OECD[9].

Following Song et al. (2019), we restrict the sample to only individuals between the age 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)[10]. This is to ensure that there are enough observations to calculate the within-firm variance.

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 private sector employees is mainly due to the higher participation rate of women as well as population growth and immigration[11].

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

[7] 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.

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

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

[10] 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.

[11] Figure A4 displays labour force participation by gender. We can see the steady increase in participation of women, while the rate for men is flat.

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.

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. Furthermore, we show in section 3.6 that our results are robust to lowering the minimum firm size threshold to 5 workers per firm or removing the restriction completely.

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 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 Descriptive Analysis of Earnings Inequality

3.1 Evolution of annual earnings in Italy

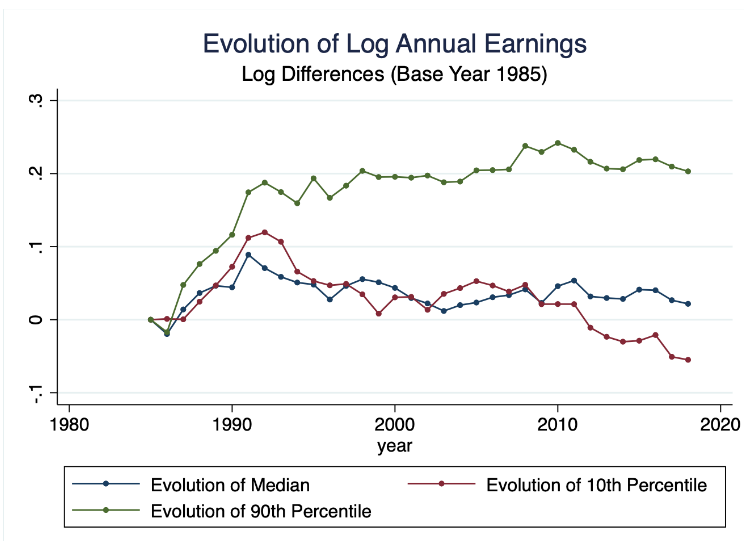
The evolution of the distribution of annual earnings in Italy is characterised by very little growth in average earnings, but a significant increase in the dispersion of earnings. Mean real annual earnings (expressed in 2018 Euros) stood at 24,806 in 1985 and they were just 27,050 in 2018 (Table 2(b)).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

Figure 1 shows the evolution of various percentiles of log annual earnings between 1985 and 2018. While median earnings stagnated throughout the period, with only a very small increase in the late 1980s and early 1990s, the 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 fell persistently, finishing 6 log points lower compared to 1985. To sum up, it seems that between 1985 and mid-1990s, the 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 3(a) which shows that the 90th to 50th percentile ratio of annual earnings was growing mainly between

1985 and 2003 and the 50th to 10th percentile ratio was growing mainly in the later period, after 2005.

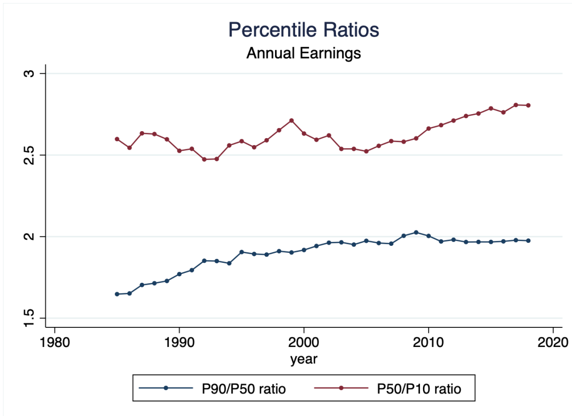
Total variance of log annual earnings rose from 0.354 in 1985 to 0.450 in 2018 (Table 3), representing an increase of 9.6 log points. We can see from Figure 3(b) that this increase was persistent and not episodic, the dispersion was rising throughout the period[12]. Given that we impose the same sample 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 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.

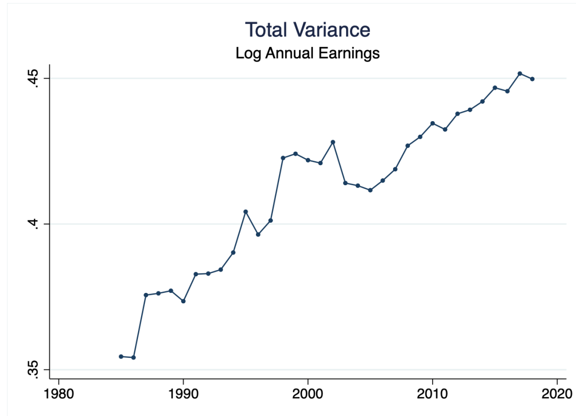


[12]With a brief slowdown around 2000.

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

3.2 Variance Decomposition

To study the role of firms in accounting for earnings inequality in Italy, we first perform the following variance decomposition into between-firm and within-firm variance:

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

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.

Additionally, we decompose total variance of log annual earnings into between-sector variance and within-sector variance:

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

where y_{is} denotes the log annual earnings of a worker i in sector s in a given year, n_s is the number of workers employed in sector s and $\bar{y_s}$ gives the average log annual earnings of sector s.

Next, we separately investigate the contribution of sectors and of firms within sectors to the rise in earnings inequality in Italy. 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) to obtain the following:

$$\begin{aligned} \underbrace{\frac{1}{N}\sum_{\forall i}(y_{ijs}-\bar{y})^2}_{\text{total variance}} &= \underbrace{\sum_{\forall s}\frac{n_s}{N}(\bar{y_s}-\bar{y})^2}_{\text{between-sector variance}} + \underbrace{\sum_{\forall s}\frac{n_s}{N}\sum_{\forall j|j\in s}\frac{n_j}{n_s}(\bar{y_j}-\bar{y_s})^2}_{\text{between-firm-within-sector variance}} \\ &+ \underbrace{\sum_{\forall j}\frac{n_j}{N}\frac{\sum_{\forall i|i\in j}(y_{ijs}-\bar{y_j})^2}{n_j}}_{\text{within-firm variance}}. \end{aligned} \tag{3}$$

In addition to directly calculating (3), 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[13]. This produces between-firms-within-sector variance and within-firm variance. All three methods are equivalent and generate the same outcomes. As in Song et al. (2019), we use the demeaning method.

[13]More detailed explanation is in the Appendix, Section 8.1

3.3 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 73.7% of the overall increase in inequality. Within-firm pay inequality also increased and contributed to the remaining 26.3% 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 45.6% of the total variance in 1985, but that rose to 51.6% in 2018.

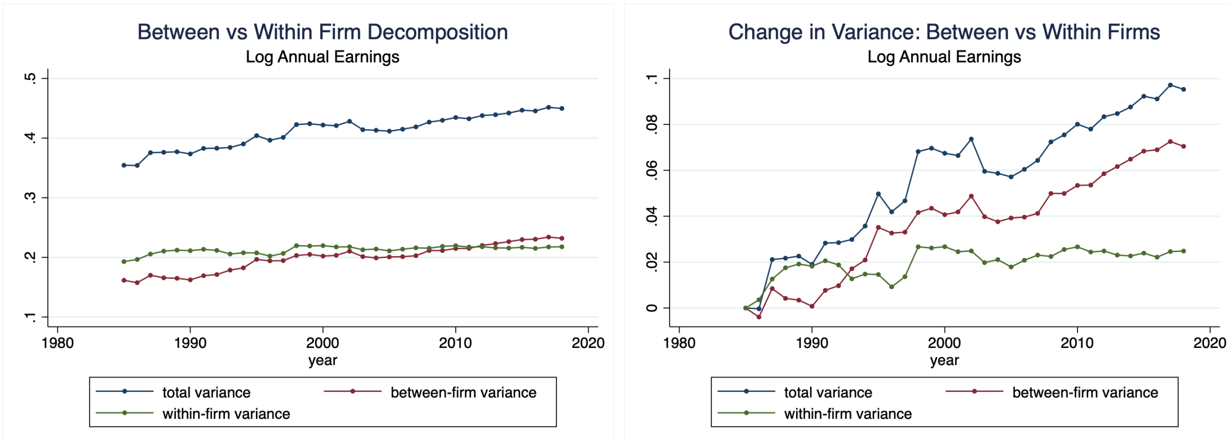
Table 3: Between versus within **firm** variance decomposition (Italy, annual earnings).

	Total	Between firm	Within firm	Between firm share	Within firm share
1985	0.355	0.162	0.193	45.6%	54.4%
2018	0.450	0.232	0.218	51.6%	48.4%
Change	0.095	0.070	0.025	-	-
% of total increase	100.0%	73.7%	26.3%	-	-

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)[14]. Across firms of all sizes the between-firm variance grows at a faster rate than the within-firm component (Figure A1).

[14] 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

3.4 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 55.8% of the rise in earnings inequality in Italy occurred between (4-digit) sectors, while 44.2% took place within sectors (Table 4)[15]. 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 23.3% in 1985 and 30.2% in 2018 (Table 4).

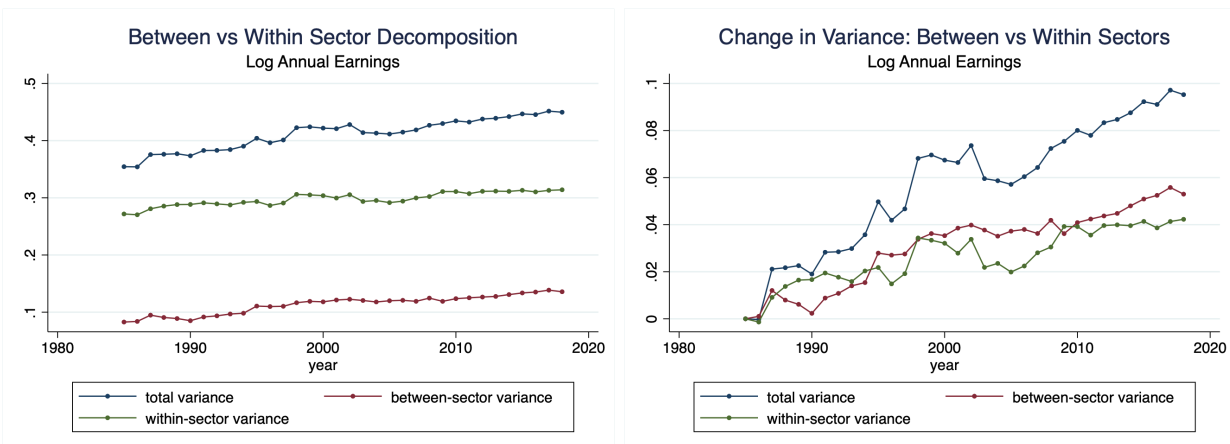
So far we have used the NACE industry classification at 4 digit level. In Table 5 we present the results of variance decomposition with 2 digit (88 industry categories), 3 digit (268 categories) and 4 digit industries (593 categories). The main conclusion is that the results are remarkably similar. The increase in between sector variance represents 57.9%, 54.7% and 55.8% 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

[15]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	0.355	0.083	0.272	23.3%	76.7%
2018	0.450	0.136	0.314	30.2%	69.8%
Change	0.095	0.053	0.042	-	-
% of total increase	100.0%	55.8%	44.2%	-	-

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 18.2%, 21.8% and 23.3% respectively. In 2018 it is 26.6%, 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	0.355
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 (88 sectors)	3 digit (268 sectors)	4 digit (593 sectors)
1985	18.2%	21.8%	23.3%
2018	26.6%	28.8%	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 3.2 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[16].

Table 28(a) shows the full variance decomposition over time with 4 digit industries. While the growth of the between-sector variance accounts for 55.8% of the total variance increase, the rise of the between-firm-within-sector variance accounts for only 17.9% and the rise of the

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

within-firm variance accounts for 26.3%. 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 28(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	0.193	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%

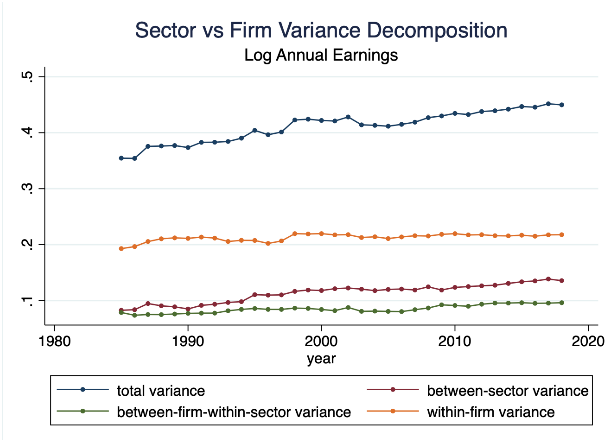
(b) Variance shares

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

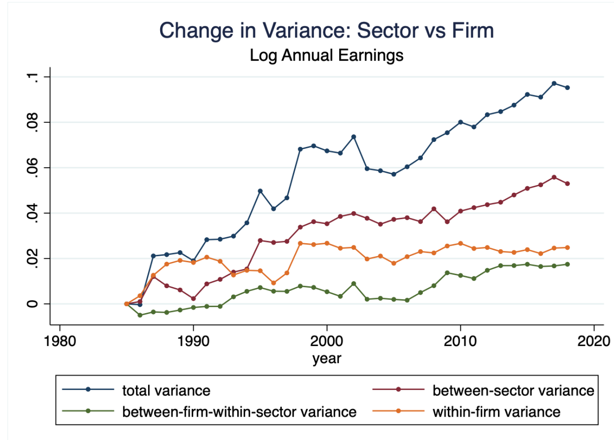
Next, we split our time period into two sub-periods: 1985 to 2003 and 2003 until 2018. There are two reasons or this. First, there was a legislative change and short-term employment contracts became increasingly common since 2003[17]. Second, we saw earlier that the patterns of rising inequality are 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

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

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



(a) Levels



(b) Change Relative to 1985

steadily rising, while inequality in the bottom half was roughly constant (Figure 3(a)). 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 7 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 role in the latter period, accounting for 41.7% of the rise in earnings inequality between 2003 and 2018. We can see from Figure 5 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.

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

Table 7: Sectors and firms: full variance decomposition, **sub-periods** (**4 digit sector**, annual earnings).

(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%

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 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. 69.8% of the rise in earnings dispersion among men occurred between firms which is very similar to the figure when including both genders (73.7%). Between-sector variance accounts for 44.8% of the overall growth in earnings inequality which is slightly less than

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

in the baseline earnings sample (55.8%). 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 30.2% which is is very similar to the baseline sample figure of 26.3%. 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 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 persistent 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.

Let us now compare our findings for Italy with the results of Song et al. (2019) and Haltiwanger et al. (2022a) for the USA who perform the same variance decompositions using log annual earnings (all three papers use the same sample restrictions and 4 digit industry classification, making comparisons easier). Song et al. (2019) use a social security data set covering workers and firms for the entire U.S. labor market. They find that of the increase in total variance of earnings between 1981 and 2013, 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 A4). The implication of Song et al. (2019) findings is that the dominant driver of rising earnings inequality in the US has been rising heterogeneity in pay between firms in the same industry. However, it has been shown that the information on sector of economic activity in Song et al. (2019) is of very poor quality (Haltiwanger et al. (2022b)).

In contrast, Haltiwanger et al. (2022a) use Longitudinal Employer-Household Dynamics (LEHD) linked employer-employee data, which contains much more reliable and comprehensive information on the industry that the firm belongs to. On the other hand, their data covers only 18 out of the 50 US states and just the period from 1996 until 2018. Haltiwanger et al. (2022a) 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 A5). Hence, they suggest that the majority of the rise in US earnings dispersion has been driven by increasing heterogeneity of pay across industries.

We find that the between-sector component accounts for about 55% of the rise in total variance of earnings which is clearly much closer to the 62% found by Haltiwanger et al. (2022a) 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. (2022a) than to the 66% figure of Song et al. (2019). Additionally, Kleinman (2022) uses the same data source as Haltiwanger et al. (2022a) 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. (2022a), in any given year the 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 A4). According to

Haltiwanger et al. (2022a) it is 64.6% in the 1996-2002 period and 58.0% in the 2012-2018 period (Table A5). 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 28(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. 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 it is in the USA.

3.5 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. (2022a) 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:

$$\underbrace{\Delta var(\bar{y}_s - \bar{y})}_{\substack{\text{between-sector}\\ \text{variance growth}}} = \sum_{s=1}^{523} \underbrace{\Delta \underbrace{\left(\frac{n_s}{N}\right)}_{\substack{\text{employment}\\ \text{share}}} \underbrace{(\bar{y}_s - \bar{y})^2}_{\substack{\text{relative}\\ \text{earnings}}}}_{\substack{\text{sector s's contribution}\\ \text{to between sector}\\ \text{variance growth}}} \tag{4}$$

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 $\Delta\left(\frac{n_s}{N}\right)(\bar{y}_s - \bar{y})^2$.

When does an industry contribute towards an increase or decrease in inequality? We can see from equation 4 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 8: 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 (4) 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)[19]. We follow Haltiwanger et al. (2022a) in grouping industries by the size of their individual contributions to between sector

[19] 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.

variance growth. We can see from Table 8 that there are 3 industries which each account 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 9. 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 9 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 9: Top 10 (2-digit) sectors in terms of increasing between-sector variance

4 digit 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 (4) 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 8 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 A6. 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. (2022a) for the USA who also use information on industries at 4-digit level[20].

There are in total 523 industries at 4-digit level of aggregation[21]. We can see from Table 10 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

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

[21] 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.

98.5% of the growth in between-sector variance (roughly 55% of the overall rise in inequality), 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%.

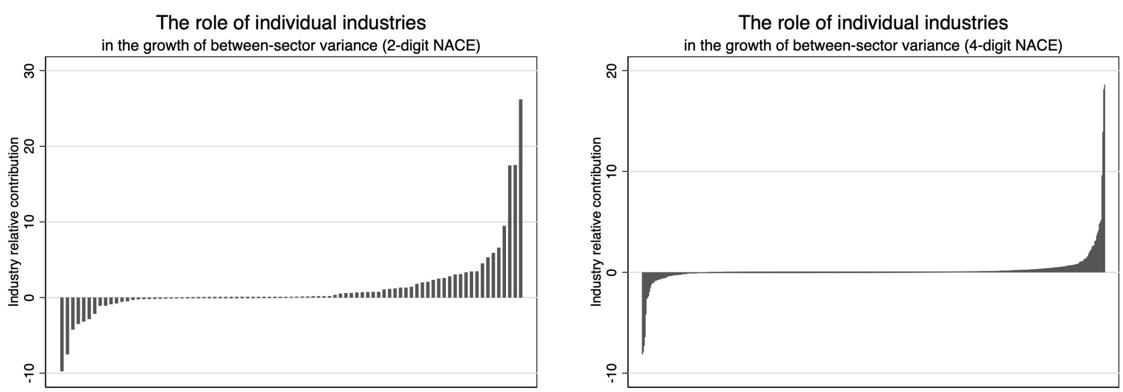
Table 10: Contribution of **4-digit** sector groups to between sector variance growth (grouped based on individual sector share)

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 (4) 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. (2022a) 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 11. Most of these 4-digit industries belong to one of the top 2-digit industries displayed in Table 9, 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 9, so it is useful to undertake analysis with the narrow industries[22].

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

Table 11: Top 14 (4-digit) sectors in terms of increasing between-sector variance

4 digit 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. See Equation 4 for definitions.

To what extent are the key industries driving the growth in inequality in Italy similar to the key industries in the USA[23]? Haltiwanger et al. (2022a) list all industries with larger than 1% contribution to the rise of between-sector variance, we do the same in Table A7. 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 contributions in both Italy and the USA. Other low-paying sectors which are important in both countries are sectors related to social care (both residential 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 phar-

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

maceutical 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 IT sectors feature more prominently and cover software publishing, computer system design and semiconductor manufacturing. Among the key low-paying sectors, the main difference seems to be that retail industries appear to be much more important in the USA than in Italy. A significant difference is that there are more high-paying sectors with large relative contributions to the rise of inequality in the USA relative to Italy. However, among low-paying sectors the patterns are very similar.

Table 12: 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	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: Employment shares are calculated as the average of 1985 and 2018 employment shares. See Equation (4) 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 5. 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 12, 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 a 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 A8. Finally, all of the patterns identified in this section hold when we restrict the sample only to males[24].

We follow Haltiwanger et al. (2022a) 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 (4)) is decomposed into the employment and earnings components in the following way:

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

where $\overline{(\bar{y}_s - \bar{y})^2}$ and $\overline{\left(\frac{n_s}{N}\right)}$ 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 12. 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 to rising inequality of the low-paying sectors in this group was mainly driven by changes in

[24] Results are available upon request.

employment shares. Both patterns are the same as identified by Haltiwanger et al. (2022a) 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 A8.

$$\underbrace{\Delta var(\bar{y}_s - \bar{y})}_{\substack{\text{between-sector} \\ \text{variance growth}}} = \underbrace{\sum_{s=1}^{523} \overline{(\bar{y}_s - \bar{y})^2} \Delta\left(\frac{n_s}{N}\right)}_{\text{total employment contribution}} + \underbrace{\sum_{s=1}^{523} \overline{\left(\frac{n_s}{N}\right)} \Delta(\bar{y}_s - \bar{y})^2}_{\text{total earnings contribution}} \tag{6}$$

However, when applying the shift-share decomposition of (5) to every industry, and then summing employment and earnings components separately across all the industries (as shown in (6)), we find that the 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 12 that shifts in employment, holding relative earnings of industries constant, account in total for 17% of the rise in between-sector variance[25]. In Haltiwanger et al. (2022a) 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, the 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.

Finally, we can split the sample by gender. We saw earlier that earnings inequality increased substantially among men, but not among women, so we analyse the rise in male

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

between-sector variance. We check whether the patterns found for the whole population still hold when restricting the sample to just men. We find that the rise in between-sector variance was similarly concentrated, with a small number of industries playing a disproportionate role (Table A9 for 2-digit and Table A11 for 4-digit industries). We also find that the key industries were the same, with very few exceptions (Table A10 for 2-digit and Table A12 for 4-digit industries).

3.6 Robustness of results

This section summarises results of robustness exercises that are available in the Online Appendix B. First, we relax the sample restriction of a minimum of 10 workers per firm. We apply this restriction in the baseline results for comparability with Song et al. (2019) and Haltiwanger et al. (2022a) and to have enough observations to calculate variance within firms. However, one of the typical features of Italian economy is a very high number of very small firms. Section 9.1 presents results of analysis of annual earnings inequality when applying cutoff of 5 workers per firm. Section 9.2 does the same for the case with no firm size restriction. We find that this has no effect on our findings. Still around 55% of the rise in inequality took place between industries, the degree of concentration is very similar and the key industries are the same as in the baseline results. The only difference is that the 2-digit sector "Food and beverage service activities" (56) and its 4-digit components become even more important as drivers of between-sector earnings inequality, and a new important low-paying sector emerges, "Hairdressing and other beauty treatment" (9602).

The second concern that we address relates to the continuity of the coverage of INPS administrative data in terms of industries. We repeat our analysis while restricting the sample to only those sectors with no change in the coverage of INPS data since 1985, these are industries with 2-digit NACE code between 10 and 84 (Section 9.3 in Appendix B). The results are almost identical to the baseline results. None of the key inequality-increasing sectors are affected by this restriction.

The third concern that we address are potential changes in the degree of informality in Italian economy between 1985 and 2018. One might worry that some of the growth in the INPS population of private sector employment (Table 1) could be due to a decline in informality, i.e. more employment relationships being declared for tax purposes, and that this could bias our results. However, Figure A5 shows that the aggregate informality rate (estimated employment in the informal sector as a share of total employment) is approximately constant over the period that we study. Still, there could be changes in the degree of informality at the level of industries and some of the changes in industry employment shares that we observe could be driven by this. Exploring changes in informality at the level of NACE Sections (industry groups), we find that except for Accommodation and food service activities (Section I), there is no overall trend over time (Figure A5). As a robustness check we drop observations for Section I and repeat the analysis (results shown in section 9.4 in Appendix B). In this case we are removing two 2-digit NACE sectors that play a prominent role in our baseline results, Accommodation (55) and Food and beverage service activities (56), and therefore it is not surprising that the growth in total variance is slightly smaller (0.082 vs 0.095). Contribution of between-sector variance to the overall inequality growth is also slightly smaller (48.8% vs 55.8%), but the main findings still hold. Between-sector variance is still the main driver of inequality and it is very concentrated in terms of industries.

The fourth issue that we deal with is a considerable rise in employment via work agencies in Italy as represented by rising employment share of the sector Employment activities (78). Unfortunately, there is no data available to link workers in this sector to the client companies that they actually work for. As a robustness check, we repeat the analysis while removing all workers in this sector (results shown in section 9.5 in Appendix B). We find that this has minimal effect on our results.

4 Decomposing Earnings using AKM

4.1 Empirical framework of worker and firm effects

In order to better understand the role that workers and firms play in determination of pay inequality, we estimate the linear AKM model (Abowd et al. (1999)). We estimate the model

for five 7-year intervals: 1985-1991, 1992-1998, 1999-2005, 2006-2012 and 2013-2019. Following Song et al. (2019) and Haltiwanger et al. (2022a) we assume that annual earnings $y_t^{i,j,s,p}$ are the sum of the worker effect of worker i in interval p, $\theta^{i,p}$, a firm effect of firm j in sector s in interval p, $\psi^{j,s,p}$, and a vector of time-varying observable characteristics $X_t^{i,p}\beta^p$ for worker i at time t, which have different effects by interval p given by β^p. Thus we estimate the following regression model:

$$y_t^{i,j,s,p} = \theta^{i,p} + \psi^{j,s,p} + X_t^{i,p}\beta^p + \epsilon_t^{i,j,s,p} \tag{7}$$

where $\theta^{i,p}$ is typically interpreted as capturing the underlying worker earning ability that is mobile between firms, while $\psi^{j,s,p}$ should capture persistent earnings differences between firms after accounting for variation in worker ability across firms. The vector of time-varying observable characteristics contains controls for year effects and for worker age. We include a set of year dummies to control for differences in earnings across years within panels. We follow Card et al. (2016) in centering age around 40, we include a quadratic and cubic transformation of worker age, but not the linear term. This way we maintain maximum comparability with Haltiwanger et al. (2022a).

While the AKM model has proven to be a popular empirical approach to separating the role of worker and firm heterogeneity, it has faced a great deal of scrutiny. The most serious potential issue is the limited mobility bias arising from a low number of switching workers per firm found in most real-world datasets (Andrews et al. (2008)). It has been shown that this yields an upward bias in the variance of firm effects and a downward bias in the covariance between firm and worker fixed effects. However, recent research such as Bonhomme et al. (2023) find little bias in the contribution of the components of variance to the change in total variance over time which is the focus of this paper. It is in this spirit, of explaining change in inequality over time, that the AKM model has been used in recent years e.g. Card et al. (2013), Alvarez et al. (2018), Song et al. (2019) and Haltiwanger et al. (2022a)[26].

Using Equation (7) variance of annual earnings in a given interval can be decomposed into variance of worker effects, variance of firm effects, variance of observable time-variant characteristics, their covariances and variance of residuals. This can be expressed as ((hereafter dropping the superscript for interval p):

$$\begin{aligned} Var(y_t^{i,j,s}) = \; & Var(\theta^i) + Var(\psi^{j,s}) + Var(X_t^i\beta) \\ & + 2Cov(\theta^i, \psi^{j,s}) + 2Cov(\theta^i, X_t^i\beta) \\ & + 2Cov(\psi^{j,s}, X_t^i\beta) + Var(\epsilon_t^{i,j,s}) \end{aligned} \tag{8}$$

As mentioned above, we are mainly interested in how much of the increase in overall earnings variance can be accounted for by changes in the size of individual components in equation (8).

Song et al. (2019) combine the AKM framework with decomposition of variance into between firm and within firm components. They show that between firm variance consists of three parts: i) dispersion of firm fixed effects (pay premia) across firms; ii) sorting of workers across firms (given by covariance of firm effects with worker effects and time-variant characteristics); and finally iii) segregation which reflects how similar workers are within firms. Within-firm variance then consists of variance of worker effects and time-variant characteristics within firm, their covariance within firm and variance of residuals.

We follow Haltiwanger et al. (2022a) in extending this variance decomposition to account

[26]This implicitly assumes that biases are similar across intervals.

separately for dispersion between industries and between firms within industries. In this case within-firm components of variance remain the same as in Song et al. (2019), but the dispersion of firm effects, sorting and segregation are each separated into their between-sector and between-firm-within-sector components as shown in (9):

$$
\begin{aligned}
Var(y_t^{i,j,s}) = {} & \underbrace{Var(\bar{\psi}^s)}_{between-sector\ pay\ premia} + \underbrace{2Cov(\bar{\psi}^s, \bar{\theta}^s) + 2Cov(\bar{\psi}^s, \bar{X}^s\beta)}_{between-sector\ sorting} \\
& + \underbrace{Var(\bar{\theta}^s) + Var(\bar{X}^s\beta) + 2Cov(\bar{\theta}^s, \bar{X}^s\beta)}_{between-sector\ segregation} + \underbrace{Var(\psi^{j,s} - \bar{\psi}^s)}_{between-firm\ within-sector\ pay\ premia} \\
& + \underbrace{2Cov(\bar{\theta}^{j,s} - \bar{\theta}^s, \bar{\psi}^{j,s} - \bar{\psi}^s) + 2Cov(\bar{\psi}^{j,s} - \bar{\psi}^s, \bar{X}^{j,s}\beta - \bar{X}^s\beta)}_{between-firm\ within-sector\ sorting} \\
& + \underbrace{Var(\bar{\theta}^{j,s} - \bar{\theta}^s) + Var(\bar{X}^{j,s}\beta - \bar{X}^s\beta) + 2Cov(\bar{\theta}^{j,s} - \bar{\theta}^s, \bar{X}^{j,s}\beta - \bar{X}^s\beta)}_{between-firm\ within-sector\ segregation} \\
& + \underbrace{Var(\theta^i - \bar{\theta}^{j,s}) + Var(X_t^i\beta - \bar{X}_t^{j,s}\beta) + 2Cov(\theta^i - \bar{\theta}^{j,s}, X_t^i\beta - \bar{X}_t^{j,s}\beta) + Var(\epsilon_t^{i,j,s})}_{within-firm\ person\ effect,\ observables,\ their\ covariance\ and\ residual}
\end{aligned} \tag{9}
$$

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

Between-sector sorting is defined as $2Cov(\bar{\psi}^s, \bar{\theta}^s) + 2Cov(\bar{\psi}^s, \bar{X}^s\beta)$. This captures the extent to which highly-paid workers are employed in sectors with a high average pay premium. We distinguish this from between-firm within-sector sorting given by $2Cov(\bar{\theta}^{j,s} - \bar{\theta}^s, \bar{\psi}^{j,s} - \bar{\psi}^s) + 2Cov(\bar{\psi}^{j,s} - \bar{\psi}^s, \bar{X}^{j,s}\beta - \bar{X}^s\beta)$. This reflects the degree to which workers who have high earnings ability relative to the average of that sector tend to work in firms which pay relatively high pay premiums for that sector.

Between-sector segregation is given by $Var(\bar{\theta}^s) + Var(\bar{X}^s\beta) + 2Cov(\bar{\theta}^s, \bar{X}^s\beta)$. This captures the extent to which high-paid workers work together with other high-paid workers in the same industry rather than working with low-paid workers. The greater the differences in average worker fixed effects across industries, the greater is between-sector segregation, as sectors differ more in what kind of workers they employ. Segregation that takes place between firms within sectors is given by $Var(\bar{\theta}^{j,s} - \bar{\theta}^s) + Var(\bar{X}^{j,s}\beta - \bar{X}^s\beta) + 2Cov(\bar{\theta}^{j,s} - \bar{\theta}^s, \bar{X}^{j,s}\beta - \bar{X}^s\beta)$. This again reflects the extent to which within sectors, similar workers (in terms of earnings ability) are grouped together in the same firm.

Finally, within-firm variance is composed of: i) variance of worker effects within firms, $Var(\theta^i - \bar{\theta}^{j,s})$, ii) variance of time-variant characteristics within-firms, $Var(X_t^i\beta - \bar{X}_t^{j,s}\beta)$, iii) covariance between worker effects and time-variant characteristics within-firms, $2Cov(\theta^i - \bar{\theta}^{j,s}, X_t^i\beta - \bar{X}_t^{j,s}\beta)$, and iv) variance of residuals, $Var(\epsilon_t^{i,j,s})$[27]. Now that we have completed the exposition of our empirical framework, we can proceed to analyse the results of our AKM-based variance decompositions.

4.2 Implementing AKM Model

In order to implement the two-way fixed effects model of (7) we create five seven-year panels from the universe of social security records, in each keeping one observation per worker in a given year, summing earnings across all job spells in a year, and allocating worker to the firm that is the most significant source of earnings in that seven-year interval. We apply the same sample restrictions as in the previous descriptive analysis that are set out in Section 2. Subsequently, we create the largest connected set (set of firms and their workers connected by worker flows) within each panel. This results in 33.9 million worker-year observations

[27]Full decomposition of variance of earnings also includes covariance of residuals with worker effects and with time-variant characteristics, $2Cov(\theta^i - \bar{\theta}^{j,s}, \epsilon_t^{i,j,s})$ and $2Cov(X_t^i\beta - \bar{X}_t^{j,s}\beta, \epsilon_t^{i,j,s})$. However, the estimated residual from 7) is by design orthogonal to worker effects and time-variant characteristics, so these two covariances are equal to zero which we also confirm empirically.

in the 1985-1991 panel and 59.0 million observations in the 2013-2019 panel (Table 13). The number of workers is 6.9 and 11.4 million and the number of firms is 162 and 300 thousand respectively. By restricting to the largest connected set we only lose less than 1% of observations.

4.3 Results of AKM-based Decompositions

Table 13 shows results of the simple AKM variance decomposition given by (8) 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.

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 pay 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. 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[28]. This is the same as the finding of Song et al. (2019) for the USA[29]. 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.

Table 14 displays results of industry-enhanced AKM variance decomposition given by (9), for the first (1985-1991) and the last interval (2013-2019) and the change over time. We use 4-digit industries as in Section 3. We can see that of the increase in total variance of log annual earnings between the first and the last interval (0.081), 60.5% is accounted for by the rising between-sector variance, 33.3% is accounted for by the rising between-firm-within-sector variance and just 7.4% is due to rising within-firm variance. Thus, when comparing the first and the last interval, instead of the first and the last year (as in Section 3), the results are even stronger. More than 90% of the growth in earnings inequality took place between firms and a clear majority took place between industries. The contribution of industry is virtually the same as in Haltiwanger et al. (2022a) (60.5% vs 61.9%).

Of the 60.5% contribution of between-sector variance, 30.5% is due to sorting and 34.3% is due to segregation, while variance of sector pay premiums (average firm effects) declined and has a negative contribution of -4.7%. Thus, the majority of the rise in Italian earnings inequality is due to an increase in sorting of highly paid workers to high-pay industries

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

[29]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.

and due to increasing differences in average worker quality across industries (measured by average worker fixed effect), as highly-paid workers are more likely to work with each other. Equivalently, workers with low earnings ability (small worker fixed effect) are more likely to work with other low-income workers in the same industry, such as Food and beverage service activities (56) and they are more likely to work in industries with particularly low firm premia. Thus the rising between-sector variance is entirely due to changing allocation of workers across industries and not due to firm wage policies becoming more different across industries.

The 33.3% contribution of between-firm-within-sector variance consists of a large 39.1% contribution of sorting, a small 5.8% contribution of segregation and a negative contribution of -12.1% of firm pay premiums. Thus, we can see that increasing positive sorting of workers across firms within sectors plays an important role in driving the rise in earnings inequality, while declining variance of firm fixed effects within industries goes in the opposite direction. It is interesting that while sorting of workers to firms plays an important role both between sectors and between firms within sectors, increasing segregation is a predominantly between-sector phenomenon.

Variance of person effect (worker fixed effect) within firms actually increased significantly and represents 38.8% of the overall rise in earnings inequality. However, this was offset primarily by falling variance of residuals (contribution of -17.3%) and falling variance of time-variant characteristics within firms (-5.1% contribution) and falling covariance between person effect and time-variant characteristics within firms (-9.4% contribution). This is why the within-firm component of variance only accounts for 7.4% of the total increase in earnings variance.

Our findings are in line with the results of Haltiwanger et al. (2022a) who find that increasing industry-level sorting and segregation account for more than half of the total rise in the US earnings inequality. Furthermore, when comparing our results to the findings of Song et al. (2019), we find that sorting and segregation play an even larger role in Italy than in the USA. Song et al. (2019) find that about two thirds of the rise in earnings inequality in the USA was due to total sorting and total segregation. We find that in Italy these two forces account for almost all of the growth in inequality[30].

[30] Total contribution of sorting (combining between-sector and within-sector components) is 69.6%. Total contribution of segregation is 40.1%. Contribution of within-firm variance is just 7.4% and total contribution of variance of pay premiums is -16.8%.

Table 13: AKM variance decomposition

	Interval 1		Interval 5		Growth	
	1985-1991		2013-2019		1 to 5	
	Comp.	Share	Comp.	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 equations (7) and (8) for definitions. 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 14: Industry-enhanced AKM variance decomposition

	Interval 1 1985-1991		Interval 5 2013-2019		Growth 1 to 5	
	Comp.	Share	Comp.	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 (9) for definitions.

5 Weekly earnings vs weeks worked

In this section we investigate how much of the dispersion in log annual earnings is due to differences in how much people work (only being employed part of the year or working part-time), how much is due to differences in the rate of pay and how much is due to the covariance between the rate of pay and quantities of labour supplied. To do this, we exploit a feature of the Italian social security data that the number of weeks worked is known for each job spell and that for part-time job spells the full-time equivalent number of weeks is provided (e.g. if someone 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.

We start our decomposition of annual earnings with the following expression:

$$Y_t^i = W_t^i H_t^i \tag{10}$$

where Y_t^i are total annual earnings of worker i in year t, H_t^i is the total number of FTE weeks worked by worker i in year t, and W_t^i are 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 $W_t^i = Y_t^i / H_t^i$.

Taking log of both sides of (10) we obtain the following:

$$y_t^i = w_t^i + h_t^i \tag{11}$$

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.

Variance of log annual earnings is then given by:

$$Var(y_t^i) = Var(w_t^i) + Var(h_t^i) + 2Cov(w_t^i, h_t^i) \tag{12}$$

Thus, the variance of log annual earnings in a given year, $Var(y_t^i)$, is composed of: 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.

Table 15 shows results of this decomposition. The most striking result is that the main driver of the increase in variance of log annual earnings is actually the rising positive covariance between weekly earnings and weeks worked in the year. The covariance term, $2Cov(w_t^i, h_t^i)$, increased from 0.027 in 1985 to 0.086 in 2018. This increase of 0.059 represents 61.5% of the increase in variance of log annual earnings. In contrast, variance of log of full-time equivalent weeks worked in a year, $Var(h_t^i)$, fell from 0.168 in 1985 to 0.158 in 2018. This decline of -0.01 is equivalent to 10% of the total increase in annual earnings variance. Variance of log weekly earnings, $Var(w_t^i)$, increased substantially from 0.159 to 0.205. This increase of 0.046 accounts for 47.9% of the growth in annual earnings variance. Thus, the two drivers of rising annual earnings inequality in Italy between 1985 and 2018 are growing inequality in the rate of pay and 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).

We can also see from Table 15 that at the start of our period, in 1985, the covariance term was a relatively small share of the variance of log annual earnings, at just 7.6%, and that variance of log weekly earnings and of log weeks worked had roughly similar importance, with variance shares of 45.0% and 47.6%. However, by 2018, the covariance term represents 19.2% of log annual earnings variance and variance of log weekly earnings represents 45.7%, while the variance share of log weeks worked falls to just 35.2%.

Figures 8(a)-8(d) display evolution of individual components of the decomposition in (12) over time. Figure 8(a) shows that variance of log annual earnings is rising throughout the 1985-2018 period, with the exception of a brief slowdown around the year 2000. From

Table 15: 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%

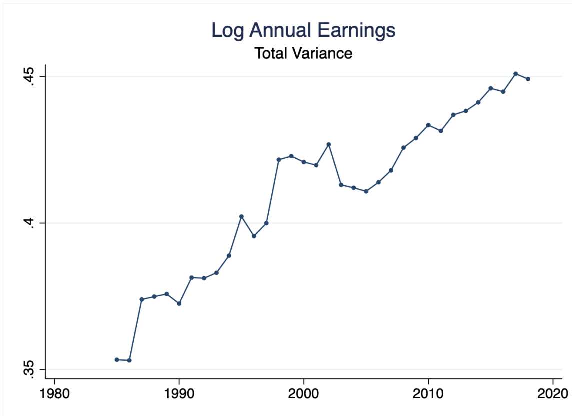
(b) Variance shares

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

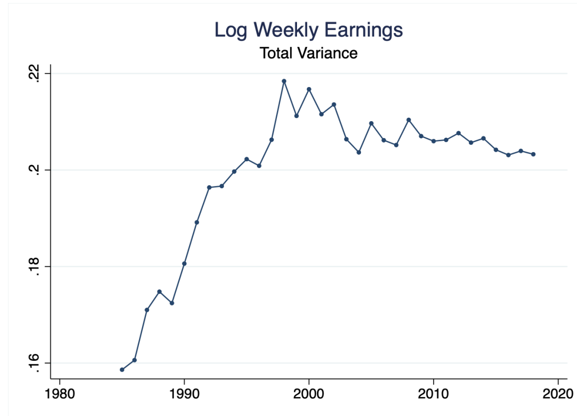
Figure 8(b) we can see that variance of log weekly earnings was rising sharply from 1985 until around 2000 and it has plateaued since. This is in line with the findings of Devicienti et al. (2019) who suggest that Italian wage inequality was growing fast in the second half of 1980s and in 1990s and has been flat since 2000. However, we show that inequality of annual earnings has continued to increased at a fast pace in the last two decades. Our decomposition can explain why. Figure 8(c) shows that variance of log of (FTE) weeks worked in a year decreased slightly over the 1985-2018 period. However, it actually reached the lowest point around 2005 and has been growing since then, reversing some of the decline in previous years. However, when we plot all three components of annual earnings in the same graph, as in Figure 8, we see that changes in the dispersion of labour supply quantities were quite small relative to the other components and that this variance was roughly flat over the period that we consider. Finally, Figure 8(d) shows the steep rise in the covariance between weekly earnings and weeks worked that is particularly pronounced in the period after 2000.

Thus, it seems that the main driver of rising inequality of annual earnings in the 1985-2000 period was rising inequality in the rate of pay, while in the 2000-2018 period the main driver was 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.

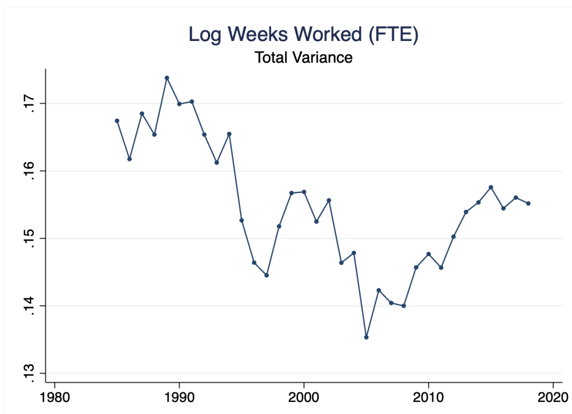
Figure 7: Decomposing annual earnings into weeks worked (full-time equivalent) and average weekly earnings



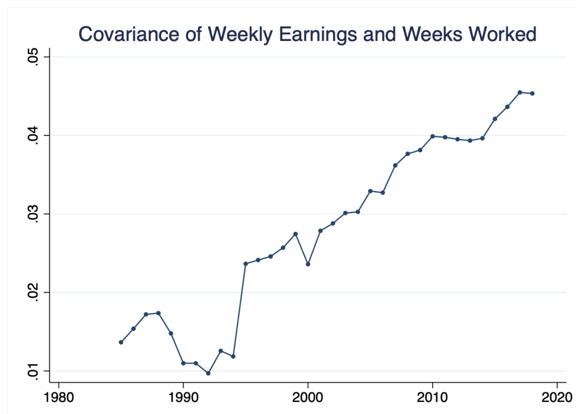
(a) Variance of log annual earnings



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



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

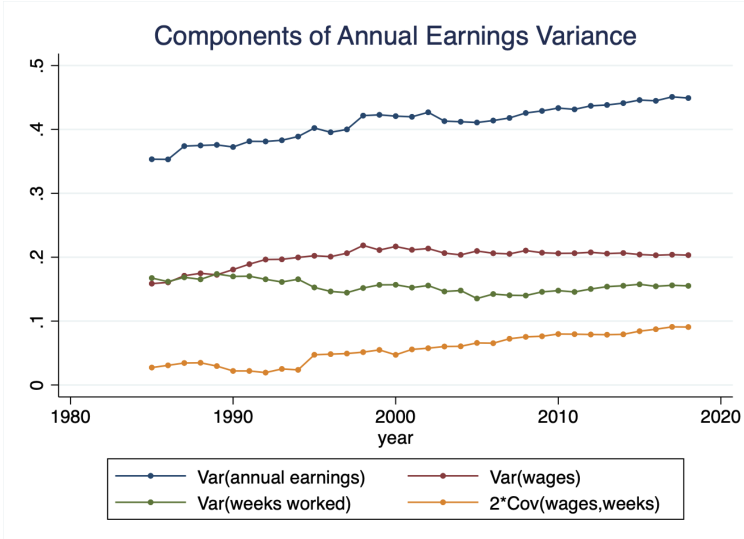


(d) Covariance between log of weeks worked (FTE) and log average weekly wages

Next, we perform decomposition into the between-sector, between-firm-within-sector and within-firm components for variance of weekly earnings (Table A13 and Figure A8), variance of weeks worked (Table A14 and Figure A9) and covariance of weekly earnings and weeks worked (Table A15 and Figure A10).

We learn that 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

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



component and 38.3% by the within-firm component. Thus the majority of the rise in Italian wage inequality did take 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. Thus the majority of the rise in the positive association between the average rate of pay and how much individuals work took place between industries. Increasingly, those sectors that employ workers for only a part of the year also offer low rate of pay. We can see this growing positive association between the rate of pay and labour supply at industry level on Figure 9, comparing 1985 and 2018.

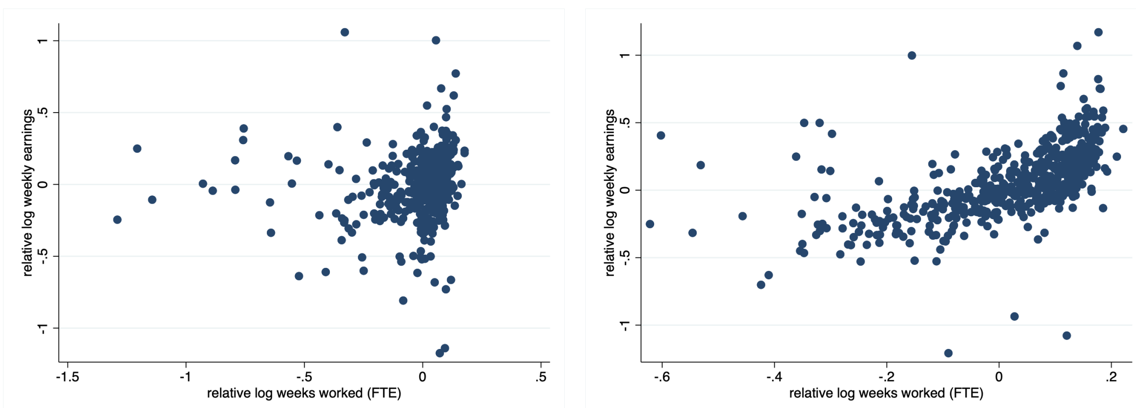
We know that the between-sector variance of annual earnings increased by 0.053 between 1985 and 2018 (Table 4). We now learn that this consisted of an increase in between-sector variance of weekly earnings of 0.017 and an increase in the between-sector covariance component of 0.034. In contrast, between-sector variance of weeks worked was roughly constant with an increase of just 0.001[31]

We saw earlier that the between-sector variance of annual earnings was growing both in

[31] Thus these components sum approximately to the increase in between-sector variance of annual earnings.

1985-2000 and 2000-2018 intervals (Table 5). We can see from Figures A8, A9, and A10 that during the 1985-2000 period, rising annual earnings dispersion between industries was driven by both a rising wage inequality between industries, and by a rising positive association between wage rates and labour supply quantities across industries. However, in the 2000-2018 period, both wage rate dispersion and labour supply dispersion across industries had no overall trend, and the rise in annual earnings dispersion across industries was driven purely by the rising between-sector covariance of the rate of pay and labour supply quantities. Hence, average rates of pay and average weeks worked at industry level were changing in the direction of greater positive association, but in a way where their variance was remaining roughly constant.

Figure 9: 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.

Finally, we investigate whether the large falls in relative annual earnings of the key inequality-increasing industries (that we identify in section 3.5) were mainly due to falling relative rate of pay or falling relative labour supply quantities in those industries. Table 16 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.

Table 16: Top 14 (4-digit) sectors in terms of increasing between-sector variance

4 digit NACE code	Industry title	Relative log weekly earnings 1985	2018	Relative log weeks worked 1985	2018	Relative log annual earnings 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

6 Discussion of the results

To sum up the main findings of the paper, we find that despite very little growth in average real earnings, there has been a substantial increase in the dispersion of annual earnings in Italy. The majority, specifically 55%, of the rise in earnings inequality in Italy between 1985 and 2018 took place between industries. Furthermore, the growth in earnings dispersion across industries was very concentrated, with a small fraction of industries playing a disproportionate role. These were mainly low-paying service sectors related to food and drink, accommodation, social care, cleaning of buildings and work agencies. These key industries were contributing towards greater inequality both by becoming much larger as a share of total employment, as well as by their average earnings falling relative to the economy average. The large declines in average annual earning of these sectors were mainly due to falling average rate of pay, and not due to falling labour supply quantities.

We find that the increase in earnings inequality was mainly driven by changes in the allocation of workers across industries, with the variance of firm pay premiums actually slightly declining. 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 premia (between-sector sorting).

Annual earnings depend on both how much an individual works over the year and the rate of pay that the individual receives. We find that the dispersion in labour supply quantities across workers has remained broadly constant in Italy, and the growth in inequality of annual earnings has been driven by rising variance of wage rates and in particular, by rising positive association between the rate of pay and how much individuals work. More than half of this rising association takes place between industries. Increasingly, sectors that employ workers part-time or for only a part of the year also offer low rate of pay.

We believe that the best candidate in accounting for the patterns above are shifts in industry-level labour demand, driven by structural transformation, trade or Routine-Biased Technical Change (RBTC). The falling pay and rising employment in the key low-skill service sectors can be explained as a combination of an increase in labour demand and an even larger increase in labour supply in these sectors, as workers move there from declining sectors and there are relatively little barriers to entry. It is possible that import substitution or international outsourcing reduced demand for certain tradable goods (e.g. manufacturing), while the key low-paying industries are all non-tradable service sectors. Structural change where employment falls in manufacturing and rises in services, including in low-skill low-paying services, is also consistent with the observed patterns. Within the context of the RBTC theory, jobs in our key low-paying industries would be categorised as manual non-routine jobs that cannot be easily automated (Autor and Dorn (2013)).

RBTC theory 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 highly skilled creative work (Autor et al. (2003)). Therefore demand for both the lowest and highest-paid occupations should increase, whereas demand should fall for those occupations with a medium level of pay which mainly involve skilled, but repetitive tasks (Autor et al. (2006)). A prediction of the theory is employment polarization, where the employment share of low-skilled jobs and very high-skilled jobs rises, while the share of employment in middle-skill occupations falls (Goos and Manning (2007),Goos et al. (2014)). There is of course a great deal of overlap between occupations and industries, with low-paying industries employing mainly low-paying occupations. Hence if these technological forces were operating in Italy, we might find employment polarization in terms of industries.

We investigate the issue of polarization in our data. Figure 10 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 is those with the highest earnings.

The main pattern that stands out from Figure 10 is that there was a very large decline in the employment share of the 4th quantile and a very large increase in the 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 polarization, 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 the employment share of industries between the 40th and 80th percentile fell, while the employment share of industries below the 40th percentile and also those above the 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 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

Figure 10: Changes in employment shares by industry quantiles (ranked by mean earnings in 1985)

be explained by the fact that there are very low barriers of entry to employment in these industries in terms of required formal qualifications.

Additionally, some role was almost certainly played by domestic outsourcing. Let's take the cleaning sector as an example. 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 company that is a subcontractor to this firm. We can see from Table 9 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 also 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. Thus domestic outsourcing could explain some of the changes in both employment shares and the average rate of pay of different industries.

Additionally, domestic outsourcing can also explain changes in the patterns of allocation of workers across industries that we observe. Let's take the example of the cleaning sector again. If all cleaning jobs are moved to the cleaning industry, this will increase between-sector segregation. These outsourced workers with low earnings ability will thus be working in the same industry with other similar low-income workers. The original industries are also becoming more homogeneous in terms of their workforce. On the other hand, the gaps in average worker fixed effects across industries are becoming larger. Additionally, the outsourced cleaners would be moving to an industry with particularly low average pay premiums. This is increasing the extent of between-sector sorting, as workers with low personal component of pay are increasingly working in sectors with low firm pay premiums.

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. (2022a) results for the USA, given that there are enormous differences between the two countries in the way that wages are set. We take this as suggestive evidence that the underlying forces were likely similar.

In Italy industry-level country-wide collective agreements specify obligatory minimum wages for each occupation or job title ("livelli di inquadramento")[32]. Job titles are defined

[32] 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.

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)[33]. Overall, over 90% of workers in Italy are covered by collective agreements (Visser 2016)[34]. 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[35]. While firms in Italy cannot pay below the wages set at the 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[36]. 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

[33] However, the mapping of collective agreements to industries is not simple, some industries have multiple collective agreements and sometimes a single collective agreement covers multiple industries (Fanfani 2019).

[34] Collective agreements apply to all workers in the covered firms irrespective of the union membership status (Devicienti et al. 2019).

[35] Furthermore, firms cannot downgrade workers to lower-paid job titles, as workers can only move up in the firm's hierarchy (Fanfani 2019).

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

supply at the industry level were likely reflected in the bargained wages. It is possible, as Devicienti et al. (2019) suggest, that the system of collective bargaining had some degree of control over the overall increase in wage inequality. This is consistent with our 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[37].

7 Conclusion

It has been shown that the majority of the rise in earnings inequality in high income countries took place between firms, rather than within firms. Increasingly, some firms pay little and some firms pay a lot (Song et al. (2019)). This paper investigates whether earnings inequality is growing mainly between firms in the same industry, or between firms in different industries. This question is important for understanding whether drivers of inequality operate at the level of industries, or they are related to firm heterogeneity within industries. Using data covering the universe of private sector employment in Italy we find that between-industry variance was the dominant source of earnings inequality growth. Specifically, of the total increase in log annual earnings variance in Italy between 1985 and 2018: 55% took place between industries, 18% between firms within the same industry and 27% within firms. Furthermore, the growth in earnings dispersion across industries was very concentrated, with a small fraction of industries playing a disproportionate role. These were mainly low-paying service sectors and they contributed towards greater inequality both by growing their employment share and by their average rate of pay falling relative to the economy average.

We find that 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 what kind of workers they employ and due to an increase in sorting. Workers

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

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 premia (between-sector sorting).

The patterns of rising inequality of annual earnings that we identify for Italy are remarkably similar to the ones found by Haltiwanger et al. (2022a) for the USA. This is despite very large differences in institutions, particularly related to wage bargaining, between the two countries. We take this as suggestive evidence that the underlying forces were likely similar. The patterns that we find are consistent with shifts in industry-level labour demand, driven by structural transformation, trade or Routine-Biased Technical Change, further complemented by domestic outsourcing.

Unlike Song et al. (2019) and Haltiwanger et al. (2022a), in addition to earnings, we have information on how much individuals work over the year. This enables us to quantify the roles of average rate of pay, labour supply quantities and their covariance to the change in inequality of annual earnings. We find that the dispersion in labour supply quantities across workers has remained broadly constant in Italy, despite significant labour market reforms that introduced more flexibility in hiring. The growth in inequality of annual earnings has been driven by rising variance of wage rates and in particular, by rising positive association between the rate of pay and how much individuals work. More than half of this rising covariance takes place between industries. Increasingly, sectors that employ workers part-time or for only a part of the year also offer low rate of pay. It seems that relative wage rates have declined precisely in those industries where people tend to work more casually (e.g. restaurants, bars, hotels). This then amplified the effect of rising wage inequality on inequality of annual earnings. Our findings highlight the importance of studying inequality in wage rates, labour supply and their covariance separately.

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8 Appendix A

8.1 Controlling for 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.

$$w_{ijs} = \sum_{s=1}^{s=S} \beta_s D_s + \epsilon_{ijs}, \tag{13}$$

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:

$$\underbrace{\frac{1}{N}\sum_{\forall i}(\epsilon_{ij} - \bar{\epsilon})^2}_{\text{within-sector variance}} = \underbrace{\sum_{\forall j} \frac{n_j}{N}(\bar{\epsilon_j} - \bar{\epsilon})^2}_{\text{between-firm-within-sector variance}} + \underbrace{\sum_{\forall j} \frac{n_j}{N} \frac{\sum_{\forall i|i \in j}(\epsilon_{ij} - \bar{\epsilon_j})^2}{n_j}}_{\text{within-firm variance}}, \tag{14}$$

where ϵ_{ij} is the residual from (13) 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 (13) 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 (13) 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 (13). The demeaned observations are then used to calculate (14).

Table A1: Between versus within firm variance decomposition for different firm sizes.

(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.

8.2 Tables

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

(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%

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	0.221	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%

Table A4: 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).

Table A5: Haltiwanger et al. (2022a): **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. (2022a).

Table A6: Top 10 (2-digit) sectors in terms of decreasing between-sector variance

4 digit NACE 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 (4) for definitions.

Table A7: Sectors with larger than 1% contribution to the growth of between-sector variance (29 sectors, 4-digit)

4 digit 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%
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 (4) for definitions.

Table A8: Sector contributions to between sector variance growth, by average earnings (2-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 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: Employment shares are calculated as the average of 1985 and 2018 employment shares. See Equation (4) 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 5. 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.

Table A9: Only men: 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	2.8%	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: See Equation (4) for definition of the contribution of a particular sector to between sector variance growth.

Table A10: Only men: Top 10 (2-digit) sectors in terms of increasing between-sector variance

4 digit NACE 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	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: Relative earnings is the gap between average log earnings of a particular industry and the economy average. See Equation (4) for definitions.

Table A11: Only men: 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%	0.031	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: See Equation (4) for definition of the contribution of a particular sector to between sector variance growth.

Table A12: Only men: Top 20 (4-digit) sectors in terms of increasing between-sector variance

4 digit NACE code	Industry title	Employment share 1985	Employment share 2018	Relative earnings 1985	Relative earnings 2018	Share of between sector variance growth
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: Relative earnings is the gap between the average log earnings of a particular industry and the economy average. See Equation 4 for definitions.

Table A13: 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%

Table A14: 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

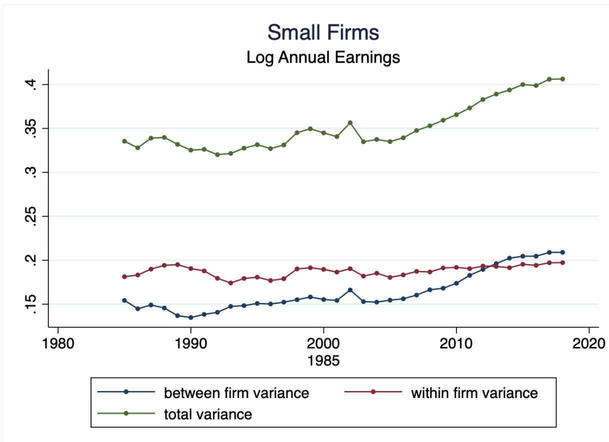
	Between sector	Between firms within sector	Within firm
1985	11.1%	21.1%	67.8%
2018	12.6%	17.5%	69.9%

Table A15: Decomposition of covariance of log weekly earnings and log weeks worked (FTE).

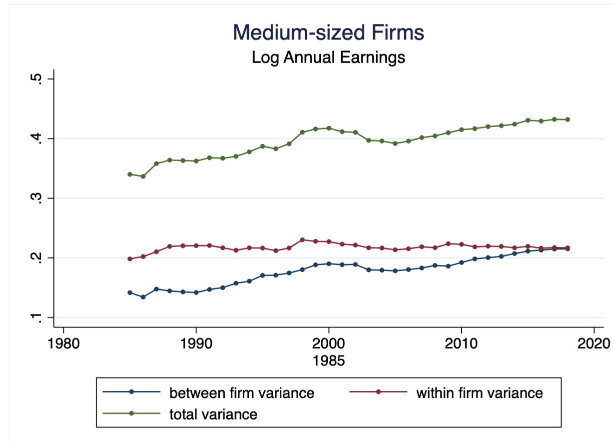
	Total	Between sector	Within sector	Between sector share	Within sector share
1985	0.013	0.010	0.003	74.3%	25.7%
2018	0.043	0.027	0.016	63.4%	36.6%
Change	0.030	0.017	0.012	-	-
% of total increase	100.0%	56.7%	40.0%	-	-

8.3 Figures

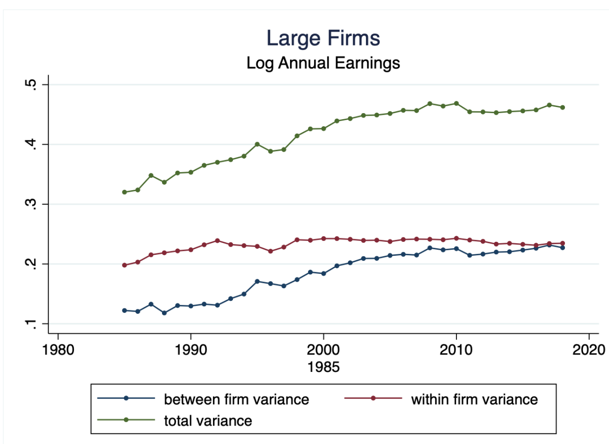
Figure A1: Different firm sizes: between versus within firm variance in Italy 1985-2018 (annual earnings).



(a) Small firms



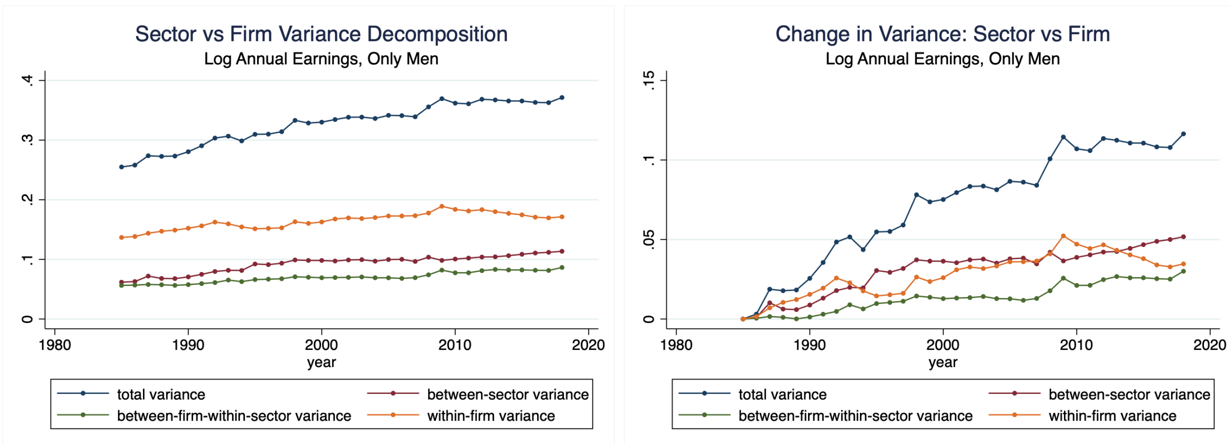
(b) Medium firms



(c) Large firms

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

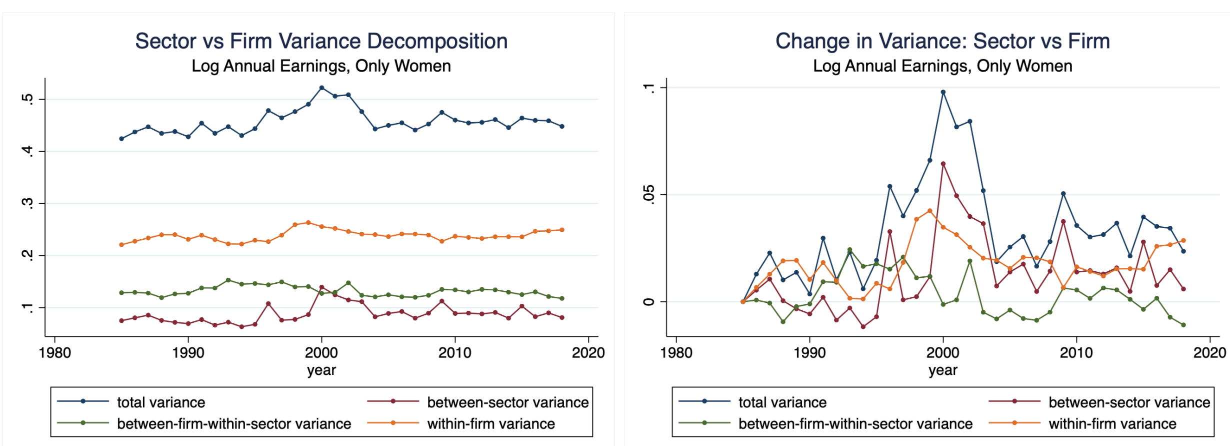
Figure A2: Sector and firm: full variance decomposition. (annual earnings, only men).



(a) Levels

(b) Change Relative to 1985

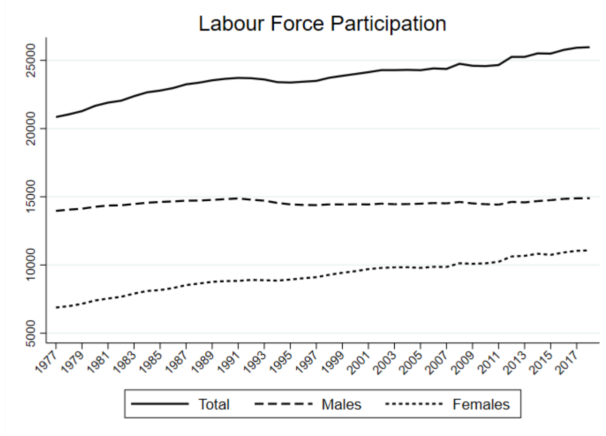
Figure A3: Sector and firm: full variance decomposition. (annual earnings, only women).



(a) Levels

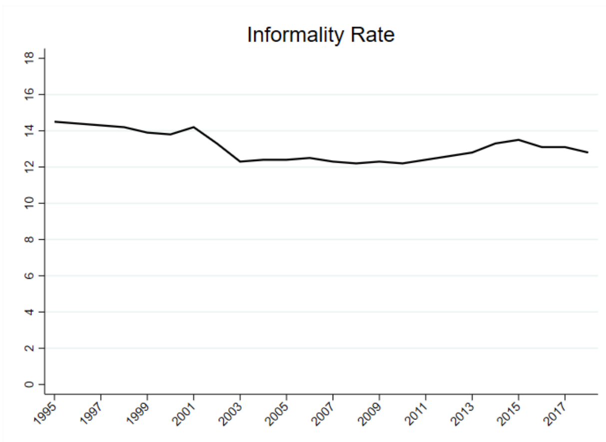
(b) Change Relative to 1985

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

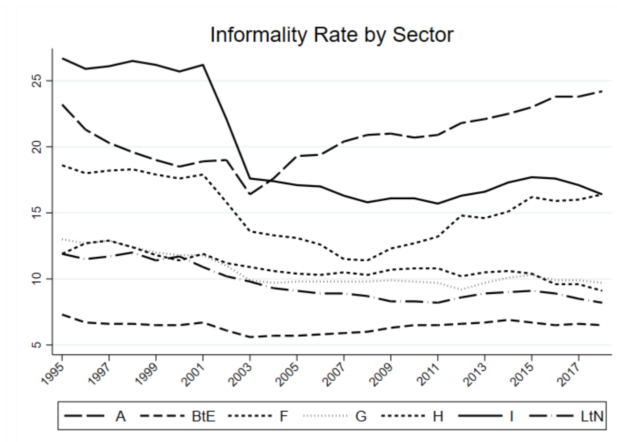


Source: Italian Institute of Statistics.

Figure A5: Informality rate.



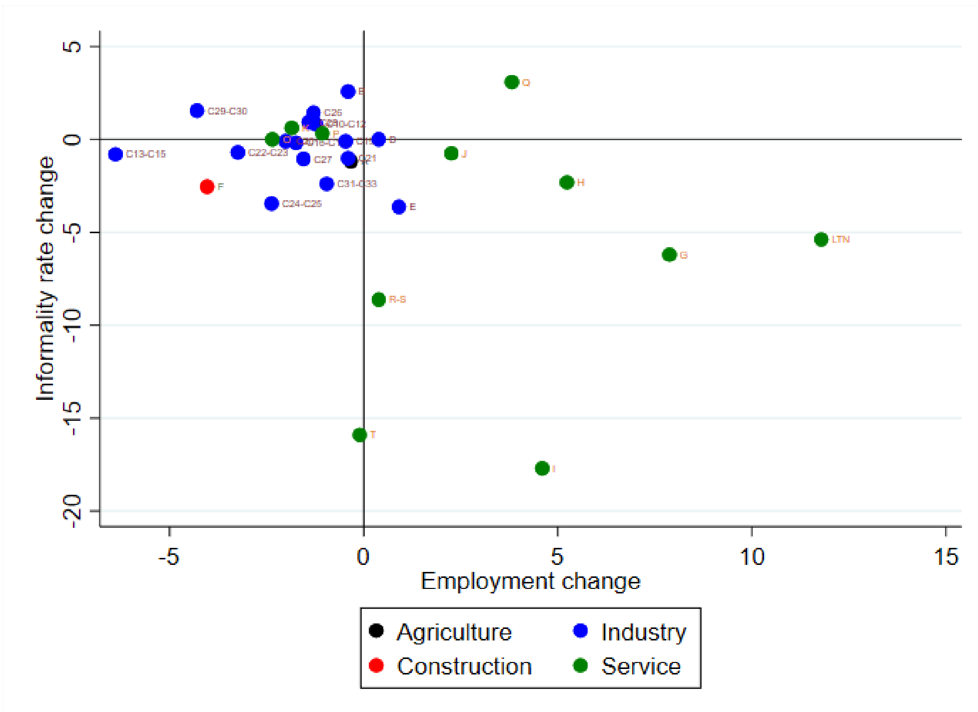
(a) Informality Rate



(b) Informality Rate by Sector

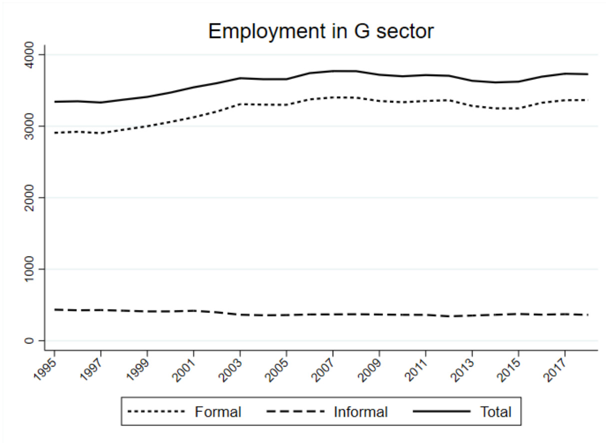
Note: The informality rate is computed as the ratio between employment in the informal sector and total employment. Sectors are classified as: A (agriculture, forestry and fishing), BtE (mining and quarrying, manufacturing, electricity, gas, steam and air conditioning supply, water supply, sewerage, 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: Change in employment and informality rate by sector.

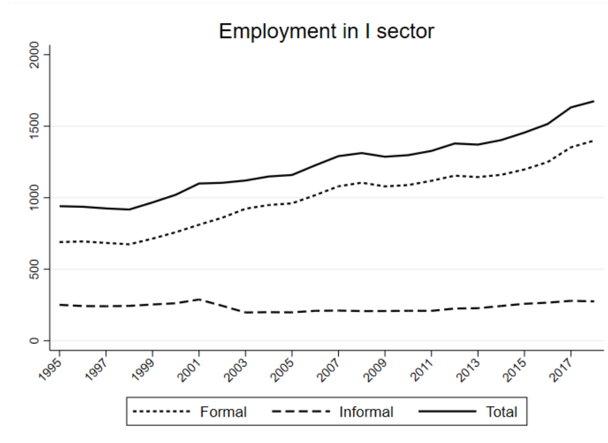


Note: The informality rate change is computed as the change in the informality rate between 1995 and 2018 (first year of data availability). The employment change is the change in the employment share between 1985 and 2018.
Source: Italian Institute of Statistics.

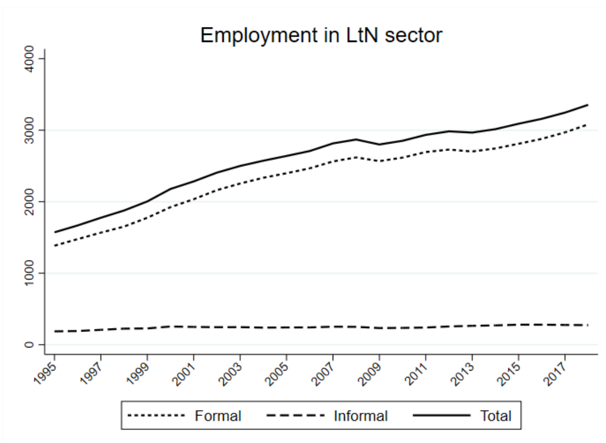
Figure A7: Formal and informal employment by sector.



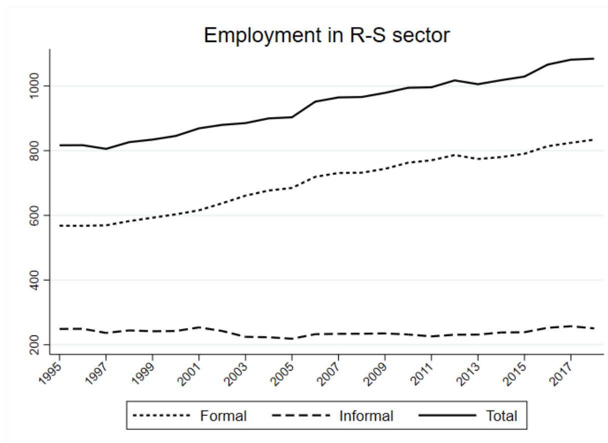
(a) G Sector



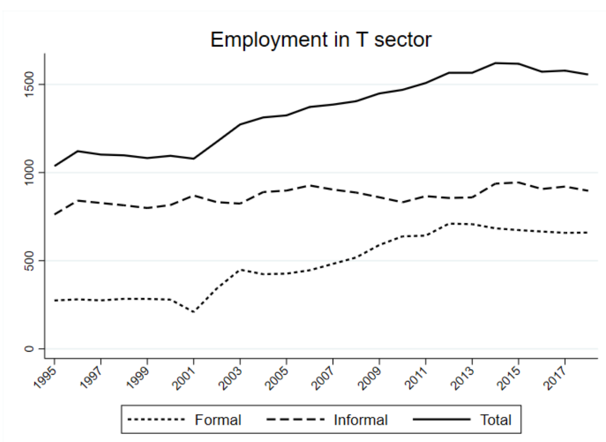
(b) I Sector



(c) LtN Sector



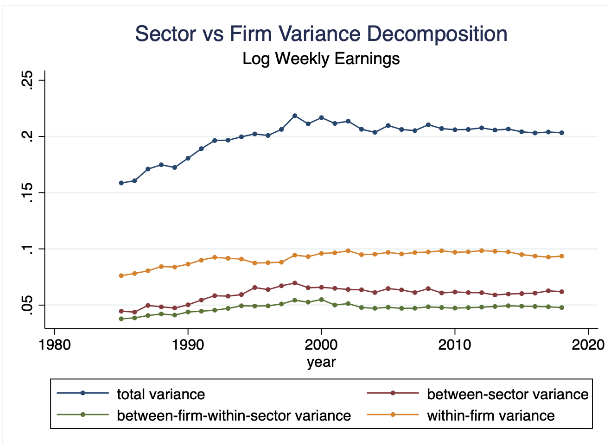
(d) RS Sector



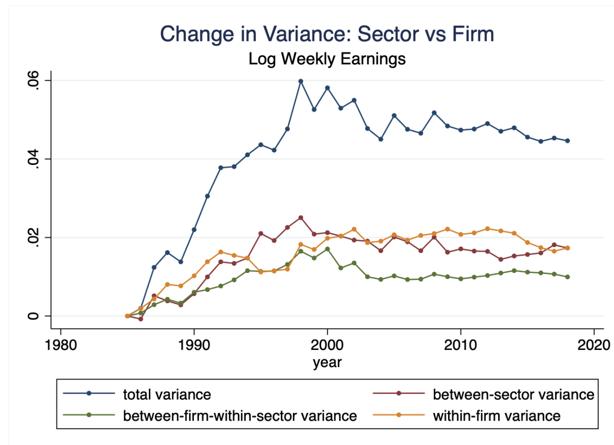
(e) T Sector

Note: Sectors are classified as: 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), R-S (Arts, entertainment and recreation; other services activities), T (Activities of households as employers; undifferentiated goods).
Source: Italian Institute of Statistics.

Figure A8: Decomposition of log weekly earnings.

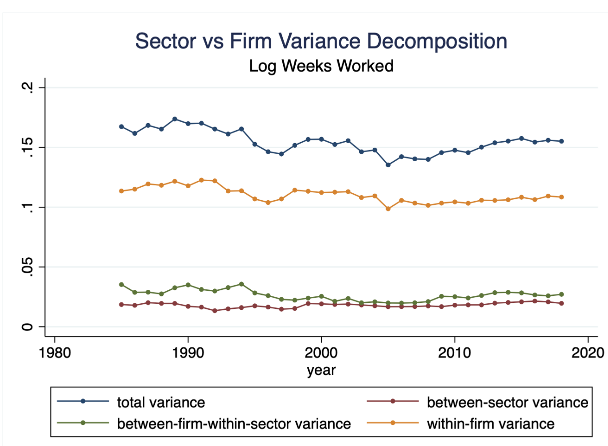


(a) Levels

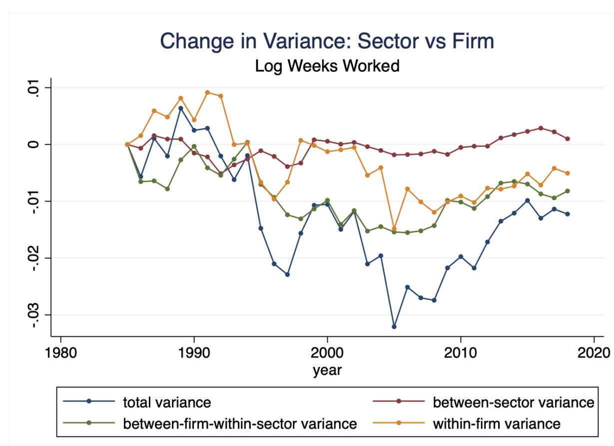


(b) Change Relative to 1985

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

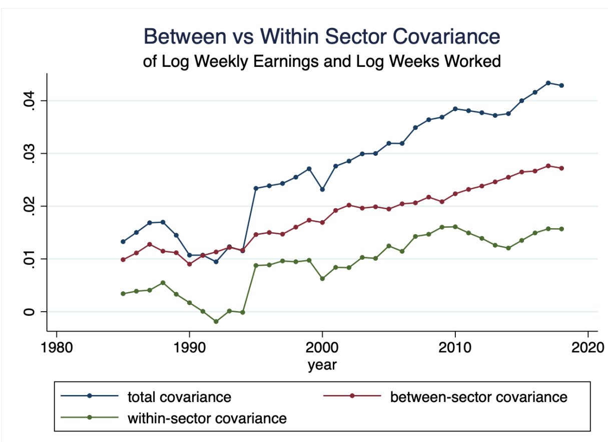


(a) Levels

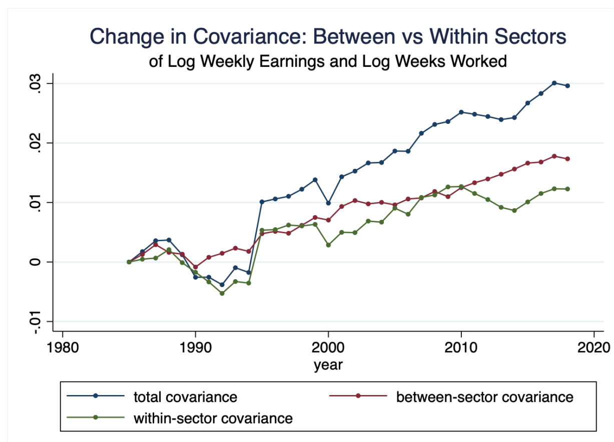


(b) Change Relative to 1985

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



(a) Levels



(b) Change Relative to 1985

9 Appendix B: Online Appendix

9.1 Firm size cutoff of 5 employees

Table B1: Sectors and firms: full variance decomposition (**4 digit sector**, annual earnings).

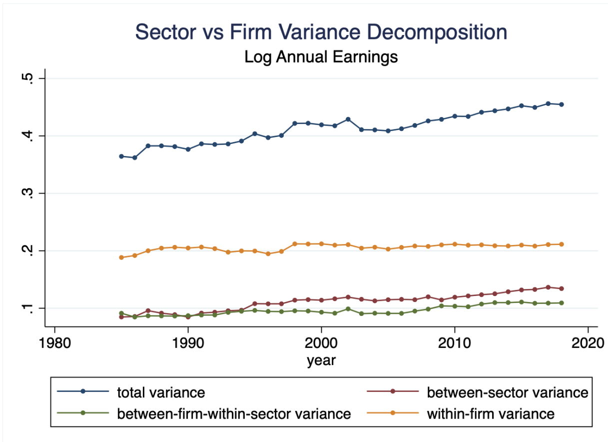
(a) Variance change over time

	Between sector	Between firms within sector	Within firm	Total
1985	0.085	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%

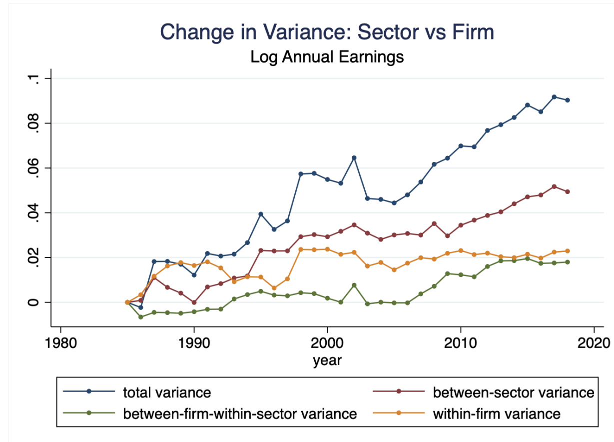
(b) Variance shares

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

Figure B1: Sector and firm: full variance decomposition (annual earnings).



(a) Levels



(b) Change Relative to 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	2.7%	0.033	66.0%
4.8% to 10%	5	11.9%	0.015	30.4%
0.05% to 4.8%	37	46.8%	0.023	46.6%
-0.05% to 0.05%	18	8.8%	0.000	0.0%
< -0.05%	24	29.9%	-0.022	-43.1%
Total	87	100.0%	0.050	100.0%

Note: See Equation (4) for definition of the contribution of a particular sector to between sector variance growth.

Table B3: Top 2-digit sectors in terms of increasing between-sector variance

4 digit NACE 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	1.2%	5.6%	-0.31	-0.60	37.4%
81	Services to buildings and landscape activities	1.5%	3.4%	-0.50	-0.58	15.2%
78	Employment activities	0.0%	4.3%	0.38	-0.40	13.4%
88	Social work activities without accommodation	0.5%	2.4%	-0.22	-0.41	7.7%
28	Manufacture of machinery and equipment n.e.c.	4.1%	2.8%	0.18	0.40	6.3%
33	Repair and installation of machinery and equipment	5.6%	5.2%	0.07	0.25	6.1%
55	Accommodation	1.5%	2.6%	-0.46	-0.48	5.4%
35	Electricity, gas, steam and air conditioning supply	0.3%	0.6%	0.53	0.72	4.8%

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

Table B4: 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%

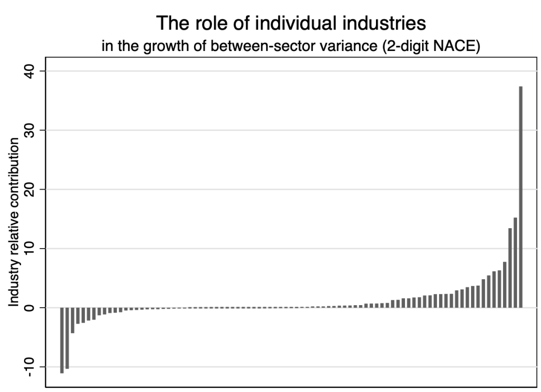
Note: See Equation (4) for definition of the contribution of a particular sector to between sector variance growth.

Table B5: Top 4-digit sectors in terms of increasing between-sector variance

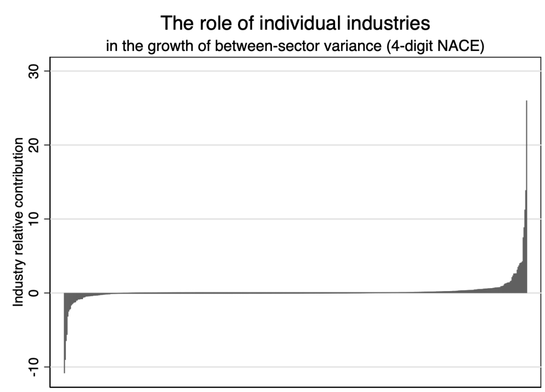
4 digit NACE code	Industry title	Employment share 1985	Employment share 2018	Relative earnings 1985	Relative earnings 2018	Share of between sector variance growth
5610	Restaurants and mobile food service activities	0.5%	3.5%	-0.35	-0.62	26.0%
7830	Other human resources provision	0.0%	4.3%	0.38	-0.39	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 4 for definitions.

Figure B2: 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

Table B6: 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	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 (4) 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 5. 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.

9.2 No firm size cutoff

Table B7: Sectors and firms: full variance decomposition (**4 digit sector**, annual earnings).

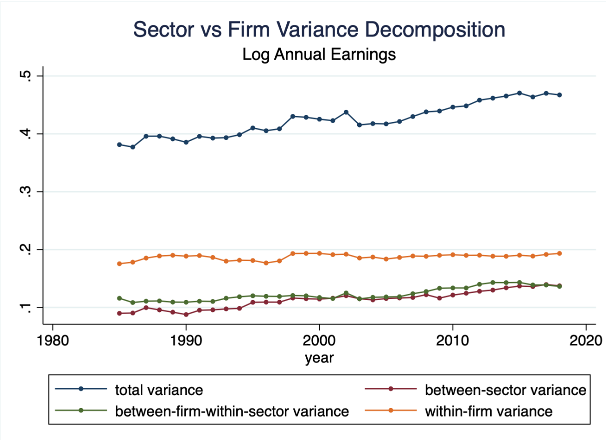
(a) Variance change over time

	Between sector	Between firms within sector	Within firm	Total
1985	0.090	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%

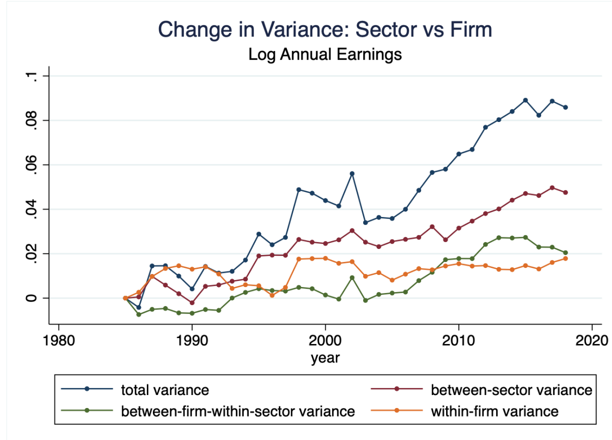
(b) Variance shares

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

Figure B3: Sector and firm: full variance decomposition (annual earnings).



(a) Levels



(b) Change Relative to 1985

Table B8: 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	0.072	0.084	0.090	0.381
2018	0.118	0.130	0.137	0.467
Change	0.046	0.046	0.048	0.086
% of total increase	53.5%	53.5%	55.8%	100.0%

(b) Variance shares

	Between sector		
	2 digit (88 sectors)	3 digit (268 sectors)	4 digit (593 sectors)
1985	18.8%	22.0%	23.6%
2018	25.2%	27.9%	29.4%

Table B9: 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%	2	2.9%	0.026	57.1%
5.1% to 10%	6	10.4%	0.019	41.0%
0.05% to 5.1%	33	44.7%	0.022	46.9%
-0.05% to 0.05%	17	4.2%	0.000	0.1%
< -0.05%	29	37.9%	-0.021	-45.1%
Total	87	100.0%	0.046	100.0%

Note: See Equation (4) for definition of the contribution of a particular sector to between sector variance growth.

Table B10: Top 2-digit sectors in terms of increasing between-sector variance

4 digit NACE 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	1.5%	6.5%	-0.36	-0.59	45.4%
81	Services to buildings and landscape activities	1.4%	3.1%	-0.46	-0.52	11.7%
78	Employment activities	0.0%	3.7%	0.33	-0.33	8.6%
33	Repair and installation of machinery and equipment	5.3%	4.7%	0.09	0.29	7.9%
96	Other personal service activities	0.6%	1.9%	-0.44	-0.49	7.3%
28	Manufacture of machinery and equipment n.e.c.	3.7%	2.5%	0.22	0.45	6.9%
88	Social work activities without accommodation	0.5%	2.1%	-0.22	-0.35	5.2%
35	Electricity, gas, steam and air conditioning supply	0.2%	0.5%	0.58	0.77	5.1%

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

Table B11: 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%

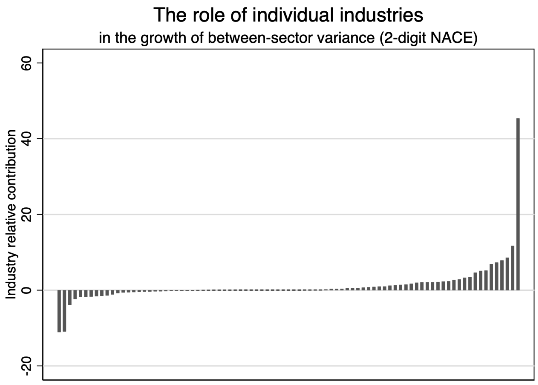
Note: See Equation (4) for definition of the contribution of a particular sector to between sector variance growth.

Table B12: Top 4-digit sectors in terms of increasing between-sector variance

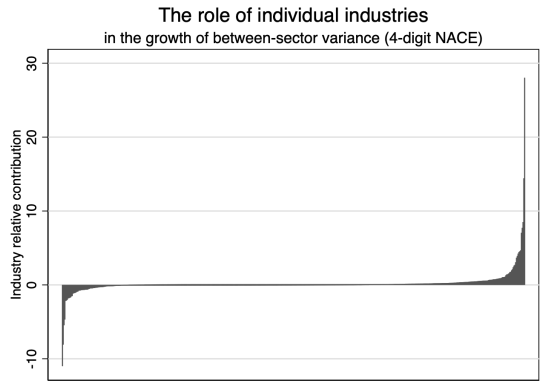
4 digit NACE code	Industry title	Employment share 1985	Employment share 2018	Relative earnings 1985	Relative earnings 2018	Share of between sector variance growth
5610	Restaurants and mobile food service activities	0.7%	3.9%	-0.41	-0.60	28.0%
5630	Beverage serving activities	0.4%	1.9%	-0.43	-0.62	14.4%
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 4 for definitions.

Figure B4: 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

Table B13: 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	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 (4) 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 5. 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.

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

Table B14: Sectors and firms: full variance decomposition (**4 digit sector**, annual earnings).

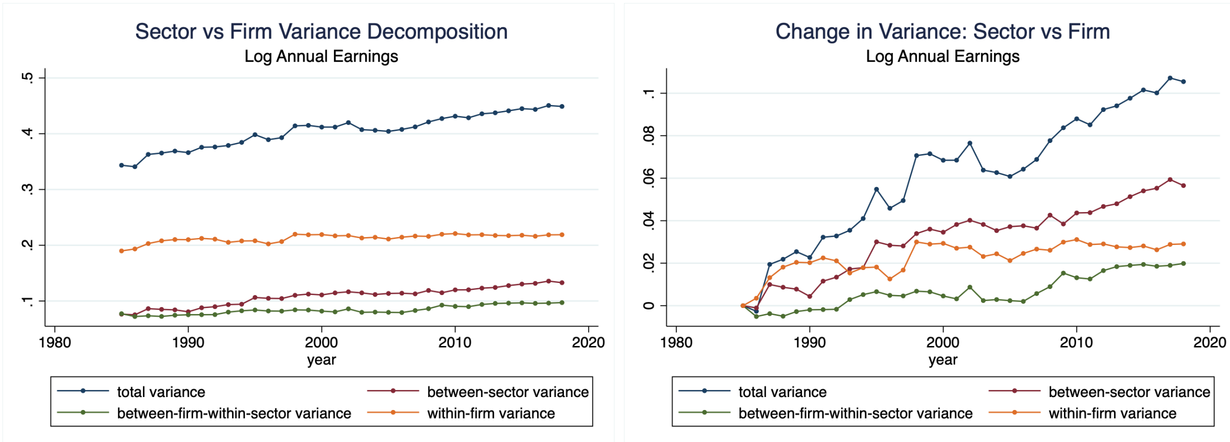
(a) Variance change over time

	Between sector	Between firms within sector	Within firm	Total
1985	0.076	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%

Figure B5: Sector and firm: full variance decomposition (annual earnings).



(a) Levels

(b) Change Relative to 1985

Table B15: 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	0.058	0.071	0.076	0.343
2018	0.117	0.127	0.133	0.449
Change	0.059	0.056	0.057	0.105
% of total increase	56.2%	53.3%	54.3%	100.0%

(b) Variance shares

	Between sector		
	2 digit (88 sectors)	3 digit (268 sectors)	4 digit (593 sectors)
1985	17.0%	20.7%	22.2%
2018	26.1%	28.2%	29.6%

Table B16: 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	2.7%	0.042	71.5%
4.2% to 10%	5	13.1%	0.016	26.6%
0.05% to 4.2%	29	52.4%	0.019	32.9%
-0.05% to 0.05%	7	0.8%	-0.000	-0.0%
$<$ -0.05%	20	31.0%	-0.018	-30.9%
Total	64	100.0%	0.059	100.0%

Note: See Equation (4) for definition of the contribution of a particular sector to between sector variance growth.

Table B17: Top 2-digit sectors in terms of increasing between-sector variance

4 digit NACE 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	1.1%	5.0%	-0.29	-0.61	30.2%
78	Employment activities	0.0%	5.5%	0.39	-0.47	20.8%
81	Services to buildings and landscape activities	1.7%	4.1%	-0.54	-0.64	20.5%
55	Accommodation	1.5%	2.8%	-0.44	-0.52	8.0%
28	Manufacture of machinery and equipment n.e.c.	4.8%	3.3%	0.13	0.35	5.5%
33	Repair and installation of machinery and equipment	6.1%	5.9%	0.04	0.21	4.5%
35	Electricity, gas, steam and air conditioning supply	0.3%	0.8%	0.49	0.66	4.4%
82	Business support activities	0.4%	3.7%	0.22	-0.27	4.2%

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

Table B18: 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%

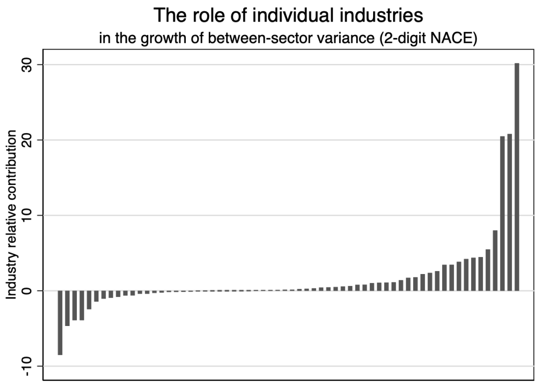
Note: See Equation (4) for definition of the contribution of a particular sector to between sector variance growth.

Table B19: Top 4-digit sectors in terms of increasing between-sector variance

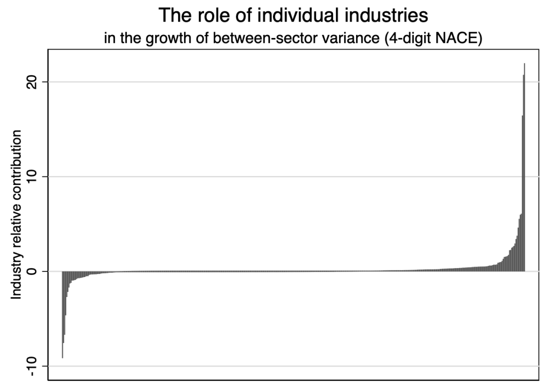
4 digit NACE code	Industry title	Employment share 1985	Employment share 2018	Relative earnings 1985	Relative earnings 2018	Share of between sector variance growth
7830	Other human resources provision	0.0%	5.5%	0.39	-0.47	22.0%
5610	Restaurants and mobile food service activities	0.4%	2.9%	-0.30	-0.63	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 4 for definitions.

Figure B6: 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

Table B20: 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 (4) 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 5. 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.

9.4 Without sectors Accommodation (55) and Food and beverage service activities (56)

Table B21: Sectors and firms: full variance decomposition (**4 digit sector**, annual earnings).

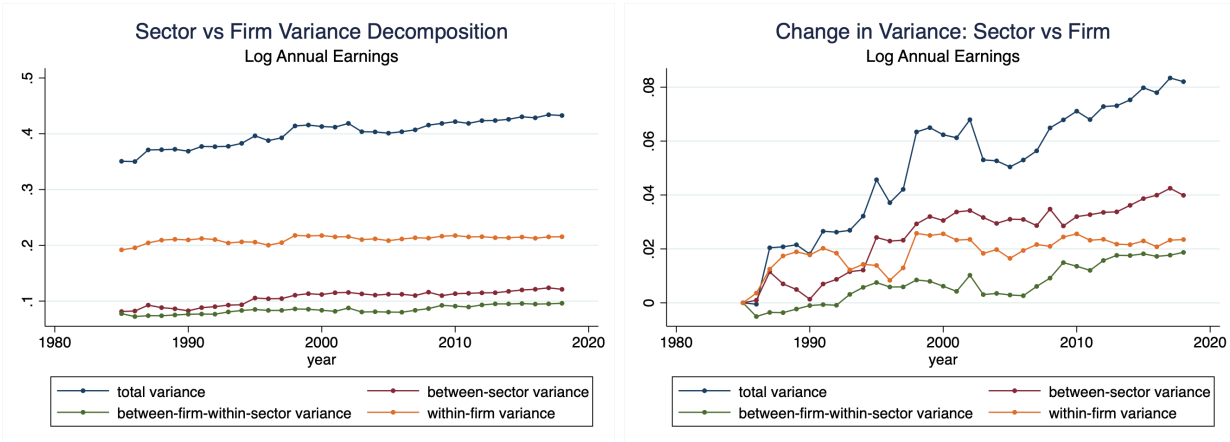
(a) Variance change over time

	Between sector	Between firms within sector	Within firm	Total
1985	0.081	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%

Figure B7: Sector and firm: full variance decomposition (annual earnings).



(a) Levels

(b) Change Relative to 1985

Table B22: 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	0.063	0.076	0.081	0.351
2018	0.104	0.115	0.121	0.433
Change	0.041	0.039	0.040	0.082
% of total increase	50.0%	47.6%	48.8%	100.0%

(b) Variance shares

	Between sector		
	2 digit (88 sectors)	3 digit (268 sectors)	4 digit (593 sectors)
1985	17.9%	21.6%	23.2%
2018	24.1%	26.5%	28.0%

Table B23: 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	2.1%	0.032	76.5%
6.2% to 10%	3	7.8%	0.008	19.2%
0.05% to 6.2%	37	55.0%	0.025	60.7%
-0.05% to 0.05%	12	1.1%	0.000	0.1%
< -0.05%	28	34.0%	-0.023	-56.4%
Total	83	100.0%	0.041	100.0%

Note: See Equation (4) for definition of the contribution of a particular sector to between sector variance growth.

Table B24: Top 2-digit sectors in terms of increasing between-sector variance

4 digit NACE code	Industry title	Employment share 1985	Employment share 2018	Relative earnings 1985	Relative earnings 2018	Share of between sector variance growth
81	Services to buildings and landscape activities	1.6%	4.0%	-0.53	-0.66	30.2%
78	Employment activities	0.0%	5.3%	0.40	-0.48	30.0%
88	Social work activities without accommodation	0.5%	2.9%	-0.22	-0.49	16.3%
28	Manufacture of machinery and equipment n.e.c.	4.5%	3.2%	0.14	0.34	6.6%
82	Business support activities	0.4%	3.6%	0.23	-0.28	6.4%
47	Retail trade, except of motor vehicles and motorcycles	2.9%	9.0%	-0.04	-0.17	6.2%

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

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%	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%

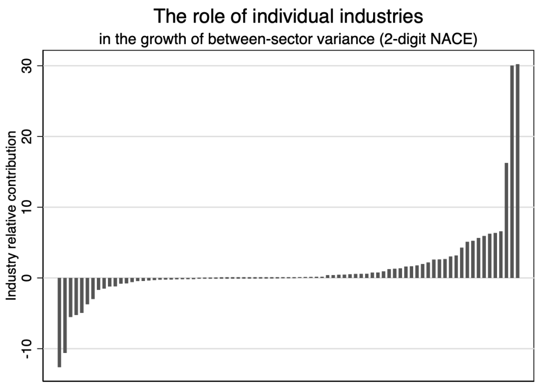
Note: See Equation (4) for definition of the contribution of a particular sector to between sector variance growth.

Table B26: Top 4-digit sectors in terms of increasing between-sector variance

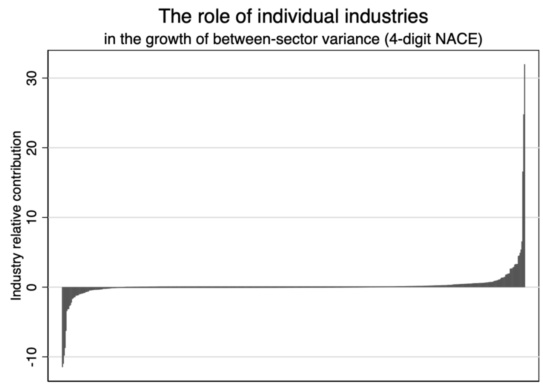
4 digit NACE code	Industry title	Employment share 1985	Employment share 2018	Relative earnings 1985	Relative earnings 2018	Share of between sector variance growth
7830	Other human resources provision	0.0%	5.3%	0.40	-0.48	32.0%
8129	Other cleaning activities	1.5%	3.4%	-0.54	-0.64	24.8%
8899	Other non-residential 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 4 for definitions.

Figure B8: 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

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	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 (4) 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 5. 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.

9.5 Without sector Employment activities (78)

Table B28: Sectors and firms: full variance decomposition (**4 digit sector**, annual earnings).

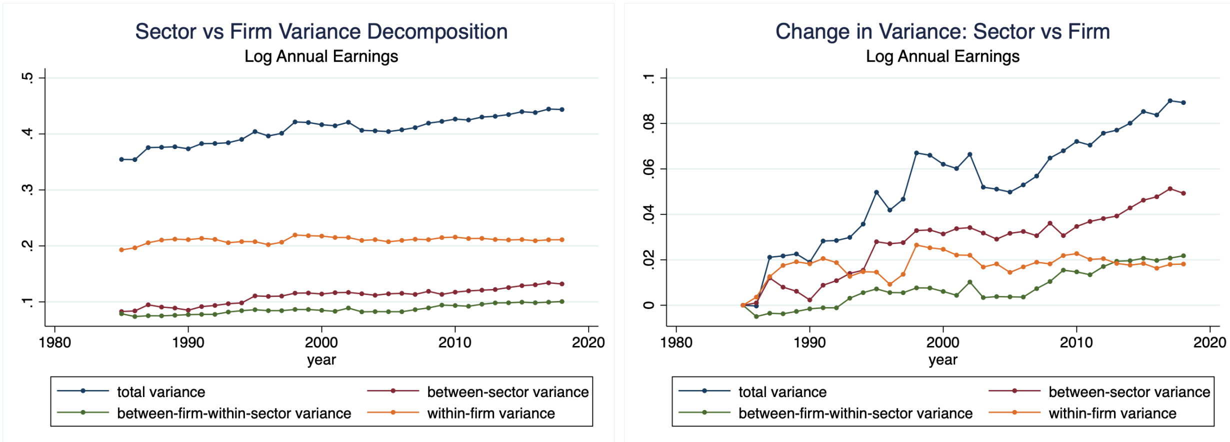
(a) Variance change over time

	Between sector	Between firms within sector	Within firm	Total
1985	0.083	0.079	0.193	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%

Figure B9: Sector and firm: full variance decomposition (annual earnings).



(a) Levels

(b) Change Relative to 1985

Table B29: 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	0.115	0.126	0.132	0.444
Change	0.051	0.048	0.049	0.089
% of total increase	57.3%	53.9%	55.1%	100.0%

(b) Variance shares

	Between sector		
	2 digit (88 sectors)	3 digit (268 sectors)	4 digit (593 sectors)
1985	18.2%	21.8%	23.3%
2018	26.0%	28.3%	29.8%

Table B30: 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	3.0%	0.034	67.3%
4.4% to 10%	5	11.8%	0.015	28.9%
0.05% to 4.4%	36	49.8%	0.024	46.7%
-0.05% to 0.05%	14	2.4%	0.000	0.1%
< -0.05%	26	32.9%	-0.022	-43.0%
Total	84	100.0%	0.051	100.0%

Note: See Equation (4) for definition of the contribution of a particular sector to between sector variance growth.

Table B31: Top 2-digit sectors in terms of increasing between-sector variance

4 digit NACE 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%	4.7%	-0.27	-0.61	32.6%
81	Services to buildings and landscape activities	1.5%	3.9%	-0.52	-0.64	22.6%
88	Social work activities without accommodation	0.5%	2.8%	-0.21	-0.48	12.0%
55	Accommodation	1.4%	2.6%	-0.42	-0.52	9.0%
28	Manufacture of machinery and equipment n.e.c.	4.4%	3.1%	0.15	0.35	5.8%
33	Repair and installation of machinery and equipment	5.6%	5.6%	0.06	0.22	4.9%
35	Electricity, gas, steam and air conditioning supply	0.3%	0.7%	0.50	0.66	4.8%
87	Residential care activities	0.2%	1.1%	-0.07	-0.45	4.4%

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

Table B32: 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%

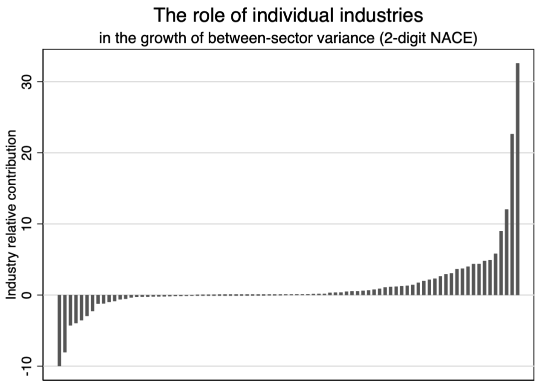
Note: See Equation (4) for definition of the contribution of a particular sector to between sector variance growth.

Table B33: Top 4-digit sectors in terms of increasing between-sector variance

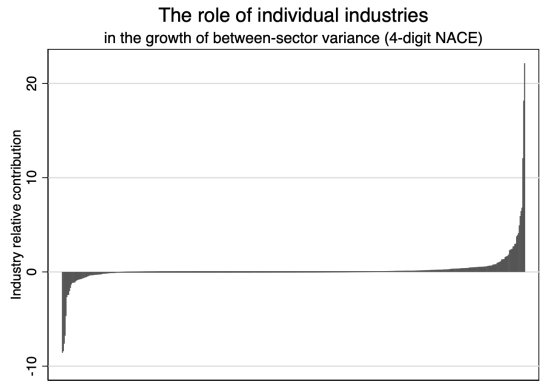
4 digit NACE code	Industry title	Employment share 1985	Employment share 2018	Relative earnings 1985	Relative earnings 2018	Share of between sector variance growth
5610	Restaurants and mobile food service activities	0.4%	2.8%	-0.28	-0.63	22.1%
8129	Other cleaning activities	1.5%	3.4%	-0.54	-0.63	18.2%
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 4 for definitions.

Figure B10: 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

Table B34: 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 (4) 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 5. 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.

Table B35: NACE sector classification

A	Agriculture, forestry and fishing	A.01	Crop and animal production, hunting and related service activities
		A.02	Forestry and logging
		A.03	Fishing and aquaculture
B	Mining and quarrying	B.05	Mining of coal and lignite
		B.06	Extraction of crude petroleum and natural gas
		B.07	Mining of metal ores
		B.08	Other mining and quarrying
		B.09	Mining support service activities
C	Manufacturing	C.10	Manufacture of food products
		C.11	Manufacture of beverages
		C.12	Manufacture of tobacco products
		C.13	Manufacture of textiles
		C.14	Manufacture of wearing apparel
		C.15	Manufacture of leather and related products
		C.16	Manufacture of wood and of products of wood and cork, except furniture; manufacture of articles of straw and plaiting materials
		C.17	Manufacture of paper and paper products
		C.18	Printing and reproduction of recorded media
		C.19	Manufacture of coke and refined petroleum products
		C.20	Manufacture of chemicals and chemical products
		C21	Manufacture of basic pharmaceutical products and pharmaceutical preparations
		C.22	Manufacture of rubber and plastic products
		C.23	Manufacture of other non-metallic mineral products
		C.24	Manufacture of basic metals
		C.25	Manufacture of fabricated metal products, except machinery and equipment
		C.26	Manufacture of computer, electronic and optical products
		C.27	Manufacture of electrical equipment
		C.28	Manufacture of machinery and equipment n.e.c.
		C.29	Manufacture of motor vehicles, trailers and semi-trailers
		C.30	Manufacture of other transport equipment
		C.31	Manufacture of furniture
		C.32	Other manufacturing
		C.33	Repair and installation of machinery and equipment
D	Electricity, gas, steam and air conditioning supply	D.35	Electricity, gas, steam and air conditioning supply
E	Water supply; sewerage; waste management and remediation activities	E.36	Water collection, treatment and supply
		E.37	Sewerage
		E.38	Waste collection, treatment and disposal activities; materials recovery
		E.39	Remediation activities and other waste management services
F	Construction	F.41	Construction of buildings
		F42	Civil engineering
		F.43	Specialised construction activities
G	Wholesale and retail trade; repair of motor vehicles and motorcycles	G.45	Wholesale and retail trade and repair of motor vehicles and motorcycles
		G.46	Wholesale trade, except of motor vehicles and motorcycles
		G.47	Retail trade, except of motor vehicles and motorcycles
H	Transporting and storage	H.49	Land transport and transport via pipelines
		H.50	Water transport
		H.51	Air transport
		H.52	Warehousing and support activities for transportation
		H.53	Postal and courier activities
I	Accommodation and food service activities	I.55	Accommodation
		I.56	Food and beverage service activities
J	Information and communication	J.58	Publishing activities
		J.59	Motion picture, video and television programme production, sound recording and music publishing activities
		J.60	Programming and broadcasting activities
		J.61	Telecommunications
		J.62	Computer programming, consultancy and related activities
		J.63	Information service activities
K	Financial and insurance activities	K.64	Financial service activities, except insurance and pension funding
		K.65	Insurance, reinsurance and pension funding, except compulsory social security
		K.66	Activities auxiliary to financial services and insurance activities
L	Real estate activities	L.68	Real estate activities
M	Professional, scientific and technical activities	M.69	Legal and accounting activities
		M.70	Activities of head offices; management consultancy activities
		M.71	Architectural and engineering activities; technical testing and analysis
		M.72	Scientific research and development
		M.73	Advertising and market research
		M.74	Other professional, scientific and technical activities
		M.75	Veterinary activities
N	Administrative and support service activities	N.77	Rental and leasing activities
		N.78	Employment activities
		N.79	Travel agency, tour operator and other reservation service and related activities
		N.80	Security and investigation activities
		N.81	Services to buildings and landscape activities
		N.82	Office administrative, office support and other business support activities
O	Public administration and defense; compulsory social security	O.84	Public administration and defense; compulsory social security
P	Education	P.85	Education
Q	Human health and social work activities	Q.86	Human health activities
		Q.87	Residential care activities
		Q.88	Social work activities without accommodation
R	Arts, entertainment and recreation	R90	Creative, arts and entertainment activities
		R.91	Libraries, archives, museums and other cultural activities
		R.92	Gambling and betting activities
		R.93	Sports activities and amusement and recreation activities
S	Other services activities	S.94	Activities of membership organizations
		S.95	Repair of computers and personal and household goods
		S.96	Other personal service activities
T	Activities of households as employers; undifferentiated goods - and services - producing activities of households for own use	T.97	Activities of households as employers of domestic personnel
		T.98	Undifferentiated goods- and services-producing activities of private households for own use
U	Activities of extraterritorial organisations and bodies	U.99	Activities of extraterritorial organisations and bodies