The Role of Industries in Rising Inequality*

Juraj Briskar† Rafael Lopes de Melo‡ Edoardo Di Porto§
José V. Rodríguez Mora¶ Cristina Tealdi‖

June 30, 2025
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Abstract

While the sharp rise in earnings inequality since the 1980s is well documented, its underlying structure and causes remain contested. This paper provides new evidence on the evolution of earnings inequality over several decades, based on exceptionally detailed Italian administrative data. We first offer a comprehensive decomposition of the inequality trend across sectors and firms, showing that the predominant component of the rise is sectoral rather than firm-specific. This shift is closely associated with increased sorting between worker skills and sectoral attributes, as well as heightened segregation of workers across sectors. To interpret these patterns, we develop a parsimonious Roy-style model of sectoral choice with assortative matching. Calibrating the model to the data, we find that the observed increase in segregation and sorting can be accounted for by a rise in the dispersion of skill-biased sectoral productivity. Our findings highlight the central role of sector-level heterogeneity in shaping long-run trends in earnings inequality.

Keywords: earnings inequality, industries, sorting, segregation.

*We thank Alan Manning, John Moore, Mike Elsby, Claudio Michelacci, Jonathan Thomas, John Van Reenen, Fabiano Schivardi, Marco Pagano, Lorenzo Cappellari, Bernardo Fanfani, Salvatore Lattanzio, and Salvatore Morelli. We also thank participants at the 2023 EEA-ESEM, EALE, ESPE, AIEL and SIEP conferences, 2023 CEP-LSE Labour Workshop, 2022 VisitINPS workshop, the VisitINPS seminar, and the 2022 MacCaLM conference for their useful comments. All remaining errors are our own. The findings and conclusions expressed are solely those of the authors and do not represent the views of INPS.

†SQW.

‡University of Edinburgh.

§Universita' Federico II Napoli, CESifo Munich, UCFS Uppsala, and CSEF.

¶CUNEF Universidad, University of Edinburgh and CEPR.

‖Heriot-Watt University, EH14 4AS Edinburgh (UK) and IZA Institute of Labor. Email: c.tealdi@hw.ac.uk.

1 Introduction

While it is well established that earnings inequality has increased sharply since the 1980s, the features and the reasons for this increase remain a matter of debate (Hoffmann et al. 2020). In the first part of our paper, we use extremely detailed administrative data to provide a thorough descriptive analysis of the structure of the inequality increase across sectors and firms in Italy over a long period of time, documenting that the bulk of the rise in inequality is sector-related (not firm-related), mapping it into a substantial increase of sorting between worker and sector characteristics, and of segregation of workers across sectors. In the second part of our paper, we construct a parsimonious Roy-style model of sector choice with assortative matching in order to rationalize these findings. A calibration of the model to our data strongly suggests that the main driver of the increase in inequality, manifested in the increase of segregation and sorting, is an increase in the dispersion of skill-biased productivity across sectors.

A large body of literature has focused on understanding the role of firms, showing that the majority of the rise in earnings inequality occurred between firms.[1] A question that is often overlooked, with the exception of Haltiwanger et al. (2024), is whether earnings inequality is growing primarily between firms within the same industry or between firms across different industries. To the best of our knowledge, no such study has been conducted in Europe. Determining whether the factors driving inequality are primarily rooted in industry-level dynamics or are connected to the heterogeneity across firms within the same sectors is crucial for understanding the problem.

In recent years, 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

[1] Song et al. (2019), Barth et al. (2016) and Haltiwanger et al. (2024) for the US, Faggio et al. (2010) for the UK, Card et al. (2013) for West Germany and Alvarez et al. (2018) for Brazil.

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

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. To investigate this issue, we use a social security administrative dataset covering the universe of private-sector employment in Italy. We first document the evolution of real annual earnings in Italy in the last thirty years, which we show to be characterised by a lack of growth and rising dispersion. We perform several variance decompositions, estimate an AKM model (Abowd et al. 1999), and calculate the industry-enhanced AKM variance decomposition (Haltiwanger et al. 2024) to assess the role of industries and firms in explaining the observed increase in earnings variance. Specifically, we explore the extent of sorting (high-wage workers are more likely to work in industries with high average firm effects) and segregation (high-wage workers are more likely to work together in the same industry).

We document a rise in the variance of log annual earnings of about half the size of the US and around 10 log points.[3] Interestingly, similar to the US, we find that the large majority of the total increase in annual earnings variance between 1985 and 2018 took place between industries (55%), corresponding to approximately 5.3 log points. Less than half of it took place within firms (27%) and the remaining 18% between firms within the same industry.[4]

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

[4]Differently, Song et al. (2019) shows that the role of industry is much smaller. The divergence in findings across studies, ours, Haltiwanger et al. (2024), and Song et al. (2019) can be explained by differences in the industry classification systems employed. Our analysis uses NACE Rev. 2 (2007), which, like NAICS in the US, groups firms based on their production processes. In contrast, Song et al. rely on the older SIC system, which uses a hybrid of production and product-market logic. Fort and Klimek (2018) highlight this distinction, noting that NAICS categories are explicitly production-based, while SIC includes market orientation and customer types. Because production-based classifications more accurately reflect differences in firm technology and organization, they are better suited for explaining earnings dispersion related to structural economic changes. Our findings, like those in Haltiwanger et al. (2024), show that between-

This large increase in the between-sector variance component is even more concentrated than in the US, with a small number of industries playing a disproportionate role (14 out of 523 sectors in Italy compared to 30 out 301 sectors in the US). However, while in Italy the key industries driving inequality are low-paying service sectors related to food and drink, accommodation, social care, cleaning of buildings and work agencies, and account for 4.2 log point out of the total 10 log point increase, in the US the driving industries are equally split between low-paying and high-paying. In Italy, these low-paying sectors contributed towards greater inequality by both attracting more employment and experiencing declining relative earnings.

We also find that the growth in earnings inequality is mainly due to the rising dispersion in the worker-specific component of pay and to the increased (positive) sorting of workers into firms and industries. Comparing AKM-based variance decomposition over time, we show that industries are increasingly different in the average earnings ability of their workers (segregation) and workers with low earnings ability are more likely to work in industries with low average firm pay premiums (sorting).

We shed light on the role of industries in rising inequality in a country with an institutional setting different from the US, but similar to many European countries. Despite stark differences (national collective agreements, union representation),[5] we find patterns which are very similar to the ones found by Haltiwanger et al. (2024) for the US. This is suggestive evidence that the underlying forces are likely similar.

industry inequality becomes more salient when classification systems align with production heterogeneity.

[5]Italy and the US differ substantially in labor market institutions. Italy features stronger employment protection, centralized collective bargaining, and higher union coverage, even in the private sector (Boeri and Burda 2009, OECD 2019) In contrast, the U.S. labor market is highly liberalized, with decentralized wage setting and minimal employment protections (Freeman 2007). Moreover, trade and outsourcing exposure differs across the two countries. The U.S. has experienced deep integration into global value chains, particularly with China and India, often via offshoring of routine jobs (Autor et al. 2003), while Italy's production structure is more rooted in small and medium-sized firms in less offshorable sectors (Bugamelli et al. 2012). Immigration patterns are also different. The U.S. admits both high- and low-skilled migrants via structured visa systems, whereas Italy has experienced primarily low-skilled immigration concentrated in personal services and agriculture (Dustmann et al. 2016).

In the second part of the paper, we develop a model of industry choice in the lines of Roy (1951), Eaton and Kortum (2002), Hsieh et al. (2019), Lagakos and Waugh (2013), and Burstein et al. (2019). Our main innovation is to introduce a second dimension of worker heterogeneity that complements sector productivity in production. This complementarity generates a rich pattern of sorting and segregation of workers within and across sectors.

We calibrate the model to our Italian micro data, and use our results to draw additional insights about the drivers of inequality in Italy: (i) the changes in inequality are not driven by changes in worker skill, be that either general or sector-specific. (ii) The changes in inequality are not driven by factor-neutral shocks to sectors such as changes in relative sector prices due to international trade. (iii) The increases in inequality, sorting, and segregation are primarily explained by an increase in the dispersion of skill requirements across sectors, and by an increase in the complementarities between sector-biased productivity and worker skill.

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

In addition to the extensive literature that studies sectoral choice using a Roy model, our work is also related to models of worker sorting across sectors where worker skill is single-dimensional and workers sort based on comparative advantage, such as Teulings (1995) and Costinot and Vogel (2010). Gola (2021) studies a two-sector Roy model with assortative matching, but the focus of that paper is within-sector wage inequality, whereas we are focused on between-sector wage inequality.

The remainder of the paper is organized as follows. Section 2 describes the data. Section 3 presents a 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 6, we present and develop the model used to interpret the data. In Section 7, we calibrate the model to the data and explore the implications of the data in light of the model. Finally, in Section 8, we discuss the possible explanations for our findings and provide a conclusion.

2 Data

We use a matched employer-employee administrative dataset provided by the Italian Social Security Institute (INPS),[6] which contains the universe of Italian social security records of private-sector employees (excluding agriculture) between 1975 and 2018. We focus on the period 1985-2018. The data includes information on labour earnings (no upper limit), the number of weeks worked, unique worker and firm identifiers, the location of the firm, type of contract and demographic information of the worker (gender, year, and place of birth). Uniquely, the database includes information on the sector (NACE industry classification at 4 digits)[7] of the worker and the firm.[8] We sum income across all employment spells in a given year for each worker and we link each worker to the firm that accounts for the

[6] Istituto Nazionale della Previdenza Sociale.

[7] The statistical classification of economic activities in the European Community (NACE) segments firms according to the specific production activities they perform. An economic activity, in this context, involves the combination of inputs (e.g., capital goods, labor, techniques) through a production process to generate specific outputs (goods or services). Thus, the classification reflects the underlying production process, not just the type of product or market served. We use consistently across all years in our sample NACE Rev. 2 (2007) to ensure comparability over time and avoid distortions that could arise from changes in industry classifications.

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

largest share of her income. We also set a threshold level of annual earnings below which all observations are dropped to remove any bias brought about by individuals who are not strongly attached to the labour market. Although Italy does not have a statutory national minimum wage, we compute the threshold level by multiplying the lowest hourly rate of pay in 2018 (which amounts to 6.77 Euro)[9] by 13 working weeks (one quarter) by 40 hours a week.[10] We adjust this threshold for all the other years (1985-2018) using the nominal wage growth series provided by the OECD.[11] We restrict the sample to individuals between the age of 20 and 60 and to firms with at least 10 workers for our baseline analysis.[12] The latter criteria ensures that the number of observations is sufficient to calculate a meaningful within-firm variance and it is consistent with other studies in the literature, thus assuring comparability of results. Nevertheless, our results are robust to lowering the minimum firm size threshold to 5 workers per firm or removing the restriction altogether (Section 3.5).

Table 1: Descriptive statistics.

	Number of	Number of	Distribution of annual earnings				
	firms	workers	Mean	sd	10%	50%	90%
Universe - 1985	643,160	6,934,287	16,518	3,425	19,983	34,407	
Our Sample - 1985	87,852	4,580,723	24,806	16,830	8,901	23,124	38,095
Universe - 2018	1,480,243	14,836,334	21,729	22,253	2,697	19,135	41,050
Our Sample - 2018	191,930	9,182,330	27,050	23,229	8,426	23,633	46,675

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

The original INPS data set (the entire universe) contains about 640,000 firms and approximately 6.9 million workers in 1985 and 1.5 million firms and 14.8 million workers in

[9]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.

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

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

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

2018 (Table 1).[13] Our sample contains approximately 88,000 firms and 4.6 million workers in 1985 and approximately 192,000 firms and 9.2 million workers in 2018. The restrictions, especially the firm size requirement, imply that our sample includes about 13% of the total number of firms and two-thirds of the total number of workers. The mean annual earnings are higher in the sample than in the original data set due to the imposed minimum threshold of annual earnings (Table 1).[14]

3 Descriptive Analysis of Earnings Inequality

3.1 Evolution of annual earnings in Italy

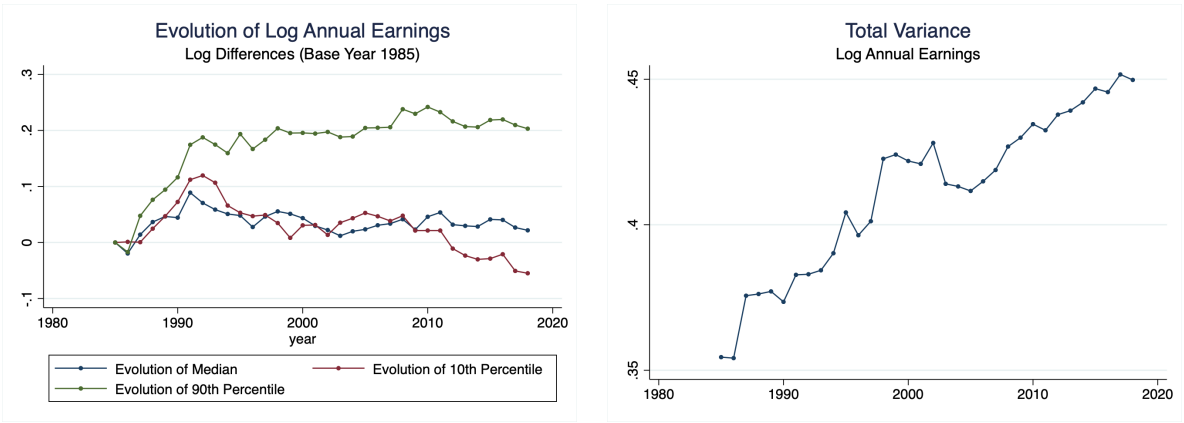
The evolution of the annual earnings distribution in Italy is characterised by little growth in the average, but a significant increase in the dispersion. Mean real annual earnings stood at 24,806 euros in 1985 and 27,050 euros in 2018 (Table 1). Median earnings saw virtually no growth in the 33-year window, changing from 23,124 euros in 1985 to 23,633 euros in 2018 (Figure 1). Conversely, the 90th percentile of earnings increased by 20 log points, with most of the growth happening between 1985 and 1995; the 10th percentile increased between 1985 and the mid-1990s, but fell persistently afterwards, ending up 6 log points lower compared to 1985. Therefore, the increased dispersion between 1985 and mid-1990s was mainly due to the fast growth in earnings at the top of the distribution, while between 1995 and 2018 the increased dispersion was mainly driven by falling earnings at the bottom.[15]

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

[14] Firms are on average larger in our sample due to the imposed minimum firm size: the median number of workers per firm in 2018 is 3 in the universe and 17 in our sample; the mean firm size in 2018 is 10 in the original data and 47.8 in our sample (Table A1 in Appendix A).

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

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



(a) Evolution of Log Annual Earnings.

(b) Overall Inequality.

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

Over the time period under consideration, total variance of log annual earnings rose from 0.35 in 1985 to 0.45 in 2018 (Figure 1), representing an increase of 9.6 log points. This increase was persistent and not episodic, i.e., the dispersion was rising throughout the period. Despite the growth in earnings inequality in Italy being about half the level of the US (Song et al. 2019), it is still quite remarkable and worth investigating.

3.2 Variance Decomposition

Our starting point in assessing the role of firms in the rise of earnings inequality in Italy is to decompose the total variance of earnings into between-firm and within-firm components. This variance decomposition allows us to quantify how much of the increase in inequality can be attributed to differences in average earnings across firms versus earnings dispersion among workers within the same firm:

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

where y_{ij} denotes the log annual earnings of worker i at firm j in a given year, N denotes the total number of workers, n_j is the number of workers employed at firm j, $\bar{y}_j = \frac{1}{n_j}\sum_{\forall i|i\in j} y_{ij}$ is the value of average log annual earnings at firm j and $\bar{y} = \frac{1}{N}\sum_{\forall i} y_{ij}$ is the economy-wide average of log annual earnings. Then, we further decompose the between-firm variance in the between-sector and the between-firm-within-sector components to investigate the role of industries.[16]:

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

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

3.3 Inequality between firms and sectors

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

[16] In addition to directly computing the components of Equation (2), the same decomposition results can be obtained by first controlling for sectoral differences—either by estimating a regression with sector fixed effects and using the residuals, or by demeaning the data using sectoral averages. Performing the between- and within-firm variance decomposition on this adjusted data yields the between-firm-within-sector and within-firm components of earnings variance. All three approaches are equivalent and produce identical results (see Appendix, Section 10.1).

26.3% is due to the rise of the within-firm component.[17][18]

Table 2: Sectors and firms: full variance decomposition.

	Variance change over time				Variance shares		
	Between sector	Between firms within sector	Within firm	Total	Between sector	Between firms within sector	Within firm
1985	0.083	0.079	0.193	0.355	23.3%	22.2%	54.4%
2018	0.136	0.096	0.218	0.450	30.2%	21.4%	48.4%
Change	0.053	0.017	0.025	0.095	+6.9%	-0.8%	-6.0%
% of total increase	55.8%	17.9%	26.3%	100.0%			

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

Similar to other countries,[19] we find that the majority of the rise in earnings inequality in Italy between 1985 and 2018 took place between firms, and this was overwhelmingly driven by the rising dispersion of average earnings across industries, but only partially driven by the rising dispersion of average earnings across firms within industry. The between-firm variance also became a larger relative component of the total variance of log annual earnings. The dispersion in average earnings across firms represented 45.6% of the total variance in 1985, and rose to 51.6% in 2018 (Table 2).[20] The level of aggregation of the sector does not matter for this result: the increase in between sector variance represents 57.9%, 54.7% and 55.8% of the total variance increase with 2 digit, 3 digit and 4 digit industry categories, respectively (Table 3). Thus, inequality grew mainly between broad industries.[21]

To understand the role of gender in explaining the previous results, we split the sample

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

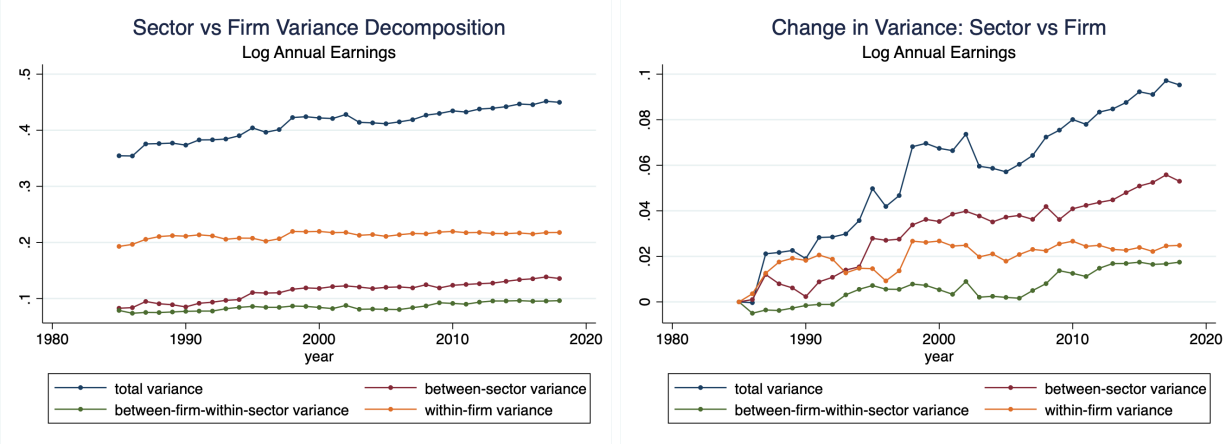
[18]Although all three components were growing over time (Figure 2), the between-sector component grew as a share of total variance, while the shares of both the between-firm-within-sector and the within-firm components fell during the period considered (Table 2).

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

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

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

Figure 2: Sector and firm: full variance decomposition.



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

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

Table 3: Between sector variance with 2, 3 and 4 digit sectors.

	Variance change over time			Variance shares		
	2 digit	3 digit	4 digit	2 digit	3 digit	4 digit
1985	0.065	0.077	0.083	18.2%	21.8%	23.3%
2018	0.120	0.130	0.136	26.6%	28.8%	30.2%
Change	0.055	0.052	0.053	+8.4%	+7.0%	+6.9%
% of total increase	57.9%	54.7%	55.8%			

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

and calculate the variance decomposition for men and women separately. Overall, the results for men are consistent with the baseline sample (Figure A2). The patterns for women are different. While earnings dispersion is higher for women, it has not increased over time (Table A4). The total variance of log annual earnings in the female sample was 0.42 in 1985 and 0.45 in 2018. The limited rise in earnings dispersion among women is overwhelmingly due to rising within-firm dispersion. This is the net effect of an increase in between-sector variance and a much larger fall in between-firm-within-sector variance (Figure A3).

3.4 The industries driving growth in inequality

We identify the sectors which are responsible for the growth in between-industry inequality and calculate the contribution of each individual sector to the between-sector variance growth using the following expression:

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

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

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

We identify five 4-digit sectors with individual relative contributions of more than 5% that jointly account for 66% of the increase in between-sector variance (and thus about a third of the overall earnings inequality increase), while only representing 3% of employment in 1985 (Table 4).[22] An additional nine sectors with individual contributions between 2.6%

[22]There are 523 industries at 4-digit level. We restrict the analysis to those industries that exist in the

and 5% together account for 33% of the rise in between-sector variance, while collectively having an employment share of 5% in 1985. Thus, 14 out of the total of 523 industries together account for around 99% of the growth in between-sector variance (roughly 55% of the overall rise in inequality), while representing only around 8% of total employment in 1985[23].

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

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

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

The remaining 509 industries have offsetting contributions with a joint impact close to zero. This consists of 188 industries with a positive impact on between-sector variance growth[24] that jointly represent around 67% of the total increase. There are further 246 industries with roughly zero impact on the change in between-sector variance, and 75 industries with a negative impact on between-sector variance growth with joint contribution of -67%.[25] The growth in earnings inequality was extremely concentrated: less than 3% of industries (14 out of 523) accounted for around two thirds of the positive contributions to the rise of between-sector variance, while representing only 7.7% of total employment in 1985

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.

[23]Results are similar when restricting the sample to just men (Table A6).

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

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

(see Figure B1 in Appendix). Details on the top 14 (4-digit) industries are reported in Table A2 in the Appenidx .[26]

Table 5: Sector contributions to between sector variance growth, by average earnings.

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

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

Among the top 14 industries with the largest contributions to the rise of between-sector variance, there are five high-paying industries which account for 16% of between-sector variance growth and nine low-paying industries which account for 83% of the growth in between-sector variance (Table 5). Thus, in Italy low-paying sectors play a dominant role. Conversely, in the US the contributions of high and low-paying sectors is more balanced.[27]

Using the shift-share decomposition proposed by Haltiwanger et al. (2024), we disentangle

[26]The industry with the largest contribution is "Other Human resources provision" which accounts for around 19% of the between-sector variance growth (Table A2). This is a peculiar sector which includes employment agencies providing workers to different industries. This raises the question of whether the observed increase in between-sector variance is overstated. To address this concern, we conduct a robustness exercise where we exclude the entire industry, demonstrating that the results remain consistent (Section 3.5). The second most important sector is "Restaurants and mobile food service activities" which accounts for 18% of the between-sector variance growth, followed by "Other cleaning activities" (14%), "Other non-residential social work" (10%) and "Other food service activities" (5%). These top five industries experienced a decline in their annual earnings relative to the economy average and a massive increase in their employment share between 1985 and 2018 (Table A2). The top inequality-increasing industries are almost identical when restricting the sample to just men (Table A7) in the Appendix.

[27]These same patterns hold when using broad 2-digit industries (Table B5 in the Online Appendix). Moreover, these patterns hold when we restrict the sample only to males. Results are available upon request.

the contribution of changes in employment shares and in relative earnings. Specifically, the contribution of sector s to the between-sector variance growth (Equation (3)) is decomposed into the employment and earnings components in the following way:

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

where $\overline{(\bar{y}_s-\bar{y})^2}$ and $\overline{\left(\frac{n_s}{N}\right)}$ denote averages of 1985 and 2018 relative earnings and employment share, respectively. The employment component of the contribution of a given sector represents the effect of the change in the employment share of that industry on the between-sector variance when keeping the relative earnings of the industry fixed, while the earnings component characterises the changes in the relative earnings in the industry, while keeping the employment share of the industry constant.[28]

Focusing on the top 14 sectors with the largest contribution to the growth of inequality, the contribution of the high-paying industries is mainly driven by changes in relative earnings (Table 5). In contrast, the contribution of the low-paying sectors is mainly due to changes in employment shares. Interestingly, both patterns are similar to the ones reported in Haltiwanger et al. (2024) for the US.[29]

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

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

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

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

Shifts in employment, holding relative earnings of industries constant, account in total for just 17% of the rise in between-sector variance (Table 5).[30] This is the net effect of changes in employment shares across all industries (for growing industries the employment component is positive, for shrinking industries it is negative). Differently from the results of the previous exercise when looking at the top 14 industries, the growing dispersion of relative earnings across industries is the primary source of the growth of between-sector variance in the economy as a whole.

3.5 Robustness

The first robustness we present is the decomposition analysis as described in Section 3.4, where we relax the sample restriction of a minimum of 10 workers per firm. We report results when applying a cutoff of 5 workers per firm (Online Appendix, Section 10.5) and when no firm size restriction is applied (Section 10.6). Our findings are unchanged: around 55% of the rise in inequality took place between industries, the degree of concentration is similar and the key industries are the same as in the baseline results. The only difference is that the "Restaurant" sector becomes even more important as a driver of the between-sector earnings inequality, and a new low-paying sector emerges, i.e., "Hairdressing and other beauty treatment".

A possible concern is that administrative data over long time periods can change significantly due to change in the administrative coverage non-related to economic factors. For instance, workers in the entertainment sector were not present in our social security data until early 2000. Therefore, the second robustness focuses on the continuity of the industry coverage over time. As in Citino et al. (2023), we restrict the sample to only those sectors with no change in the coverage of INPS data since 1985. Results are very similar to the baseline specification (Section 10.7).

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

It is well known that the share of informality in Italy is large. Some of the growth in the INPS population of private sector employment (Table 1) could be due to a decline in informality following amnesty reforms. This could potentially bias our results. Figure A5 shows that the aggregate informality rate, defined as employment in the informal sector as a share of total employment, is approximately constant over the period of study. Exploring changes in informality by industry, we find that except for "Accommodation and food service activities", there is no trend over time (Figure A5). For this reason, we repeat the analysis dropping observations in that specific sector.[31] While the main findings still hold, not surprisingly, the growth in the total variance is slightly smaller (0.08 vs 0.10) and the contribution of the between-sector variance to the overall inequality growth is lower (49% vs 56%) (Section 10.8).

The final check deals with the considerable rise in employment via work agencies in Italy as represented by the rising employment share of the sector "Other human resources provision". Unfortunately, there is no data available to link workers in this sector to the client companies that they work for; therefore, we repeat the analysis removing all workers in the 2-digit sector "Employment activities", which includes the aforementioned 4-digit industry (Section 10.9). This change has minimal effects on our results.

4 Decomposing Earnings using AKM

4.1 Empirical framework of worker and firm effects

To explore the extent to which high-wage (low-wage) workers sort into industries with better (worse) wage policies and/or are more likely to cluster in the same industry, we perform an AKM analysis (Abowd et al. 1999) with the aim of calculating the industry-enhanced AKM variance decomposition developed by Haltiwanger et al. (2024). Specifically, we estimate

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

an AKM model for five 7-year intervals: 1985-1991, 1992-1998, 1999-2005, 2006-2012 and 2013-2019. Per each panel, as in our previous analysis, we keep one observation per worker in a given year, we sum earnings across all job spells in a year, allocate each worker to the firm that is the most significant source of earnings in that seven-year interval and apply the same sample restrictions (Section 2). Subsequently, we create the largest connected set within each panel. This results in around 34 million worker-year observations (around 7 million workers and 162 thousand firms) in the 1985-1991 panel and 59 million observations (around 11 million workers and 300 thousand firms) in the 2013-2019 panel (Online Appendix, Table B8).[32] Thus, allowing for the standard assumptions, we estimate the following AKM model:

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

where $\theta^{i,p}$ is typically interpreted as capturing the underlying worker earning ability, $\psi^{j,s,p}$ captures the persistent earnings differences between firms after accounting for variation in worker ability across firms. The vector of time-varying observable characteristics includes controls for year-fixed effects and worker age.[33] Using Equation (6), the variance of annual earnings in a given interval can be decomposed into the variance of worker effects, the variance of firm effects, the variance of observable time-variant characteristics, their covariances and the variance of residuals. Following Haltiwanger et al. (2024), we extend the standard variance decomposition to account separately for dispersion between industries, between firms within industries and within firms:

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

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

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

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

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

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

the greater the between-sector segregation, as sectors differ more in the type of workers they employ.

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

Finally, the within-firm variance is composed of i) variance of worker fixed effects within firms ($Var(\theta^{i} - \bar{\theta}^{j,s})$), ii) variance of time-variant characteristics within-firms ($Var(X_t^i\beta - \bar{X}_t^{j,s}\beta)$), 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 ($Var(\epsilon_t^{i,j,s})$).[34]

4.2 Results of AKM-based Decompositions

Table 6 displays results of the industry-enhanced AKM variance decomposition (Equation (7)), for the first interval (1985-1991), the last interval (2013-2019) and the change between the two periods.[35] [36] Interestingly, 60% of the 8 log point increase in the total variance of log annual earnings between the first and the last periods is accounted for by the rising between-sector variance, 33% by the rising between-firm-within-sector variance and around 7% is due to rising within-firm variance. More than 90% of the growth in earnings inequality took place between firms and a large majority took place between industries. Strikingly, the contribution of industry is similar to the estimate for the US (60% vs 62%).

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

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

[35]Results of the standard AKM decomposition are reported in Section 10.4.

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

Table 6: Industry-enhanced AKM variance decomposition.

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

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

Thus, the majority of the rise in Italian earnings inequality is due to an increase in the sorting of highly paid workers to high-pay industries and due to increasing differences in average worker quality across industries (measured by average worker fixed effect), as highly-paid workers cluster in the same industries. Equivalently, workers with low earnings ability are more likely to work with other low-income workers in the same industry and more likely to work in industries with particularly low firm premiums[37]. Therefore, the growth of the between-sector variance is entirely due to the change in the allocation of workers across industries and not due to increasing heterogeneity in firm wage policies across industries.[38]

[37]Focusing on the top 14 sectors with the largest contribution to the rise of earnings inequality (Section 3.4), we find that low-paying industries experienced declines in the average worker earnings ability (as measured by worker fixed effects), while the opposite happened in high-paying sectors, with relatively little change in the average firm effects (Table A9).

[38]The role of between-industry sorting is highlighted by the fact that the correlation of average firm fixed effect and average worker effect across industries is just 0.10 in the 1985-1991 period, but it is 0.69 in the

The 33% contribution of between-firm-within-sector variance consists mainly of sorting (39%), less of segregation (around 6%) and a declining dispersion of firm pay premiums (-12%). Therefore, the increasing positive sorting of workers across firms within sectors plays an important role in driving the rise in earnings inequality, while the declining variance of firm fixed effects within industries moves in the opposite direction. At the same time, the sorting of workers to firms plays an important role both between sectors and between firms within sectors, while increasing segregation is a predominantly between-sector phenomenon.

The variance of the worker fixed effect within firms increased significantly and represents around 39% of the overall rise in earnings inequality. This was offset by the falling variance of the residuals (-17%), of the time-variant characteristics within firms (-5%) and of the covariance between worker fixed effect and time-variant characteristics within firms (-9%). This is the reason why the within-firm component of variance only accounts for around 7% of the total increase in earnings variance.[39]

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

5 Comparison with US

When comparing our findings for Italy with the results of Haltiwanger et al. (2024) for the US, we find similar results.[40] Specifically, they find that 61.9% of the rise in the US earnings inequality between 1996 and 2018 occurred between industries, while 23.1% between

2013-2019 period. With 2-digit industries, the correlation is even higher, 0.30 in the first interval and 0.85 in the last interval.

[39]Results of the industry-enhanced AKM variance decomposition on the sample of men only are presented in Table A8.

[40]Haltiwanger et al. (2024) use Longitudinal Employer-Household Dynamics (LEHD) linked employer-employee data, covering only 18 out of the 50 US states for the period 1996-2018 and containing comprehensive information on the industry that the firm belongs to.

firms in the same industry and 14.9% within firms (Table 1 in Haltiwanger et al. (2024)). Our numbers (55%, 18% and 27%) are not too far away. Using the same data source as Haltiwanger et al. (2024), Kleinman (2022) shows that when considering a longer time period, the importance of the between-sector component declines slightly: just under half of the rise in earnings inequality took place between 4-digit industries in the US between 1980 and 2017. Comparing (Haltiwanger et al. 2024, Table 3)'s list of all industries with larger than 1% contribution to the rise of between-sector variance with our list (Table A5) we observe that industries related to "Food and Drink" and "Employment Services" feature most prominently in both countries.[41] Other low-paying industries which are important in both countries are sectors related to social care (both residential and non-residential), cleaning and maintenance of buildings and sectors related to hotels and other types of accommodation. High-paying industries which feature in both countries are pharmaceutical manufacturing and sectors related to financial services and insurance. Sectors related to IT appear on both lists, but whereas in Italy it is listed as "Servicing of Personal Computers" and contributes marginally to inequality, in the US IT sectors feature more prominently and cover software publishing, computer system design and semiconductor manufacturing. While among low-paying sectors the patterns are very similar, with the only difference being that retail industries are more important in the US, the number of high-paying sectors with large relative contributions to the rise of inequality in the US is much larger compared to Italy. In both countries, the dispersion of firm pay premiums did not play a significant role and instead the growth in earnings inequality was driven by the rising dispersion of the worker-specific component of pay and by an increase in sorting.

Our results regarding the increasing industry-level sorting and segregation accounting for more than half of the total rise in earnings inequality is also in line with the findings of Haltiwanger et al. (2024). Finally, regarding the cross-sectional variance decomposition, ac-

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

cording to Haltiwanger et al. (2024), in any given year the majority of the earnings inequality in the US takes place within firms: the within-firm variance as a share of total variance is about 65% in 1996-2002 and 58% in 2012-2018 intervals. We find that the between-sector share in Italy not only increased from 23.4% in 1985 to 30.2% in 2018, but that at the end of the period it is slightly higher than any of the US estimates. Thus, either the firm or the industry that the individual is employed in is a better predictor of his/her annual earnings in Italy than in the US.

Overall, while there are significant differences in the level of inequality between the US and Italy, we observe notable similarities in the pattern of increasing inequality in both countries. Given the substantial institutional differences between them, it is reasonable to conclude that these factors have not contributed to the rise in income dispersion. In the following sections, we aim to explore the potential causes of this trend.[42]

6 Modeling Industry Choice

To rationalize the reported empirical facts, in this section we develop a parsimonious model of sector choice and assortative mating. The goal is to ascertain which fundamental shocks in the economy are the likely source of the increase of inequality. What has changed in the fundamentals of the Italian economy, resulting in a large increase of between sector inequality, a large reallocation of employment across sectors, an increase of the degree of sorting between the quality of workers and sectors, and of segregation of workers across sectors based on their individual skill.

In what follows we will abstract from differences between firms within a sector. This is because our empirical evidence points to the main factors explaining changes in inequality

[42] A possible partial explanation that we do not explore is the rise of domestic outsourcing (Autor 2003). A possible way to measure the degree to which outsourcing may have caused the results would imply merging our administrative data with VAT inter-firm transactions, which, unfortunately, are not available in Italy. In the remainding of the paper we abstract from this possibility.

being differences between sectors, and how workers sort across sectors.

We build on the literature that models sector/occupational choice using a Roy model, such as Hsieh et al. (2019), Lagakos and Waugh (2013), and Burstein et al. (2019). Our innovation is to introduce a second dimension of worker heterogeneity that is complementary in production to sector productivity, which enriches the model by generating patterns of sorting and segregation of skill across sectors in line with our facts.

To this end we develop a model of sector choice allowing for changes in the work force, in the industry structure and in the manner in which industry structure interacts with worker type. This is not obvious, as the standard Roy model tends to have negative assortative matching with respect to sector specific ability/tastes, as sectors with higher productivity attract employment, at the cost of a selection effect in which the marginal workers flowing into that sector are of lower ability.

In our set-up, sectors differ from each other in having different "skill-biased" and "total factor" productivities, both of which we allow to change in our counterfactuals. Workers and market prices react to these shocks, changing both their sorting across sectors (including the predominance of skill in different sectors) and the rewards paid in different employments and (implicitly) to different skills.

Below, we calibrate the model to the observed evolution of the labor market and inequality reported in the previous sections, and infer the shocks that lie behind the sector-driven inequality patterns that we report.

6.1 Labor Supply

Workers choose an occupation in one of the J sectors, $j \in \mathcal{J} = \{1, \ldots, J\}$. Each sector j is characterized by two sector-specific exogenous parameters $\{A_j, B_j\}_{\forall j \in \mathcal{J}}$. The first, A_j being a skill-related productivity parameter of sector j, while B_j is a measure of skill-neutral productivity in the sector. Their respective roles will be clarified below. Markets

are competitive, and in each sector individuals are paid a market wage of (w_j) per efficiency unit of labor.

Individuals differ from each other in three margins. First, agents have a certain exogenous level of general human capital (θ) drawn from a certain distribution with PDF $f(\theta)$ and CDF $F(\theta)$. [43] Second, individuals also have a certain talent for working in each specific sector j, affecting the amount of efficient hours and income that they receive in each sector and denoted z_j. Third, they have a certain taste for working on each sector j, which we will denote by v_j.

The model is static, and agents choose a sector j in order to maximize their utility function, which is assumed to be

$$U(j, \theta, z_j, v_j) = \left[w_j \, L(A_j, \theta) \; z_j\right] \times v_j \tag{8}$$

where $[w_j \, L(A_j, \theta) \; z_j]$ is the income derived to the agent by working in sector j, and v_j the non-monetary utility derived from it.

The model is, thus, akin to a standard Roy model where agents face heterogeneous trade-offs in the access to different occupations (Roy (1951)). The novelty is that we include a worker specific skill θ that interacts with sector specific characteristics. This is needed because our goal is not only to assign properly the evolution of the dispersion of incomes to within and between sector components, but also to explain the evolution of sorting across sectors. The complementarity between sector and worker characteristics derived from $L(A_j, \theta)$ allows us to generate richer sorting patterns of workers across occupations, and help us

[43] In the empirical implementation of the model we will assume this function to be a log normal distribution.

explain our facts.[44] Specifically, we posit that $L(A_j, \theta)$ takes the following form:[45]

$$L(A_j, \theta) = \left[\frac{1}{2}(A_j)^{\frac{\gamma-1}{\gamma}} + \frac{1}{2}\theta^{\frac{\gamma-1}{\gamma}}\right]^{\frac{\gamma}{\gamma-1}} \tag{9}$$

where the elasticity of substitution between sector specific skill-related productivity and worker skill is determined by $\gamma \in \mathbb{R}^+$. Thus, decreasing the value of γ increases the degree of complementarity in production. Special cases include perfect substitution between skill-related productivity and skill ($\gamma \longrightarrow \infty$), Cobb-Douglas ($\gamma = 1$) and perfect complementarity between them ($\gamma = 0$). We will consider that the degree of complementarity γ is identical across all sectors, while sectors differ in the value of A_j (and B_j, explained below).

The calibration of the model (below) strives to determine the evolution over time of γ, the distribution of A_j and B_j across sectors, and the values of θ and α to match the facts that describe the evolution of inequality.

While in principle our model could allow for a rich joint distribution of sector-specific taste and ability shocks (as in Erosa et al. (2025)), we will follow McFadden (1974), Eaton and Kortum (2002) and, particularly, Hsieh et al. (2019) in imposing restrictions to simplify computation. Specifically, we assume that workers are of one of two types, either "taste" or "productivity". The probability of being a productivity type is exogenous, identical for all workers, and equal to $\varphi \in [0, 1]$. This formulation allows us to consider both the taste and ability cases, while retaining analytical tractability.

If the individual is of "productivity-type" v_j is equal to one in all sectors, while z_j is the realization of an i.i.d. worker and sector-specific Fréchet shock with a shape parameter

[44] The framework most similar to ours is Burstein et al. (2019). In their framework individuals have two types of heterogeneity that are analogous to our θ. First, their $\epsilon(z)$ term is analogous to our $L(.)$ function in the case where θ and A_j enter multiplicatively. In that case θ does not affect sorting. Second, the way they incorporate observable characteristics λ (e.g. gender, education etc) is analogous to how we model θ, and allow for complementarities with sector characteristics. That paper focuses on explaining between group inequality, whereas we are focused on explaining cross-sector segregation.

[45] Without loss of generality we include equal weights of A and θ because we include scale parameters for both A and θ. This facilitates taking the limit of γ converging to one, which leads to a Cobb-Douglas function with equal weights.

α. If the individual is of "taste type" (the complementary event), then the exact opposite occurs: v_j is the realization of a Fréchet shock drawn from the same i.i.d. distribution as above, while z_j equals a certain constant μ that we normalize to the mean of the draws of the Fréchet distribution, $\Gamma\left(1-\frac{1}{\alpha}\right)$, for all agents of this type in all sectors. With this normalization (that we take from Hsieh et al. (2019)) the average productivity across sectors of the taste individuals equals the one of the "productivity types".[46]

Notice that the decision of working in one sector or the other is independent of the worker being a "taste" or "prodcutivity" type, and is driven by the comparison across sectors of the product of wages, $L(A_j,\theta)$ and the realization of the sector-specific Fréchet shocks. Income, on the other hand, equals $[w_j\, L(A_j,\theta)\; z_j]$, and while it depends also of the comparison of Fréchet shocks for "productivity type" workers, it equals simply $[w_j\, L(A_j,\theta)]$ for "taste type" workers.

With these assumptions, all agents choose their sector so that $k = argmax_j\, \{w_j\, L(A_j,\theta)\, x_j\}$, where x_j is either z_j or v_j, depending on the agent's type, but in both cases is drawn from the same distribution, with PDF $g(x) = \alpha\, x^{-\alpha-1}\, \exp\left[-x^{-\alpha}\right]$, and CDF $G(x) = \exp\left[-x^{-\alpha}\right]$.

In the sector chosen we have,

$$x_k \geq \frac{w_j L(A_j,\theta)}{w_k L(A_k,\theta)} x_j \quad ; \quad \forall j \neq k. \tag{10}$$

From where it follows that the probability of an agent with a certain θ choosing sector k is:

$$\pi_k(\theta) = \int g(x) \prod_{j\neq k} G\left(\frac{w_j L(A_j,\theta)}{w_k L(A_k,\theta)} x\right) dx = \frac{\left(w_k L(A_k,\theta)\right)^{\alpha}}{\sum_{\forall j\in J}\left(w_j L(A_j,\theta)\right)^{\alpha}} \tag{11}$$

Notice that in the Cobb-Douglas case ($\gamma \to 1$) where θ and A_j enter multiplicatively in the production of effective hours, sector allocations would be independent of skill. Thus, it is necessary to have stronger complementarity than in a Cobb-Douglas function in order to

[46]This is the average productivity that they have ex-ante across sectors, it is not the productivity that they have in their sector of choice, for the productivity individuals this will be larger on average

generate positive sorting between A_j and θ.

The share of workers in occupation k (the weighted share across skills), the distribution of θ conditional on sector being in sector k, and the probability distribution of being in sector k with skill θ are respectively:

$$H_k = \int_0^\infty \pi_k(\theta)\, f(\theta) d\theta; \qquad f(\theta|k) = \frac{\pi_k(\theta) f(\theta)}{H_k}; \qquad h(k,\theta) = \pi_k(\theta)\, f(\theta), \tag{12}$$

This completely describes the allocation of people to sectors for a given set of market wages and their realization of idiosyncratic shocks. Notice that these distributions are independent of the workers being taste or productivity type. However, income and effective labor supply do depend on whether the idiosyncratic shocks translate into effective hours, which itself depends on the worker's "type" (taste or productivity). We determine them next.

First, take a "taste type" individual. Once we condition on their chosen sector of activity, the realization of the Fréchet shock does not affect either their effective labor supply or their income. Thus, for an individual of skill θ in sector k effective labor supply and income are respectively:[47]

$$s^T(\theta,k) = \mu\, L(A_k,\theta); \qquad y^T(\theta,k) = w_k\, \mu\, L(A_k,\theta) \tag{13}$$

For the "productivity type" these are slightly more involved, as they depend on the realization of z_j.

$$s^P(\theta,k;z_k) = z_k\, L(A_k,\theta); \qquad y^P(\theta,k;z_k) = w_k\, z_k\, L(A_k,\theta) \tag{14}$$

The joint distribution of z and sector k for a given θ is

$$\hat{g}(z,k|\theta) = g(z) \prod_{j\neq k} G\left(\frac{w_k L(A_k,\theta)}{w_j L(A_j,\theta)} z\right) = \alpha z^{-\alpha-1} \exp\left\{-\frac{1}{\pi_k(\theta)} z^{-\alpha}\right\},$$

[47] Remember that μ is their normalized productivity

from where it follows that the distribution of z conditional on k and θ is

$$\tilde{g}(z|k,\theta) = \frac{\hat{g}(z,k|\theta)}{\pi_k(\theta)} = \frac{\alpha}{(\pi_k(\theta))^{-\frac{1}{\alpha}}} \left(\frac{z}{(\pi_k(\theta))^{-\frac{1}{\alpha}}}\right)^{-\alpha-1} \exp\left\{-\left(\frac{z}{(\pi_k(\theta))^{-\frac{1}{\alpha}}}\right)^{-\alpha}\right\} \tag{15}$$

Which is the pdf of a Fréchet distribution with scale $(\pi_k(\theta))^{-\frac{1}{\alpha}}$, and cdf $\tilde{G}(z|k,\theta) = \exp\left\{-\frac{z^{-\alpha}}{\pi_k(\theta)}\right\}$.

The total supply of effective labor conditional on sector and skill is

$$S(k,\theta) = L(A_k,\theta)\, h(k,\theta)\, \mu \left[\varphi\, (\pi_k(\theta))^{-\frac{1}{\alpha}} + (1-\varphi)\right], \tag{16}$$

which depends on the distribution of market wages implicitly via $\{\pi_k(\theta)\}_{\forall k}$ and $h(k,\theta)$. Aggregating across skills we obtain the total supply of efficiency units in each sector, which will be used in our market clearing conditions:

$$S(k) = \int S(k,\theta) f(\theta|k) d\theta \tag{17}$$

The logarithm of the income of an individual, conditional on sector, skill, is given by a lottery:

$$\ln y(k,\theta) = \begin{cases} \ln(w_k) + \ln\left(L(A_k,\theta)\right) + \ln(z) & \text{with prob } \varphi \\ \ln(w_k) + \ln\left(L(A_k,\theta)\right) + \ln(\mu) & \text{with prob } 1-\varphi \end{cases} \tag{18}$$

Notice that z is distributed according to $\tilde{g}(z|k,\theta)$, a Fréchet distribution, so its logarithm is distributed as a Gumbel distribution with location parameter $-\frac{1}{\alpha}\ln\left(\pi_k(\theta)\right)$ and scale $\frac{1}{\alpha}$.

Thus, the mean and variance of log-income conditional on k and θ are are:[48]

$$E\big(\ln y(k,\theta)\big) = \ln\left(w_k L(A_k,\theta)\right) + \left[\varphi \frac{\gamma^{EM} - \ln\left(\pi_k(\theta)\right)}{\alpha} + (1-\varphi)\ln\Gamma\left(1-\frac{1}{\alpha}\right)\right] \tag{19}$$

$$V\big(\ln y(k,\theta)\big) = \varphi(1-\varphi)\left[\frac{\gamma^{EM} - \ln\left(\pi_k(\theta)\right)}{\alpha} - \ln\Gamma\left(1-\frac{1}{\alpha}\right)\right]^2 + \varphi\frac{\pi^2}{6\,\alpha^2} \tag{20}$$

[48] Where γ^{EM} is the Euler-Mascheroni constant, and π is the constant $3.1415\ldots$

Given that we know the distribution of individuals across k and θ, $h(k,\theta)$, and the distribution of z conditional on k and θ, we can obtain the marginal distributions of income and log income, and moments from this distribution. In particular, it will be useful later to obtain the mean and the variance of log-wages in each sector.

$$E(\ln(y|k)) = \int E\big(\ln y(k,\theta)\big) f(\theta|k) d\theta \tag{21}$$

$$V(\ln(y|k)) = \int \big[E\big(\ln y(k,\theta)\big) - E(\ln(y|k))\big]^2 f(\theta|k) d\theta + \int V\big(\ln y(k,\theta)\big) f(\theta|k) d\theta \tag{22}$$

6.2 Labor Demand and Equilibrium

The final Good is produced in a perfectly competitive market using a Dixit-Stiglitz production aggregator. $Y = \left[\sum_{j\in\mathcal{J}} (B_j\, D_j)^{\frac{\phi-1}{\phi}}\right]^{\frac{\phi}{\phi-1}}$, where ϕ is the constant elasticity of substitution, while D_j is the total employment of human capital in occupation j.

While A_j is a productivity parameter that affects differently different skill levels, B_j, the weight of each industry, affects equally individuals of all skill levels. B_j is our metaphor of skill-neutral productivity. In the empirical implementation, we will strive to differentiate it from "skill-biased" productivity.

Normalizing the price of the final good to one, and assuming perfect competition for labor inputs, so that total output equals labor income, labor demand in sector j is determined by

$$D_k \;\; = (w_k)^{-\phi}\, B_k^{\phi-1} \left(\sum_{\forall j}\; w_j\, D_j\right); \qquad \sum_{j\in J} \left(\frac{w_j}{B_j}\right)^{1-\phi} = 1 \tag{23}$$

An equilibrium is a set of wages $\{w_j\}_{\forall j}$ such that labor demand D_j (defined in 23) equals labor supply S_j (defined in 17) in all sectors.

Given the wages $\{w_j\}_{\forall j}$ it is straight forward to derive the distribution employment across sectors for any skill level ($\{\pi_j(\theta)\}_{\forall j,\theta}$ in 11), the distribution of employment across sectors and skills ($h(k,\theta)$ in 12), the distribution of incomes across sectors and skills ($y(k,\theta)$ in 18,

as well as their marginal distributions and aggregations.

7 Calibration

Our goal is to calibrate the model to the observed evolution of the labor market allocations and inequality, and infer the shocks that lie behind the sector-driven inequality patterns reported. Our strategy is to pick a parametrization of the model, and select a set of moments that allow us to calibrate the parameters of the model in two time periods: 1985-1991 and 2013-2019. We then compare the measured changes in the parameters to infer the drivers of the changes in inequality patterns observed in the data.

7.1 Procedure

The most important parameters for our goals are those related to the distribution of skill-biased productivity across sectors (A_j), the distribution of skills across agents ($F(\theta)$), the complementarity between both (γ), the distribution of skill-neutral productivity across sectors (B_j), and the distribution of talent in different sectors across individuals (the shape parameter of the Fréchet distribution, α).

Before explaining how we retrieve them, it is important to notice that we obtain from the literature two predetermined parameters that are less central to our analysis. These are ϕ, the elasticity of substitution of sectors in the production function of final goods, and φ, the share of individuals who are "productivity type. We take the values of these parameters from Hsieh et al. (2019) and are simply assumed to be $\phi = 3.0$ and $\varphi = 0.78$, implying that 78% of individuals are "productivity" type. In the appendix, we conduct a robustness analysis, demonstrating that alternative values of ϕ and φ do not impact the qualitative results.

Returning to our calibrated parameters, we assume the distribution of skill across individuals (θ) to be log-normally distributed. Thus characterized by mean and variance of the log of θ; μ_θ and σ_θ respectively.

The distribution of sector characteristics is more complicated because it is infeasible to calibrate the exact values of A_j and B_j in each sector. Using a 4-digit classification that would result in close to 1000 parameters, and even using 2 digits (88 sectors), it would require matching 176 parameters, which is numerically unfeasible. For the sake of parsimony, we instead assume that A_j and B_j are drawn from independent log-normal distributions, respectively with parameters (μ_A,σ_A) and σ_B. Note that we do not include a scale parameter for B_j because A and θ already include scale parameters and $L(A, \theta)$ has constant returns to scale.[49]

This leaves us with seven parameters to be calibrated in our exercise (μ_A, σ_A, σ_B, μ_θ, σ_θ, γ, α). We select 7 moments from the data to help us pin down the value for these parameters in the initial final periods of the sample.

The first two moments are the between and within-sector components of a variance decomposition of log earnings. Together, these moments capture how total inequality has increased in Italy, and that a large share of that can be attributed to an increase in the between-sector component of the variance. The within-sector variance of earnings is informative about α, as it captures the variance of z, and σ_θ, the overall dispersion of skill in the population. The between-sector variance captures segregation and sorting, which is related to σ_A, θ, γ, and σ_B. The latter is because for workers who are taste-types, an increase in B_j increases sector wages, leading to higher earnings $w_j L(A_j, \theta)\mu$.[50] We also match the mean wage in the economy $\mathbb{E}(\log(y))$, which is a normalization for the scale parameters.

Next, we select two moments related to the dispersion of employment shares across sectors. First, we use the Herfindahl index of sector shares to capture the degree of employment concentration across industries, which is clearly related to productivity dispersion across sec-

[49]Regarding A_j, we divide the sectors by picking 88 equally split percentiles of its respective Log-Normal distribution. With respect to B_j, we take 88 draws from its distribution, independent of A.

[50]For productivity type workers, the increase in wages is counteracted by a selection effect in which workers with lower z flow into the occupation. With Fréchet idiosyncratic draws these two effects exactly offset each other, and an increase in wages leads to no change in average earnings in a sector, and only to marginal changes of average log earnings.

tors (σ_A and σ_B). Second, we use the correlation between the mean wage in an industry and its share of employment. We want the model to capture the fact that industries that pay higher on average are not necessarily larger in employment.

Finally, we pick two moments related to the segregation of skills across sectors. In particular, we use the measure of between and within-sector segregation described in Section 4 of the paper. In the data that refers to the decomposition of the variance of worker fixed effects in an AKM regression between and within sectors. In the model, we are applying the equivalent decomposition to θ. It is worth noting that the AKM regression is mispecified in our model for all parametrizations, except for the case where ($\gamma \to 1$).[51] In that case, log-income is additive in $log(\theta^{0.5})$. Because of this, we use $log(\theta^{0.5})$ as a measure of skill, to maintain comparable units in the only case where the model is consistent with AKM.

Our exercise consists, thus in finding a set of parameters to match these moments as closely as possible to the data equivalent extracted from aggregating sectors at the 2-digit level. The reason for using the coarser 2-digit aggregation instead of the 4-digit one, as above, is computational difficulty. The model solves a large nonlinear system of equations to find the equilibrium prices. It takes too long to repeat the exercise multiple times to find suitable moments, considering that there are almost 500 4-digit sectors.

7.2 Calibration results

In Table 7, we present all targeted moments and their corresponding data, and in Table 8, we present the calibrated values of the parameters for both periods.

Table 7 shows that the model aligns with the facts related to within and between earnings dispersion (total variance of $\log y$ and the share of it which is between sector), as well as the moments related to dispersion in sector shares (sector concentration, measured with

[51] Notice that for that reason, it is unwise to use sorting as a direct moment in our calibration. While in the model it is natural to correlate A_j with θ at the individual level, AKM is bound to mis-specify the manner in which the sector relates to the worker, as both A_j and B_j determine the sector "fixed effect".

the Herfindahl Index, and the correlation between sector share and average earnings), and matches qualitatively the patterns of skill segregation and sorting, albeit it understates the amount of dispersion of θ within sectors.

Notice that in the table we refer to "Sorting-Model" as the correlation between A and θ, whereas in the data that refers to the implied correlation of the "between-sector sorting" in equation 7. These are not targeted moments (as per the aforementioned discussion on why the AKM estimators are misspecified in our model, particularly in relation to sector fixed effects). They are interesting, though, as the evolution of our interpretation of sorting within our model aligns with the one measured via AKM in the data.

In Table 8 we report the parameters that match the aforementioned moments in both periods. We will comment on their evolution and its significance in section 7.4; however, it is convenient to first dive into a numerical analysis of the model to understand its workings.

7.3 Understandings the workings of the model

In this section, we demonstrate the functionality of our model by examining how outcomes respond to changes in structural parameters. Starting from the initial calibration using 1980s data, we alter one parameter at a time. Table 9 provides qualitative insights; detailed results are presented in the Appendix (Tables A10 to A18). They should be considered the marginal effect of each parameter on key model moments.

We first compare the two sources of sector-level productivity dispersions: σ_B (factor-neutral) and σ_A (skill-biased). Increasing σ_B minimally affects inter-sector inequality but significantly impacts sector share dispersion, as detailed in Table 9. To understand this, take the case where $\varphi = 1$ (all workers are productivity type). A shock to B in one sector increases the market wages and the share of workers in that sector. These incoming workers tend to have lower sector-specific abilities than the incumbent workers, which generates a selection

Table 7: Model and Data Moments Across Periods

	Period 1 (1985-1991)		Period 2 (2013-2019)		Changes	
	model	data	model	data	model	data
Between-sector earnings variance	0.06	0.06	0.11	0.10	0.05	0.04
Within-sector earnings variance	0.21	0.22	0.25	0.27	0.04	0.05
Sector Concentration	0.03	0.03	0.03	0.03	0.00	0.00
Segregation	0.02	0.02	0.03	0.04	0.01	0.03
Within-sector θ variance	0.08	0.16	0.07	0.20	-0.01	0.04
$\mathbb{E}[\log y]$	9.30	9.29	10.11	10.11	0.81	0.82
$\text{Corr}(\bar{Y}_a, s_a)$	-0.07	-0.01	-0.20	-0.18	-0.12	-0.17
Sorting-Model	0.49		0.56		0.06	
Sorting-Data		0.63		0.86		0.2
Earnings Variance	0.27	0.27	0.36	0.36	0.09	0.09
Share between sectors	0.22	0.21	0.31	0.27	0.09	0.06
Skill Variance	0.10	0.18	0.10	0.25	0.00	0.06
Share between sectors	0.25	0.10	0.33	0.18	0.09	0.08

Notes: Moments are reported for model-generated and empirical data in both periods.

- Between-sector earnings variance is $V_b^y = \sum_{\forall j} \frac{n_j}{N} (\bar{\log} y_j - \bar{\log} y)^2$, n_j being employment in sector s, and N total employment.
- Within-sector earnings variance is $V_w^y = \sum_{\forall j} \frac{n_j}{N} \sum_{\forall i \in j} \frac{1}{n_j} (y_i - \bar{y}_j)^2$
- Sector Concentration is the Herfindahl index of concentration of the sectors: $C = \sum_{\forall j} \left(\frac{n_j}{N}\right)^2$.
- Segregation is the Between-sector variance of the individual characteristic: $V_b^\theta = \sum_{\forall j} \frac{n_j}{N} (\bar{\log} \theta_s - \bar{\log} \theta)^2$. In the model θ is the log of her skill, θ. In the data, it is the individual fix effect of the AKM regression.
- Within-sector θ variance is $V_w^\theta = \sum_{\forall j} \frac{n_j}{N} \sum_{\forall i \in j} \frac{1}{n_j} (\theta_i - \bar{\theta}_j)^2$, with the same definitions of θ
- $\mathbb{E}[\log y]$
- $\text{Corr}(\bar{Y}_a, s_a)$ is the correlation between average log income and occupational share $(\frac{n_j}{N})$ across sectors.
- Sorting-Model is the correlation of $\log A_t$ and $\log \theta$ across agents in the model.
- Sorting-Data is the correlation of the individual and the sector fixed effects in the AKM regression. It is related (but not directly comparable) to the model version. This moment is not targeted.

The remaining rows are self-explanatory and are simple manipulations of the previous.

Table 8: Model Parameters

Parameter	Period 1 (1985–1991)	Period 2 (2013–2019)	Source
μ_A	7.208	8.729	Calibrated
σ_A	0.290	0.834	Calibrated
σ_B	0.500	0.490	Calibrated
μ_θ	6.242	7.085	Calibrated
σ_θ	0.661	0.649	Calibrated
γ	0.390	0.283	Calibrated
α	14.990	15.000	Calibrated
φ	0.780	0.780	Hsieh et al. (2019)
ϕ	3.000	3.000	Hsieh et al. (2019)

Table 9: Qualitative Effects of Parameters on Key Moments

	$\mathbb{E}(y)$	$\mathrm{Var}(\log y)$	Share Between	Sorting*	Segregation*	Concentration
Data	$+$	$+$	$+$	$+$	$+$	$\approx_0$
μ_A	$+$	$+$	$-$	$-$	$-$	$\approx_0$
σ_A	$\approx_0$	$\approx_0$	$+$	$+$	$+$	$\approx_0$
σ_B	$+$	$\approx_0$	$\sim_+$	$\sim_+$	$\approx_0$	$+$
μ_θ	$+$	$-$	$+$	$+$	$+$	$\approx_0$
σ_θ	$-$	$+$	$+$	$+$	$+$	$\sim_+$
γ	$+$	$-$	?	?	?	$\approx_0$
α	$-$	$-$	$+$	$+$	$+$	$\sim_+$
φ	$+$	$\sim_-$	$\sim_+$	$\approx_0$	$\approx_0$	$\approx_0$
ϕ	$-$	$\sim_+$	$\sim_+$	$\approx_0$	$\approx_0$	$+$

Note: "$+$" and "$-$" denote positive and negative effects, respectively. "$\sim_+$" indicates a weakly positive or context-dependent effect. "$\approx_0$" denotes a negligible effect. The effect of γ is non-monotone as $\gamma \to 0$.

effect that counteracts the initial increase in wages.[52] Conversely, an shock to A in one sector increases high-skilled worker presence, raising average sector income and contributing to wage inequality between sectors. This also explains why shares respond less to A shocks than to B shocks: the increase in skill level implies that a smaller increase in the number of workers is needed to generate the same increase in total efficiency units of labor.

Discussing μ_A, μ_θ, and γ together is helpful due to their interplay, especially under high complementarity and asymmetric A_j and θ distributions. To illustrate that, consider a 2x2 example with 2 sectors and 2 worker types: $\theta_1 < \theta_2 < A_1 < A_2$. In the limit ($\gamma \to 0$) this is a Leontief, with $L(A_k, \theta) = \theta$ for any k and θ, implying that sector shares afre not θ-dependent, and eliminating assortative matching. This example is relevant to our results because in our calibration, $\mu_A >> \mu_\theta$ with strong complementarities ($\gamma = 0.39$). This explains why in Table 9 increasing μ_A reduces assortative matching, while increasing μ_θ enhances it. This also explains why decreasing γ may have non-monotone effects, as seen in Table 9 and the Appendix (Table A14).

An increase in σ_θ raises overall inequality, mainly between sectors, due to model complementarities and sorting, leading to more segregation. Lowering α increases Fréchet shock variance, which boosts within-sector earnings inequality and reduces segregation and sorting.

Lastly, changes to non-calibrated parameters ϕ and φ have a negligible impact on sectoral inequality. Specifically, φ doesn't affect skill segregation across sectors, while ϕ primarily influences industry share dispersion.

7.4 What do we Learn from the model

In this section, we summarize the conclusions of our model by comparing the changes in the structural parameters listed in Table 8. We observe that some calibrated parameters show negligible changes (σ_θ, α, and σ_B), while others exhibit significant shifts (σ_A, μ_A, μ_θ,

[52] With Fréchet distribution of z, these two effects exactly counteract each other, and a shock to B would leave mean sector income unchanged.

and γ). It is worth noting that simultaneous increases in μ_A and μ_θ reflect economy-wide, factor-neutral total factor productivity (TFP) enhancements, which raise wages universally without impacting inequality or sorting. Thus, we focus on how μ_A has increased more than μ_θ, alongside changes in σ_A and γ. We explain the significance of these results below.

- The distribution of worker skills remains unchanged. This is reflected in the general human capital parameters (μ_θ and σ_θ) and sector-specific abilities and preferences (parametrized by α). Our calibration suggests no significant changes to general or sector-specific human capital, aside from universal productivity increases that do not affect inequality or sorting. This indicates that the primary drivers of inequality changes are related to sectoral productivity/demand structures rather than changes in worker skill.
- Factor-neutral productivity/demand changes across sectors have not significantly contributed to sectoral inequality shifts. Such changes might involve sector price adjustments due to international trade, local demand shocks, or non-skill-biased factor price changes. This is captured by the parameter σ_B, which shows stability over the period. As discussed in Section 7.3, σ_B minimally impacts inequality and segregation but greatly affects sectoral concentration. Given the steady sector concentration, σ_B remains largely unchanged.
- Overall TFP gains during the period are skill-biased, but alone they do not account for sectoral inequality changes. Our model shows μ_A increased more than μ_θ. As outlined in Section 7.3, this can elevate inequality levels but reduces sorting and segregation, suggesting other factors primarily drive increased sorting and segregation that we see in the data.
- The dispersion in sectors' comparative advantages for hiring skilled workers has risen, and comparative advantage has become more significant. This is reflected by the increased σ_A and the decreased γ, indicating stronger complementarities. These changes align with skill-biased technical shifts affecting sectors differently. These compara-

tive advantage shifts predominantly drive the rise in skill segregation across sectors, contributing significantly to observed inter-sectoral income inequality increases.

8 Conclusion: Drivers of Inequality

In this final section, we first take stock of our findings and then discuss their implications for our understanding of the drivers of the secular increase of inequality experienced in western societies.

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

In the second part of the paper we have constructed a parsimonious yet straightforward model of labor allocation across industries. Reading the data in light of the model suggests that sector-specific skill-biased technological change can, on its own, explain the bulk of the observed changes.

Our model suggests that the main changes over the course of the last 40 years in Italy derive from an increase in both (i) the dispersion in sector comparative advantage in hiring skilled workers (in our parlance, an increase of σ_A), and (ii) the complementarity between

skills and industry specific characteristics (our γ). We find no substantial change in the distribution of skill-neutral productivity differences across industries, and we find no evidence that the dispersion of skills across Italians has worsened.

We believe that we can take five lessons from all of this.

The first lesson is that the finding that industry dynamics, and not firm dynamics within sectors, are at the root of the increase of inequality is extraordinarily robust. Undoubtedly, between-firms variance represents a large share of the increase in inequality, but this is due to the fact that some firms are in sectors that move up, and others are in sectors that move down. Once conditioning in the sector, this essentially disappears. It does not seem that issues of decreased firm competition or of firm-specific monopsonies can explain the facts. The reason for the increase in inequality seems to lie instead in more traditional sources affecting labor demand at the industry level.

The second lesson we take is that these changes in labor demand do not seem to be caused mainly by institutional change. The labor market and taxation institutional environments in Italy and the US are notoriously different and have distinct dynamics. The structure of the evolution of inequality, on the other hand, is remarkably similar in both countries. There may be some similar political economic trends, but among the sea of differences, it seems implausible that they can produce such a remarkable similarity in the changes of the structure of inequality.

The remaining lessons depend on the model's calibration to our empirical results. Notice, however, that we use a standard Roy model, adapted to address issues of sorting and segregation across industries; consequently, it should not be excessively controversial.

Thus, the third lesson we take is that, in light of our model of labor allocation, the underlying reason for the increase in inequality does not appear to lie in international trade, at least not in a direct manner. This is because we do not find significative changes in the dispersion of skill-neutral productivity across sectors. Trade would affect factor prices, wages, and employment shares. In our model, it is captured by the skill-neutral technology

(B_j), and matching the model to the data in the 80s and 30 years later does not demand any change in their dispersion. If trade liberalization has an effect, it is through more subtle mechanisms affecting the distribution of skills.

From our exercise, we also learn that the increase in inequality in Italy does not seem to be mainly a consequence of Italians becoming more heterogeneous in their skills. At least in relation to the productive structure of the economy, the degree of heterogeneity in their abilities does not seem to have changed. It is not that Italians have become more unequal in their endowment of skills over the last thirty years. The way that the model reads our data suggests instead that the increase in inequality is rooted in a shift in how the Italian economy utilizes these skills across different sectors.

Our data, when read by the model, suggest that the primary root of the increase in inequality lies in the growing prominence of skill-biased productivity across sectors. The prominent increase in sorting and segregation across sectors that we measure demands to be explained by: (i) an increase in the complementarity between individual skills and tasks across sectors (a fall of γ, and (ii) an increase in the dispersion of skill requirements across industries (an increase of σ_A). This increase in the dispersion of skill requirements implies that some sectors (where A_j decreases) become less selective in the workers they hire, allowing masses of workers with limited skills to reallocate away from industries where requirements have become more stringent and less compatible with their abilities.

There are, however, several reasons that may have contributed to this increase in the dispersion of requirements and the complementarity of skills in industry. The most obvious one is skill-biased technical change, which maps directly into our model parameters, but there are others. The differential usage of capital as a substitute for labor in various industries can lead to routine-task substitution and job polarization, which also aligns with our model. Likewise, the opening to foreign trade could generate skill-biased technological adoption.

In any case, our whole exercise suggests that the prominence of sectors in explaining the evolution of inequality (something that we show occurs in the very different institutional

contexts of the US and Europe), and the notorious increase of sorting and segregation across industries (which again, happens in both sides of the Atlantic), wants to be explained by the increase in the bias in which different industries use different skills.

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9 Appendix A

9.1 Tables

Table A1: Distribution of firm size.

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

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

Table A2: Top 14 sectors in terms of increasing between-sector variance.

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

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

Table A3: Sectors and firms: full variance decomposition - only men.

(a) Variance change over time

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

(b) Variance shares

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

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

Table A4: Sectors and firms: full variance decomposition - only women.

(a) Variance change over time

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

(b) Variance shares

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

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

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

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

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

Table A6: Contribution of 4-digit sector groups to between sector variance growth (grouped based on individual sector share) - only men.

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

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

Table A7: Top 20 4-digit sectors contributing to increasing between-sector variance - only men.

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

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

Table A8: Industry-enhanced AKM variance decomposition - 4-digit industry - only men.

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

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

Table A9: Average worker and firm fixed effects of the top 14 (4-digit) sectors contributing to the increased between-sector variance.

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

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

Table A10: Effects of μ_A

	1	2	3	4	5
Values of μ_A	7.48	7.58	7.68	7.78	7.88
Between Sector Earnings Variance	0.06	0.06	0.05	0.05	0.04
Within Sector Earnings Variance	0.21	0.23	0.24	0.26	0.28
Concentration	0.03	0.03	0.03	0.03	0.03
Segregation	0.02	0.02	0.02	0.02	0.02
Within Sector Skill Variance	0.08	0.08	0.08	0.08	0.09
$\mathbb{E}(\log y)$	9.30	9.32	9.34	9.35	9.37
Sorting	0.49	0.47	0.44	0.42	0.39

Note: In this and subsequent tables, and as explained in the text, the first row declares the values taken by the variable on which we make comparative statics, in this case, μ_A. All other variables take their calibrated value in the first period. As for the moments, Between Sector Earnings Variance refers to the variance between sectors of $\log y$. Within Sector Earnings Variance, to its within-sector value. Concentration refers to the Herfinthal Index of Sector concentration. Segregation to the between sector variance of $\log \theta$, and Within Sector Skill Variance to its within sector value. Sorting refers to the correlation between $\log A$ and $\log \theta$ across sectors.

Table A11: Effects of σ_A

	1	2	3	4	5
Values of σ_A	0.29	0.32	0.35	0.38	0.41
Between Sector Earnings Variance	0.06	0.07	0.07	0.08	0.09
Within Sector Earnings Variance	0.21	0.20	0.19	0.19	0.18
Concentration	0.03	0.03	0.03	0.03	0.03
Segregation	0.02	0.03	0.03	0.03	0.04
Within Sector Skill Variance	0.08	0.07	0.07	0.07	0.07
$\mathbb{E}(\log y)$	9.30	9.30	9.30	9.30	9.30
Sorting	0.49	0.52	0.55	0.57	0.60

Table A12: Effects of μ_θ

	1	2	3	4	5
Values of μ_θ	6.51	6.61	6.71	6.81	6.91
Between Sector Earnings Variance	0.06	0.06	0.06	0.06	0.06
Within Sector Earnings Variance	0.21	0.19	0.18	0.16	0.15
Concentration	0.03	0.03	0.03	0.03	0.03
Segregation	0.02	0.03	0.03	0.03	0.03
Within Sector Skill Variance	0.08	0.07	0.07	0.07	0.07
$\mathbb{E}(\log y)$	9.30	9.38	9.45	9.53	9.60
Sorting	0.49	0.52	0.54	0.55	0.57

Table A13: Effects of σ_θ

	1	2	3	4	5
Values of σ_θ	0.66	0.73	0.79	0.86	0.93
Between Sector Earnings Variance	0.06	0.08	0.10	0.12	0.15
Within Sector Earnings Variance	0.21	0.24	0.27	0.30	0.33
Concentration	0.03	0.03	0.03	0.03	0.03
Segregation	0.02	0.03	0.04	0.06	0.07
Within Sector Skill Variance	0.08	0.09	0.10	0.12	0.13
$\mathbb{E}(\log y)$	9.30	9.29	9.29	9.28	9.27
Sorting	0.49	0.52	0.55	0.57	0.59

Table A14: Effects of γ

	1	2	3	4	5
Values of γ	0.39	0.35	0.31	0.27	0.23
Between Sector Earnings Variance	0.06	0.06	0.07	0.07	0.06
Within Sector Earnings Variance	0.21	0.22	0.24	0.26	0.28
Concentration	0.03	0.03	0.03	0.03	0.03
Segregation	0.02	0.03	0.03	0.02	0.02
Within Sector Skill Variance	0.08	0.08	0.08	0.08	0.08
$\mathbb{E}(\log y)$	9.30	9.28	9.25	9.22	9.19
Sorting	0.49	0.50	0.50	0.49	0.46

Table A15: Effects of α

	1	2	3	4	5
Values of α	15.00	13.50	12.00	10.50	9.00
Between Sector Earnings Variance	0.06	0.05	0.04	0.04	0.03
Within Sector Earnings Variance	0.21	0.22	0.24	0.25	0.27
Concentration	0.03	0.03	0.03	0.03	0.03
Segregation	0.02	0.02	0.02	0.02	0.01
Within Sector Skill Variance	0.08	0.08	0.08	0.09	0.09
$\mathbb{E}(\log y)$	9.30	9.33	9.36	9.40	9.46
Sorting	0.49	0.46	0.42	0.38	0.34

Table A16: Effects of ϕ

	1	2	3	4	5
Values of ϕ	1.80	2.40	3.00	3.60	4.20
Between Sector Earnings Variance	0.06	0.06	0.06	0.06	0.06
Within Sector Earnings Variance	0.21	0.21	0.21	0.21	0.21
Concentration	0.01	0.02	0.03	0.05	0.07
Segregation	0.03	0.02	0.02	0.03	0.03
Within Sector Skill Variance	0.08	0.08	0.08	0.08	0.08
$\mathbb{E}(\log y)$	12.50	10.18	9.30	8.86	8.61
Sorting	0.49	0.49	0.49	0.49	0.49

Table A17: Effects of φ

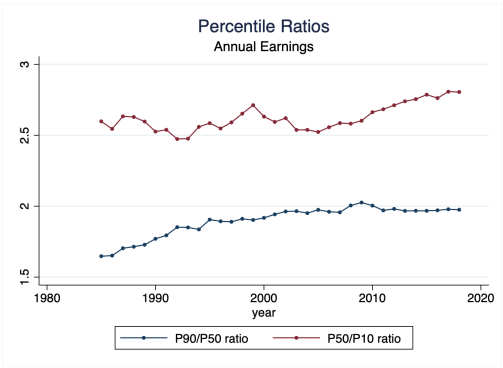
	1	2	3	4	5
Values of φ	0.58	0.68	0.78	0.88	0.98
Between Sector Earnings Variance	0.06	0.06	0.06	0.06	0.06
Within Sector Earnings Variance	0.21	0.21	0.21	0.21	0.20
Concentration	0.03	0.03	0.03	0.03	0.03
Segregation	0.02	0.02	0.02	0.03	0.03
Within Sector Skill Variance	0.08	0.08	0.08	0.08	0.08
$\mathbb{E}(\log y)$	9.25	9.27	9.30	9.33	9.35
Sorting	0.49	0.49	0.49	0.49	0.49

Table A18: Effects of σ_B

	1	2	3	4	5
Values of σ_B	0.50	0.38	0.25	0.13	0.00
Between Sector Earnings Variance	0.06	0.06	0.06	0.06	0.06
Within Sector Earnings Variance	0.21	0.21	0.21	0.21	0.22
Concentration	0.03	0.02	0.01	0.01	0.01
Segregation	0.02	0.02	0.02	0.02	0.02
Within Sector Skill Variance	0.08	0.08	0.08	0.08	0.08
$\mathbb{E}(\log y)$	9.30	9.18	9.10	9.05	9.03
Sorting	0.49	0.49	0.49	0.49	0.49

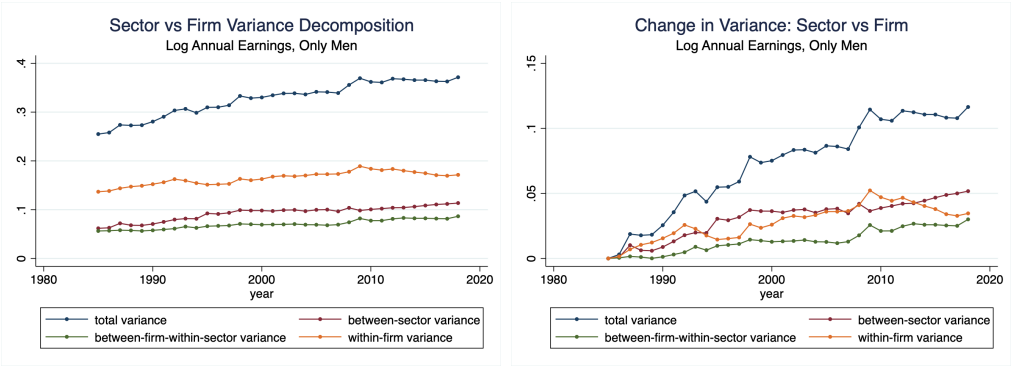
9.2 Figures

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



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

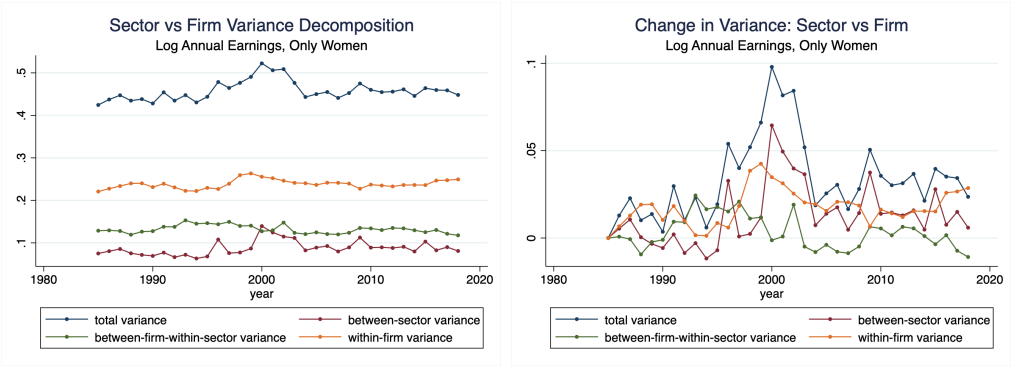
Figure A2: Sector and firm: full variance decomposition - only men.



(a) Levels (b) Change Relative to 1985

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

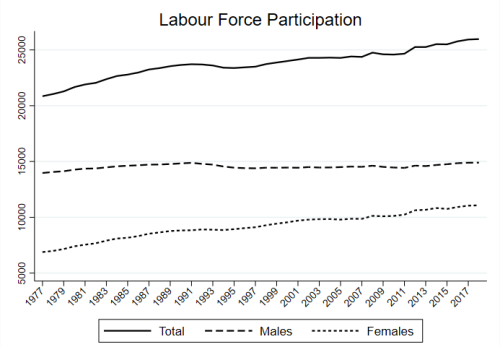
Figure A3: Sector and firm: full variance decomposition - only women.



(a) Levels (b) Change Relative to 1985

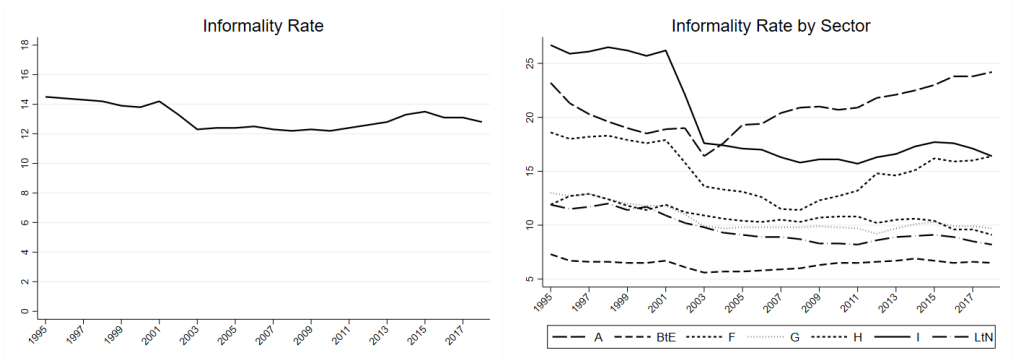
Note: The sample includes only women. See Equation (2) for definitions. Industries are disaggregated at 4-digit level.

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



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

Figure A5: Informality rate.



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

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

10 Appendix B: Online Appendix

10.1 How we control for the sector of the firm

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

$$w_{ijs} = \sum_{s=1}^{s=S} \beta_s D_s + \epsilon_{ijs}, \tag{24}$$

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:

$$\underbrace{\frac{1}{N}\sum_{\forall i}(\epsilon_{ij} - \bar{\epsilon})^2}_{\text{within-sector variance}} = \underbrace{\sum_{\forall j}\frac{n_j}{N}(\bar{\epsilon_j} - \bar{\epsilon})^2}_{\text{between-firm-within-sector variance}} + \underbrace{\sum_{\forall j}\frac{n_j}{N}\frac{\sum_{\forall i|i\in j}(\epsilon_{ij} - \bar{\epsilon_j})^2}{n_j}}_{\text{within-firm variance}}, \tag{25}$$

where ϵ_{ij} is the residual from (Equation (24)) for worker i in firm j, N still denotes the total number of workers (firm-worker matches) in the data, n_j is the number of workers employed at firm j, $\bar{\epsilon_j} = \frac{1}{n_j}\sum_{\forall i|i\in j}\epsilon_{ij}$ are the firm j's average log annual earnings after controlling for sector fixed effects and $\bar{\epsilon} = \frac{1}{N}\sum_{\forall i}\epsilon_{ij}$ is the economy-wide average of log annual earnings after controlling for sector fixed effects.

The total variance of residuals from (Equation (24)) is equal to the within-sector variance given that controlling for sector fixed effects removes the between-sector variance. Performing between versus within-firm variance decomposition on the residuals from Equation (24) produces between-firms-within-sector variance and within-firm variance.

The second method of controlling for the sector is to demean each observation by the sector of the worker i.e., for every observation subtract the average of the sector that the observation belongs to. This method also removes the between-sector variance and it is equivalent to Equation (24). The demeaned observations are then used to calculate Equation (25).

10.2 Sub-periods analysis

We split our time period into two sub-periods: 1985 to 2003 and 2003 until 2018. There are two reasons for this. First, there was a legislative change and short-term employment contracts became increasingly common since 2003.[53] Second, we saw earlier that the patterns of rising inequality are markedly different in the two sub-periods (Section 3.1). Between 1985 and 2003 inequality in the upper half of the distribution (p90/p50 ratio) was steadily rising, while inequality in the bottom half was roughly constant (Figure A1). In contrast, since 2003 inequality in the bottom of the distribution (p50/p10 ratio) has been steadily increasing, while inequality in the upper half has been stable.

Table B1: Sectors and firms: full variance decomposition.

(a) Variance change 1985-2003

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

(b) Variance change 2003-2018

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

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

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

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

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

10.3 Contribution to inequality (2-digit sectors)

We group (2-digit) industries by the size of their individual contributions to between sector variance growth. In our data three industries account individually for more than 10% of the increase in the between-sector variance (Table B2), while together account for 61.2% of the between-sector variance growth, although they only represent 2.5% of total employment in 1985.[54]. Since the rise of between-sector variance accounts for 55% of the overall increase in earnings inequality, these three industries account for a third of the rise in earnings inequality in Italy.

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

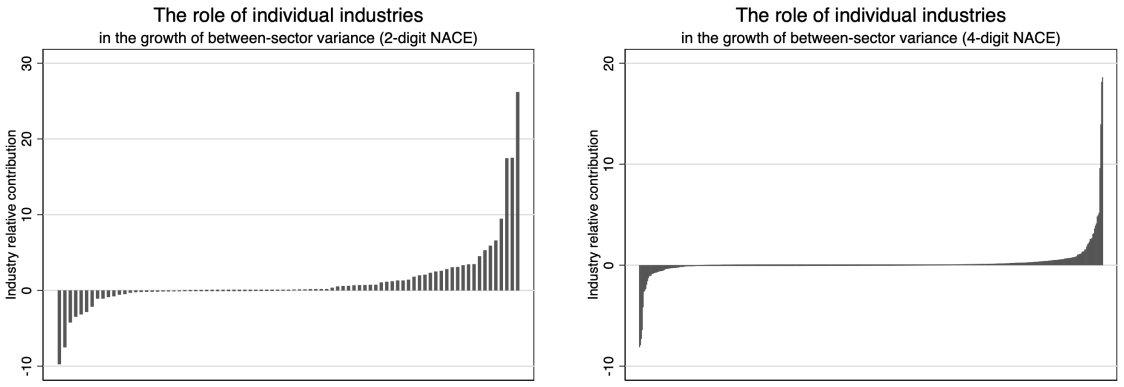
Note: The sample includes only men. See Equation (3) for definition of the contribution of a particular sector to between sector variance growth. Industries are disaggregated at 2-digit level.

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

NACE code	Industry title	Employment share		Relative earnings		Share of between sector
		1985	2018	1985	2018	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: The sample includes only men. Relative earnings is the gap between average log earnings of a particular industry and the economy average. See Equation (3) for definitions. Industries are disaggregated at 2-digit level.

Figure B1: The relative role of individual industries in the growth of between-sector variance (in percentage points) - 2 digit and 4 digit industries.



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

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

10.4 Standard AKM decomposition

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

Table B8: AKM variance decomposition

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

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

Moving on to our main interest, explaining change in earnings dispersion over time, we can see that two channels dominate. These are growing variance of worker effects and increasing sorting of highly paid workers into high-paying firms. Increase in variance of worker effects accounts for 79.0% of the total growth in earnings dispersion, while increasing sorting

accounts for 71.6%. The other components all had negative, inequality-reducing contribution, the most important being shrinking variance of firm effects and of residual variance. Variance of time-variant characteristics and their covariance with worker and firm effects also all declined in size. Furthermore, we find very similar results when restricting our sample to just men (Table B9). Based on this we can conclude that earnings dispersion in Italy between 1985 and 2019 grew not because of changes in firm wage premiums, but because of growing heterogeneity in worker personal component of pay (their earnings ability that is mobile between firms) and due to an increase in sorting where workers with high earnings ability are increasingly working at firms with high pay premiums.[55] This is the same as the finding of Song et al. (2019) for the US.[56] 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.

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

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

Table B9: AKM variance decomposition - only men.

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

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

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

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

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

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

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

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

10.5 Firm size cutoff: 5 employees

Table B12: Sectors and firms: full variance decomposition (4-digit sectors).

(a) Variance change over time

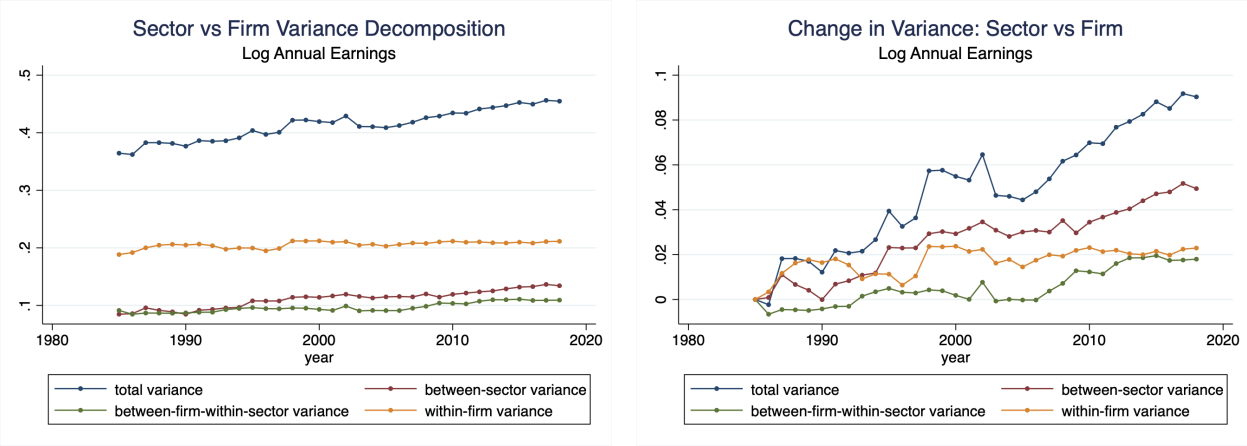
	Between sector	Between firms within sector	Within firm	Total
1985	0.085	0.091	0.188	0.364
2018	0.134	0.109	0.211	0.455
Change	0.049	0.018	0.023	0.090
% of total increase	54.4%	20.0%	25.6%	100.0%

(b) Variance shares

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

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

Figure B2: Sector and firm: full variance decomposition.



(a) Levels (b) Change Relative to 1985

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

Table B13: Contribution of 4-digit sector groups to between sector variance growth (grouped based on individual sector share).

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

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

Table B14: Top 4-digit sectors contributing to increasing between-sector variance.

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

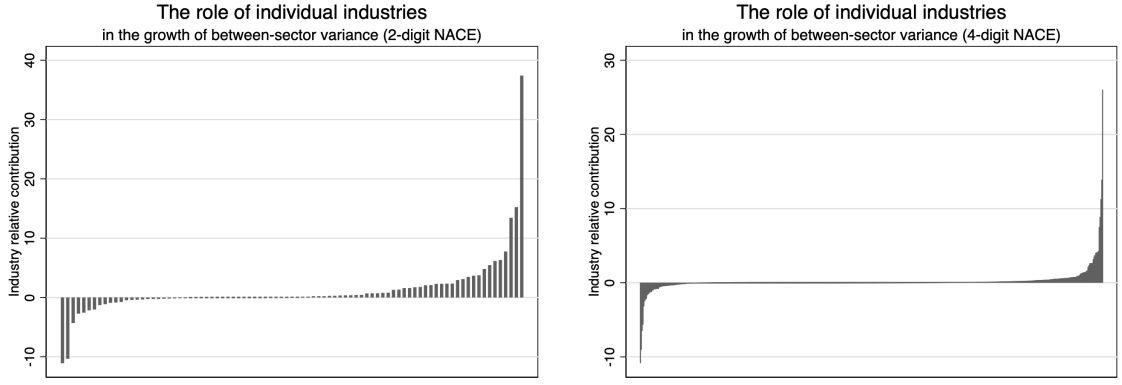
Note: Relative earnings is the gap between the average log earnings of a particular industry and the economy average. See Equation 3 for definitions. Industries are disaggregated at 4-digit level.

Table B15: Sector contributions to between sector variance growth (4-digit sectors).

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

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

Figure B3: The relative role of individual industries in the growth of between-sector variance (in percentage points): 2 digits vs 4 digits.



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

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

10.6 No firm size cutoff

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

(a) Variance change over time

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

(b) Variance shares

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

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

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

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

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

Table B18: Top 4-digit sectors in terms of increasing between-sector variance.

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

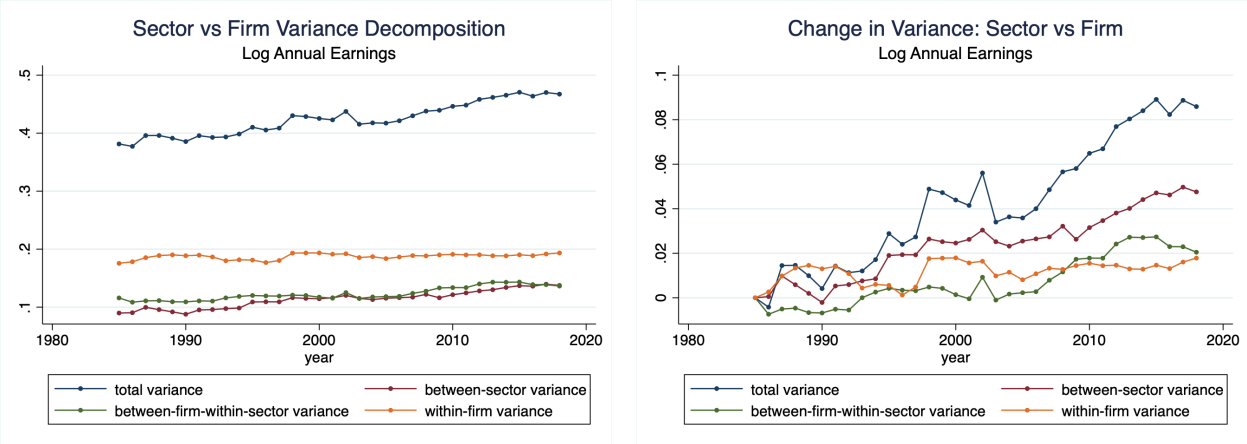
Note: Relative earnings is the gap between the average log earnings of a particular industry and the economy average. See Equation 3 for definitions. Industries are disaggregated at 4-digit level

Table B19: 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 (3) for definitions of relative earnings and of the contribution of a particular sector to between-sector variance growth. The sector is high paying (low paying) if its average relative earnings are positive (negative) where the average is taken over the 1985 and 2018 values. The total contribution of a particular sector to between-sector variance growth is decomposed into the role of employment and earnings changes as defined in Equation (4). To calculate the shares we sum the employment and earnings components across sectors and divide each by the corresponding sum of the total contribution to between sector variance growth.

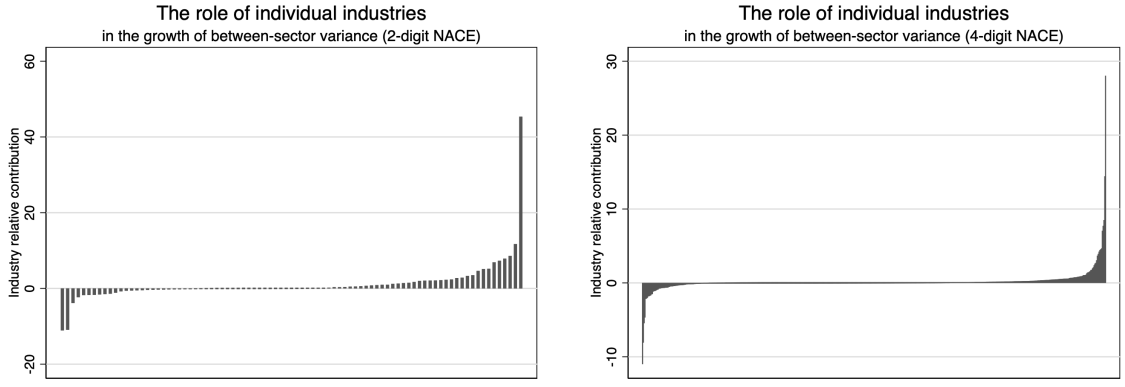
Figure B4: Sector and firm: full variance decomposition.



(a) Levels (b) Change Relative to 1985

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

Figure B5: The relative role of individual industries in the growth of between-sector variance (in percentage points): 2 digits vs 4 digits.



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

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

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

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

(a) Variance change over time

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

(b) Variance shares

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

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

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

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

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

Table B22: Top 4-digit sectors contributing to increasing between-sector variance.

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

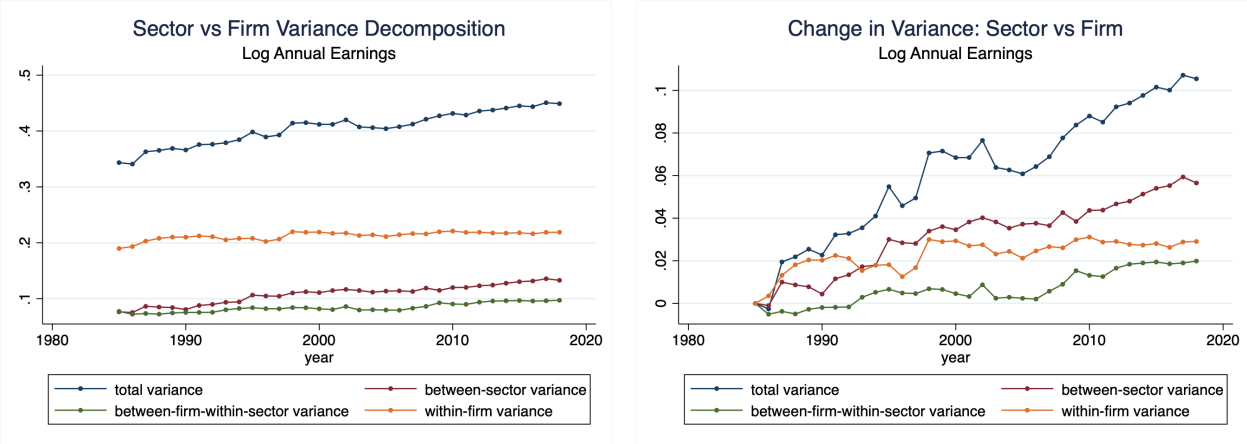
Note: Relative earnings is the gap between the average log earnings of a particular industry and the economy average. See Equation (3) for definitions.

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

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

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

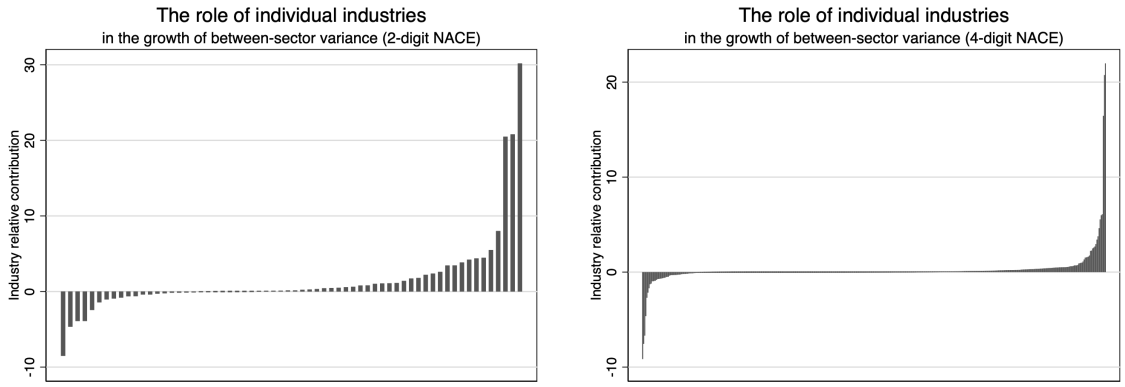
Figure B6: Sector and firm: full variance decomposition.



(a) Levels (b) Change Relative to 1985

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

Figure B7: The relative role of individual industries in the growth of between-sector variance (in percentage points): 2 digits vs 4 digits.



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

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

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

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

(a) Variance change over time

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

(b) Variance shares

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

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

Table 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%

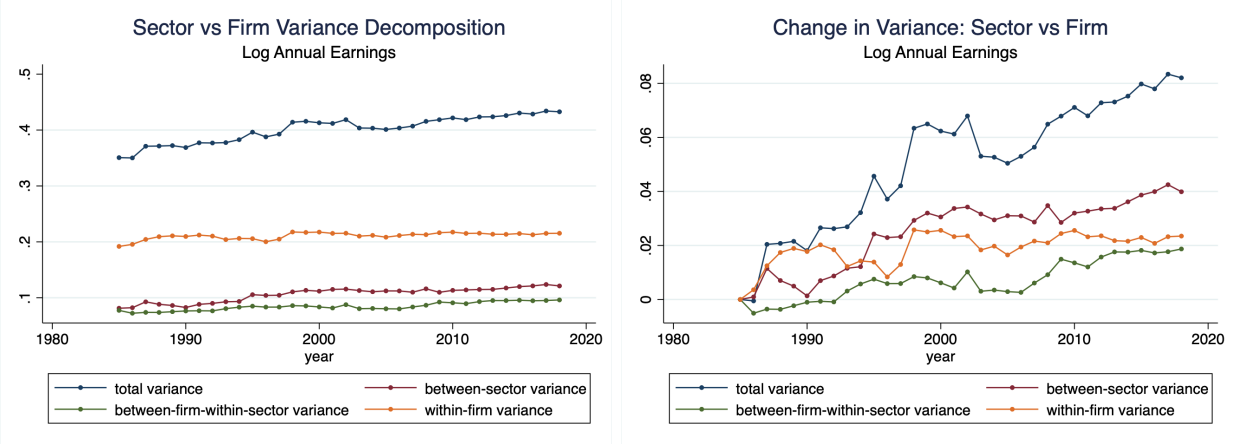
Note: See Equation (3) for definition of the contribution of a particular sector to between sector variance growth. Industries are disaggregated at 4-digit level.

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

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

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

Figure B8: Sector and firm: full variance decomposition.



(a) Levels (b) Change Relative to 1985

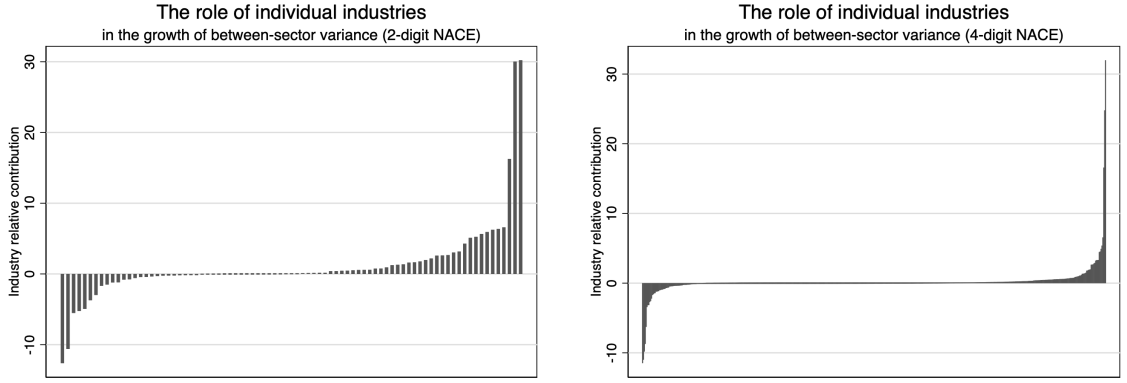
Note: See Equation 2 for definitions. Industries are disaggregated at 4-digit level.

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

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

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

Figure B9: The relative role of individual industries in the growth of between-sector variance (in percentage points): 2 digits vs 4 digits.



(a) 2-digit NACE industries

(b) 4-digit NACE industries

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

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

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

(a) Variance change over time

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

(b) Variance shares

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

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

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

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

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

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

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

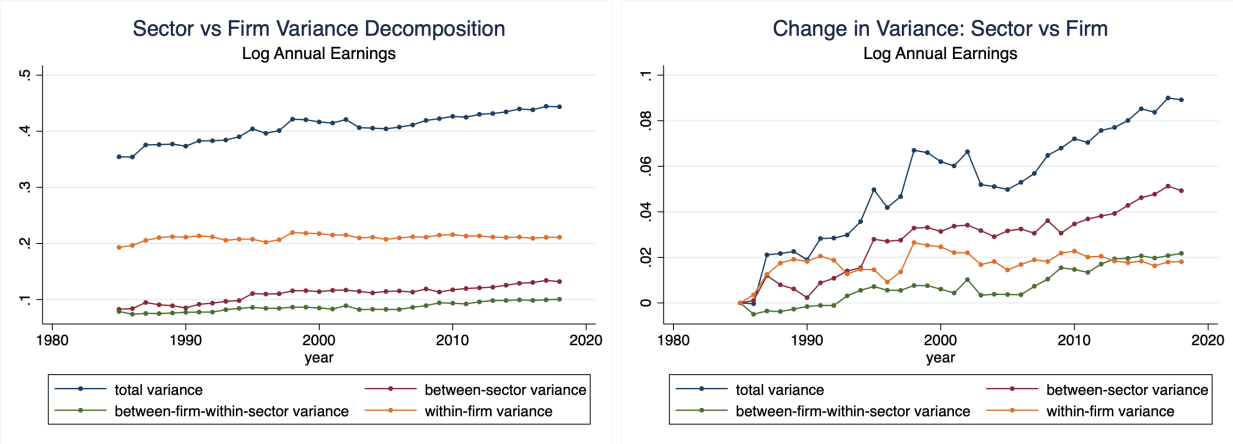
Note: Relative earnings is the gap between the average log earnings of a particular industry and the economy average. See Equation (3) for definitions.

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

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

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

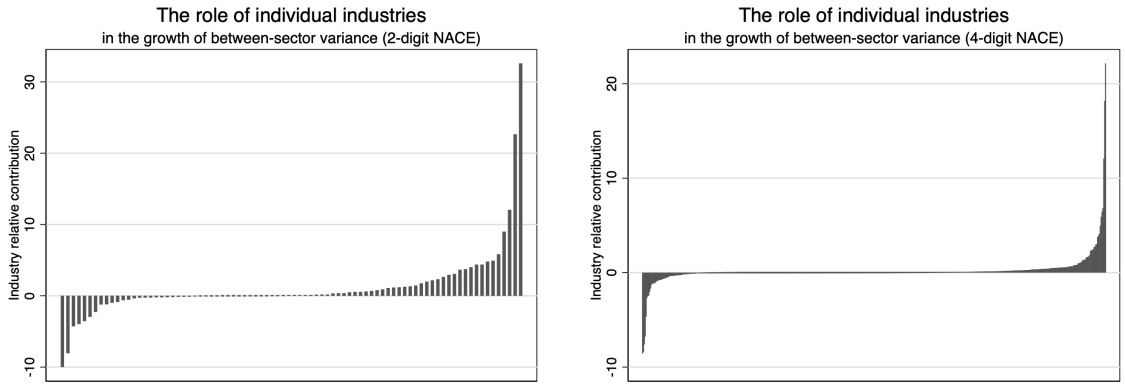
Figure B10: Sector and firm: full variance decomposition.



(a) Levels (b) Change Relative to 1985

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

Figure B11: The relative role of individual industries in the growth of between-sector variance (in percentage points): 2 digits vs 4 digits.



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

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