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Working Paper 750

April 2018

DOI: https://doi.org/10.21034/wp.750
Keywords: Income inequality; Pay inequality; Between-firm inequality
JEL classification: E23, J21, J31

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https://www.minneapolisfed.org/research/

Firming Up Inequality*

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Abstract

We use a massive, matched employer-employee database for the United States to analyze the contribution of firms to the rise in earnings inequality from 1978 to 2013. We find that one-third of the rise in the variance of (log) earnings occurred within firms, whereas two-thirds of the rise occurred between firms. However, this rising between-firm variance is not accounted for by the firms themselves: the firm-related rise in the variance can be decomposed into two roughly equally important forces—a rise in the sorting of high-wage workers to high-wage firms and a rise in the segregation of similar workers between firms. In contrast, we do not find a rise in the variance of firm-specific pay once we control for worker composition. Instead, we see a substantial rise in dispersion of person-specific pay, accounting for 68% of rising inequality, potentially due to rising returns to skill. The rise in between-firm variance, mostly due to worker sorting and segregation, accounted for a particularly large share of the total increase in inequality in smaller and medium firms (explaining 84% for firms with fewer than 10,000 employees). In contrast, in the very largest firms with 10,000+ employees, 42% of the increase in the variance of earnings took place within firms, driven by both declines in earnings for employees below the median and a substantial rise in earnings for the 10% best-paid employees. However, because of their small number, the contribution of the very top 50 or so earners at large firms to the overall increase in within-firm earnings inequality is small.

Keywords: Income inequality, pay inequality, between-firm inequality.

JEL Codes: E23, J21, J31

***Version: April, 2018**. Special thanks to Gerald Ray and Pat Jonas at the Social Security Administration for their help and support. We thank our formal discussants Pat Kline, Lin Peng, Ben Pugsley, Johannes Schmieder, Andre Shleifer, Larry Katz and five anonymous referees and seminar participants at the AEA, ASU, Berkeley, the White House CEA, Columbia, Chicago, Dartmouth, Drexel, FRBs of Atlanta, New York, and Philadelphia, Harvard, Michigan, MIT, NBER, Northwestern, Princeton, Rand, Stanford, TNIT, UCLA, and Yale for helpful comments. Benjamin Smith and Brian Lucking provided superb research assistance. We are grateful to the National Science Foundation for generous funding. To combat alphabetical inequality, author names have been randomly ordered.

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1 Introduction

The dramatic rise in U.S. earnings inequality from the 1970s to today has been well documented (see Katz and Autor (1999) and Acemoglu and Autor (2011) for detailed reviews). It is well known that the change in inequality at the bottom (or below the median of the distribution) has been "episodic"—expanding in the 1980s and subsequently contracting and plateauing—whereas the rise in inequality above the median (all the way up to the very top earners) has been persistent throughout this period (e.g., Piketty and Saez (2003) and Autor et al. (2008)). An enormous body of theoretical and empirical research has been conducted over the past two decades in an attempt to understand the causes of these trends. Until recently, the analysis of the role of employers has been absent from this literature, chiefly because of the lack of a comprehensive, matched employer-employee data set in the United States covering the period of rising inequality.

A long literature in economics has recognized that some firms pay workers with similar skills more than others (e.g., Slichter (1950), Dickens and Katz (1987), Krueger and Summers (1988), and Van Reenen (1996)). Controlling for differences in the composition of observed and unobserved worker characteristics between firms, an increasing number of studies have shown that these differences in firm pay premiums contribute substantially to the distribution of earnings (e.g., Abowd et al. (1999), Goux and Maurin (1999), Abowd et al. (2002), Gruetter and Lalive (2009), and Holzer et al. (2011)).[1]

An important question is to what extent the differences in firm pay premiums have widened, and to what extent this can explain the observed increases in earnings inequality. In a recent paper, Card et al. (2013) show that a rise in the dispersion of firm pay premiums has contributed substantially to recent increases in wage inequality in Germany. They also show that inequality rose in equal measure because of large changes in worker composition—high-wage workers became increasingly likely to work in high-wage firms (i.e., sorting increased), and high-wage workers became increasingly likely to work with each other (i.e., segregation rose).

Similar phenomena of changes in firm pay premiums and worker composition could

[1] For the clarity of the discussion in this paper, it is important to distinguish this notion of "firm pay premium"—how much a firm pays a hypothetical worker with average observable and unobservable characteristics—from what we will call "firm average earnings"—which is simply the average of the labor earnings of all employees in a given firm. (When we write about "between-firm inequality," we refer to the variance of firm average earnings, while "within-firm inequality" refers to the variance of earnings from that average.) While firm average earnings are easily measured in the data, its value depends on both the hard-to-measure firm pay net of worker characteristics, as well as the actual composition of the workers who are employed at the firm. This distinction will be important throughout the paper.

also explain some of the shifts in inequality in the United States, which has experienced a stronger and more persistent increase in inequality than has Germany (as well as most other continental European countries). Indeed, as we discuss below, many of the mechanisms considered in the U.S. literature on inequality have potential implications for the contribution of firms and worker sorting to inequality, but these have not been evaluated so far. The firm dimension is also particularly interesting because it may help us to better understand the rise in earnings at the very top, which many attribute to an increase in executive compensation, a within-firm phenomenon. Recent findings in Barth et al. (2016) suggest that compensation differences among firms and changes in worker sorting may indeed play an important role in understanding U.S. earnings inequality. Using data from several U.S. states from 1992 to 2007, they document an important rise in the variance of earnings between establishments, which they partly attribute to a change in the composition of observable worker characteristics.

In this paper, we study the contribution of firms and the role of worker flows in the rise in earnings inequality in the United States using a longitudinal data set covering both workers and firms for the entire U.S. labor market from 1978 to 2013. Our data set has several key advantages for studying firms and inequality: it is the only U.S. data set covering 100% of workers and firms for the entire period of the rise in inequality, it has uncapped W-2 earnings capturing a large share of earnings even at the very top, it has no lower earnings limit, and it has information on firms rather than establishments. Using this data set, in a first step we analyze the overall contribution of a rise in the variance of earnings between firms in explaining the evolution of U.S. earnings inequality from 1978 to today.

Our *first* main result is that the rise in the dispersion between firms in firm average earnings accounts for the majority of the increase in total earnings inequality. We show that the 19 log point increase in total variance between 1981 and 2013 is driven by a 13 point increase in the between-firm component and a 6 point increase within firms. This between-firm component captures all three components of firm-related changes in inequality—changes in firm pay premiums, worker composition, and sorting. The importance of increases in between-firm inequality in explaining pay and worker characteristics is also seen in very fine industry, location, and demographic subsets of the economy and is robust to different measures of inequality. Using a counterfactual decomposition, we find that changes in the distribution of firm average earnings explain almost all of the rise in inequality below the 80th percentile, while changes in the within-firm distribution explain some of rising inequality above that point.

Three factors could account for the rising variance of firm average earnings. First, the dispersion of firm pay premiums could increase; that is, high-paying firms would pay more, adjusting for worker composition, and the opposite would be true for low-paying firms. We refer to this as a rising variance of firm fixed effects. Second, a rise in sorting between high-earnings workers and high-pay firms (which we will refer to as "sorting") could be a contributor. Third, similar workers could be increasingly likely to work together (which we will refer to as "segregation"). Although a rise in segregation by itself does not raise earnings inequality (because of a corresponding reduction in within-firm inequality), it leads to a higher contribution of firms in explaining earnings dispersion in a descriptive sense and could reflect important underlying economic forces.

To distinguish among these factors, we follow the modeling approach of Abowd et al. (1999) [AKM] and Card et al. (2013) [CHK] to estimate unobserved permanent worker and firm components of each worker's annual earnings. Using this approach, we can decompose rising overall inequality into the portion due to the changing dispersion of worker effects, the changing dispersion of firm effects, and the changing covariance between the two.[2] Our *second* main finding is that the rising variance of worker effects—potentially due to rising returns to skill—explains 68% of rising inequality, while the rising covariance explains 35%. In contrast, the third component, the variance of firm effects, *declined* slightly during this time, making a small, negative contribution to rising inequality.

Although this last finding may appear surprising in light of our first result—that the rising dispersion of firm-wide average earnings explains more than two-thirds of the rise in the variance of total earnings—the two results are perfectly consistent, which is our *third* main finding: using the estimated worker and firm fixed effects, we can show that the rise in between-firm inequality can be completely explained by changes in the composition of workers between firms. Increases in sorting and segregation explain the entire increase in between-firm inequality in our data. Rising returns to skill, absent any firm-level changes, can account for about half of rising segregation but almost none of rising sorting.

Our *fourth* result is that, of the 31% of the increase in the total variance of annual earnings that occurs *within* firms, most comes from large firms. The increase in the within-firm variance of log earnings in firms with 10,000+ employees (a group comprising 750 firms that employ about 23% of U.S. workers in 2013) is 58% between firms and 42%

[2] We estimate this set of results separately for men and women for computational reasons. Results reported here are for men only, with similar results for women only. All other results—those that do not follow AKM and CHK—include data on both men and women.

within firms (whereas the change in the variance of log earnings in firms with 20 to 1,000 workers is 92% between and 8% within firms). This rise in within-firm inequality in large firms comes from substantial changes at the bottom and the top of the within-firm earnings distribution. For example, between 1981 and 2013, median workers at 10,000+ employee firms saw their earnings fall by an average of 7%, those at the 10th percentile saw an average drop of 17%, and those at the 90th percentile saw an average rise of 11%. Overall, we calculate that the bottom half of the distribution is responsible for 35% of the rise in within-firm dispersion from 1981 to 2013 in large firms. Changes in the 90th percentile and above explain 46% of the rise in dispersion.

We also find that in these largest firms, the very top 50 managers have seen robust earnings increases. For example, the average 50th highest-paid manager in large firms has seen earnings rise by 47% between 1981 and 2013, while the average top-paid employee (presumably the chief executive officer) has seen earnings rise by 137% over the same period. However, because there are few of these top-paid employees relative to the size of employment at these large firms (about 35,000 of them versus about 20 million total employees in these firms), we find that rising top executive earnings explain little of the increase in the variance in overall earnings. For example, the top 50 employees account for about 3% of the total increase in the within-firm dispersion of earnings from 1981 to 2013 at 10,000+ employee firms, whereas the top 5 employees account for less than 1% of the increase. Turning to smaller firms, those with less than 10,000 employees, we find that top-paid employees have seen their earnings rise more in line with the rise in the average earnings at their firm. Consequently, the contribution of top executives to the rise in overall inequality during this period was limited.

To summarize, our findings imply that the large rise in earnings inequality in the United States can be decomposed into three equally important forces—a rise in the segregation of higher-paid workers to the same firms (segregation), that these high-paid workers are typically moving into higher-paying firms (sorting), and a rise in earnings inequality within larger firms. These findings highlight several potential mechanisms underlying rising earnings inequality. For example, it has long been hypothesized that persistent differences in firm pay premiums reflect rent sharing (e.g., Dickens and Katz (1987), Katz and Summers (1989), Abowd et al. (1999)). Our finding of increasing sorting suggests that the distribution of rents may have become increasingly skewed, with an increasing share going to high-wage workers. Another explanation could be a rise in domestic outsourcing and temporary work (e.g., Weil (2014), Abraham and Taylor (1996), Segal and Sullivan (1997)). Indeed, Katz and Krueger (2016) and U.S. Government Accountability Office (2015) find that contingent workers, such as independent contractors and freelancers, make up an increasing part of the workforce. Similarly, Goldschmidt and Schmieder (2017) show that domestic outsourcing in Germany can explain both a rise in sorting and a rise in inequality. These alternative work arrangements could help explain rising segregation and sorting, as a previously diverse workforce splits into a homogeneous lead firm and a range of homogeneous suppliers and service providers.

Our results are consistent with a substantial literature documenting that technological changes have increased inequality by shifting the demand for different skill groups (e.g., Katz and Murphy (1992), Juhn et al. (1993a); see Acemoglu and Autor (2011) for a recent survey). Rising returns to skill, even with a stable distribution of skill across firms, could mechanically lead to increased sorting and segregation if more skilled employees tend to be clustered together in typically higher-paying firms. Then rising returns to skill would cause top workers to have even higher-paid coworkers (which we would see as part of higher segregation) and top firms to have even higher-paid employees (which we would see as part of sorting). Although this point is relatively straightforward, it is an important one in light of the empirical evidence on rising returns to skill during this period, so we discuss it further in Section 5.1. Finally, the reduction in earnings for low-wage workers within large firms that we document corroborates the view that low-wage workers may have experienced a decline in access to high-paying jobs for institutional reasons, such as a decline in unionization or a change in company culture.

Our findings also complement a growing body of work that documents that the variance of firm earnings or wages explains an increasing share of total inequality in a range of countries, including the United Kingdom (Faggio et al. (2010), Mueller et al. (2017)), Germany (Card et al. (2013)), Sweden (Håkanson et al. (2015)), and Brazil (Helpman et al. (2017), Alvarez et al. (2018)). In the United States, Davis and Haltiwanger (1991) were among the first to draw attention to the fact that rising inequality among workers was closely mirrored in rising inequality among establishments. However, these papers lacked data on wages within firms, which limited the scope of their analysis to between-firm data. The earlier finding was confirmed by Barth et al. (2016), who also find that a large share (about two-thirds in their analysis) of the rise in earnings inequality can be attributed to the rise in between-establishment inequality, concentrating on the period 1992 to 2007 for which they have both worker and establishment data for a subset of U.S. states. Our matched worker-firm data include information back to the 1970s and post-2007 for all workers in the United States. As a result, we can consistently examine the contribution of firms throughout the entire earnings distribution—including for the top end of the distribution that has attracted a lot of attention—for the entire period of key changes in inequality.

A smaller but growing literature has linked increases in between-firm inequality to changes in worker composition. Håkanson et al. (2015), Alvarez et al. (2018), and Card et al. (2013) document that changes in observable worker characteristics can account for an important share of the rise in the between-firm component in earnings inequality. Our approach follows that of Card et al. (2013), who use AKM's method and find that changes in unobservable worker characteristics across firms can explain an important part of rising earnings inequality in Germany. Our analysis is the only implementation of the AKM methodology for the entire U.S. labor market, which allows us to document the role of sorting and segregation for the full relevant period of increasing inequality. Barth et al. (2016) and Card et al. (2013) also note the important distinction between sorting and segregation and document its importance. Direct evidence on the role of occupational segregation across industries and firms in the United States that is consistent with our findings is provided by Kremer and Maskin (1996) and Handwerker (2015), respectively. Abowd et al. (2018) also use AKM's methodology with a smaller sample from the United States and find that workers in high-pay firms see faster earnings growth; that could lead us to understate the importance of sorting, since we would not observe most of the higher lifetime earnings received by high-pay workers who increasingly sort into high-pay firms.

Our results also speak to studies analyzing the sources of earnings inequality at the very top of the earnings distribution. Absent data on the distribution of wages within firms, a popular hypothesis has been that inequality at the very top of firms' pay distribution is a driving force leading to an increase in overall inequality (e.g., Piketty (2013), Mishel and Sabadish (2014)), based on the earnings of about the top 5 earners within each firm from Execucomp data. Other research by Smith et al. (2017) has looked at the role of business owners' business income, but does not connect it to the earnings of other employees at that firm. (As discussed below, our data do not include this business income, but the trends found by Smith et al. (2017) may in fact amplify the between-firm results we find.)

The paper is organized as follows. Section 2 describes the data set and the construction of the matched employer-employee data set and presents summary statistics from the sample. Section 3 presents the main results. Section 4 decomposes the change in earnings inequality into components related to changes in firm average earnings, worker sorting, and worker segregation. Section 5 provides additional discussion on the sources of increases in within- and between-firm inequality, and Section 6 concludes.

2 Data

The main source of data used in this paper is the Master Earnings File (MEF), which is a confidential database compiled and maintained by the U.S. Social Security Administration (SSA). The MEF contains earnings records for every individual that has ever been issued a U.S. Social Security number. In addition to basic demographic information (sex, race, date of birth, etc.), the MEF contains annual labor earnings information from 1978 to (as of this writing) 2013. Earning records are derived from Box 1 of Form W-2, which is sent directly by employers to the SSA. These earnings data are uncapped and include wages and salaries, bonuses, tips, exercised stock options, the dollar value of vested restricted stock units, and other sources of income deemed as remuneration for labor services by the Internal Revenue Service.[3] Because of potential measurement issues prior to 1981 (see Guvenen et al. (2014a)), we start most of our analysis in 1981, although results back to 1978 look similar. All earnings are converted to 2013 real values using the personal consumption expenditures (PCE) deflator.

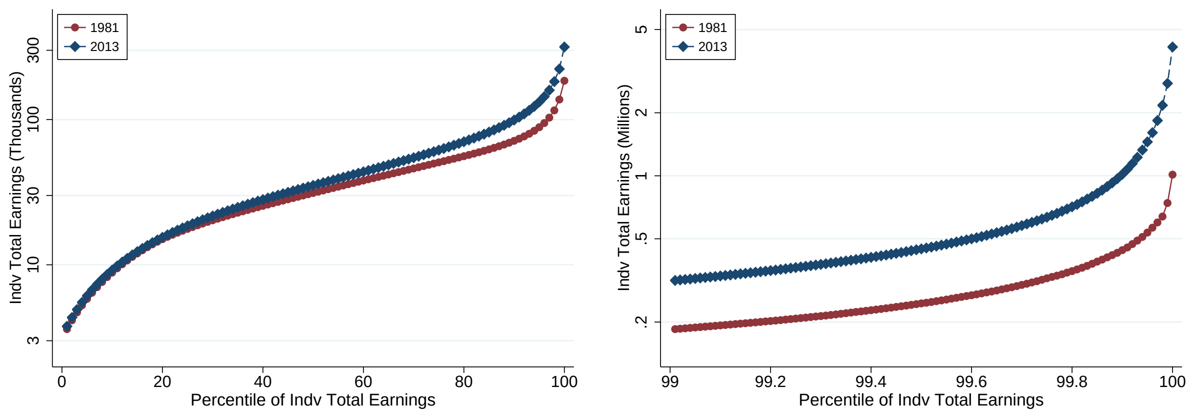
Because earnings data are based on the W-2 form, the data set includes one record for each individual, for each firm they worked in, for each year. Crucially for our purposes, the MEF also contains a unique employer identification number (EIN) for each W-2 earnings record. Because the MEF covers the entire U.S. population and has EIN records for each job of each worker, we can use worker-side information to construct firm-level variables. In particular, we assign all workers who received wage earnings from the same EIN in a given year to that firm. Workers who hold multiple jobs in the same year are linked to the firm providing their largest source of earnings for the year. Many workers have multiple W-2s, but few have multiple W-2s consistently: in 2013, 30.5% of workers had multiple W-2s, but only 4.3% had multiple W-2s every year from 2009 to 2013. The resulting matched employer-employee data set contains information for each firm on total employment, wage bill, and earnings distribution, as well as the firm's gender, age, and job tenure composition.

Although the MEF contains much data that are essential for answering questions posed in this paper, these data have several limitations. First, our data only include labor earnings, not capital or self-employment income. Because those other types of income are not generally connected to a particular firm, it is beyond the scope of this

[3]The MEF has previously been used by, among others, Davis and Von Wachter (2011) and Guvenen et al. (2014b), who describe further details of the data set. Kopczuk et al. (2010) use the 1% Continuous Work History Subsample (CWHS) extract of SSA data to conduct an extensive analysis of long-run trends in mobility.

Figure 1 – Cumulative Distributions of Annual Earnings in the SSA Data

(a) Entire Population (b) Top 1%



Notes: For each percentile, statistics are based on the minimum earnings among individuals in that percentile of earnings in each year. All values are adjusted for inflation using the PCE price index. Only individuals in firms with at least 20 employees are included. Only employed individuals aged 20 to 60 are included in all statistics, where "employed" is defined as earning the equivalent of minimum wage for 40 hours per week in 13 weeks. Individuals and firms in public administration or educational services are not included.

study on firms and inequality.[4] Second, there are several worker- and firm-level variables that could be useful but are not available to us—for example, individuals' education and occupation, or firm profits. Third, we observe only total earnings in a year without data on hours or weeks worked, so we cannot measure wage rates. As discussed in Section 2.3, we only include workers earning above a minimum threshold to minimize the effect of variation in hours worked.

In Figure 1a we plot the earnings distribution in 1981 and 2013. Looking at 2013, we observe a wide distribution of individual labor income—ranging from about $9,800 a year at the 10th percentile, to $36,000 at the median, $104,000 at the 90th percentile, and $316,000 at the 99th percentile.[5] Comparing the 1981 and 2013 distributions, we can also see the increase in inequality as the 2013 distribution is increasingly pulling away from the 1981 distribution in the upper income percentiles, most notably for the top 1% in Figure 1b. These patterns have been studied extensively in the literature on earnings inequality. Here, we focus on the role of employers in accounting for these changes.

[4]An exception is the research by Smith et al. (2017), discussed elsewhere in this paper.

[5]These figures are somewhat lower than what has been reported by Piketty and Saez (2003), primarily because they pertain to individual earnings rather than household earnings (studied by Piketty and Saez); see Figure A.7.

2.1 What Is a Firm?

Throughout the paper, we use employer identification numbers (EINs) as the boundary of a firm. The EIN is the level at which companies file their tax returns with the IRS, so it reflects a distinct corporate unit for tax (and therefore accounting) purposes. Government agencies, such as the Bureau of Labor Statistics, commonly use EINs to define firms.[6] They are also often used in research on firms based on administrative data.

An EIN is not always the same, however, as the ultimate parent firm. Typically, this is because large firms file taxes at a slightly lower level than the ultimate parent firm.[7] Although it is unclear what level of aggregation is appropriate in order to define a "firm," we follow much of the existing literature and view the EIN as a sensible concept reflecting a unit of tax and financial accounting. An EIN is a concept distinct from an "establishment," which typically represents a single geographic production location and is another commonly used unit of analysis to study the behavior of "firms" (e.g., this is the definition used by Barth et al. (2016), who study inequality using U.S. Census data). Around 30 million U.S. establishments in the Longitudinal Business Database in 2012 are owned by around 6 million EIN firms, so an establishment is a more disaggregated concept. As Figure A.4 shows, 84% of the increase in cross-establishment inequality can be accounted for by firms, so firms are an appropriate unit of analysis.

2.2 Benchmarking the MEF against Other Data Sets

Key statistics from our sample align quite well with their counterparts from aggregate data as well as from nationally representative data sets. In particular, when compared to the Current Population Survey (CPS), the SSA data match the changes in the variance of log annual earnings quite closely; see Figure A.2.[8] We also checked a range of other statistics. For example, aggregating wages and salaries from all W-2 records over all

[6] See U.S. Department of Labor, Bureau of Labor Statistics, "Business Employment Dynamics Size Class Data: Questions and Answers," http://www.bls.gov/bdm/sizeclassqanda.htm, questions 3 and 5.

[7] For example, the 4,233 New York Stock Exchange publicly listed firms in the Dunn & Bradstreet database report operating 13,377 EINs, or an average of 3.2 EINs each. For example, according to Dunn & Bradstreet, Walmart operates an EIN called "Walmart Stores," which operates the domestic retail stores, with different EINs for the Supercenter, Neighborhood Market, Sam's Club, and On-line divisions. As another example, Stanford University has four EINs: the university, the bookstore, the main hospital, and the children's hospitals.

[8] Although the change in variance is comparable, the level of variance is higher in SSA data. This may be because SSA data are not top coded and because those with lower incomes may not report them in the CPS. For reference, Figure A.3 shows the cumulative distribution of earnings in the CPS data, which is comparable to Figure 1a for SSA data.

individuals in the MEF yields a total wage bill of $6.8 trillion in 2013. The corresponding figure from the national income and product accounts (NIPAs) is $7.1 trillion, so these numbers are very close; see Figure A.1a for the two series over time. While the level of employment is higher in the MEF than in the CPS, the trend in the total number of individuals in the MEF who received W-2 income in a given year (our measure of total employment) also closely tracks total employment in the CPS (see Figure A.1b).[9] There are 6.1 million unique firms (EINs) in the MEF in 2013, each associated with at least one employee. This number is similar to the 5.8 million firms (with employees) identified by the Census Bureau's Statistics of U.S. Businesses data set in 2015. In addition, as shown in Appendix Figure A.1c, the trends in each of these data sets are similar over time (at least since 1988, when the Census data begins).

2.3 Baseline Sample

For our descriptive analysis in Section 3, we restrict our baseline sample to individuals aged 20 to 60 who were employed, where "employed" is defined as earning at least that year's minimum wage for one quarter full-time (so for 2013, 13 weeks for 40 hours at $7.25 per hour, or $3,770). These restrictions reduce the effect on our results of individuals who are not strongly attached to the labor market. We also restrict to firms (and workers in firms) with 20+ employees to help ensure that within-firm statistics are meaningful. We exclude firms (and workers in firms) in the government or educational sectors because organizations in those sectors are schools and government agencies rather than what economists think of as firms. This yields a sample of, on average, 72.6 million workers and 477,000 firms per year, rising from 55.5 million and 371,000 in 1981 to 85.2 million and 517,000 in 2013, respectively. None of our results are sensitive to these assumptions. Although there is some variation, the results look similar using all ages, all firm sizes, all industries, and minimum earnings thresholds up to full-time (2,080 hours) at minimum wage. Some statistics describing the sample are shown in Table 1. More details about the data procedures are discussed in Appendix B.

[9] In 2013, for example, the MEF measure contains 155 million workers, while the CPS indicated that, on average, 144 million individuals were employed at any given time. The difference is likely because the CPS is a point-in-time estimate; if people cycle in and out of employment, they may be missed in the CPS data but will be included in the MEF (which is an aggregate measure over the year). Furthermore, the CPS excludes the institutionalized population, whereas the MEF includes them.

Table 1 – Percentiles of Various Statistics from the Data

Year	Group	Statistic	10%ile	25%ile	50%ile	75%ile	90%tile
1981	Firm	Earnings (Unwgt)	12.6	16.6	23.8	32.5	41.9
1981	Firm	Earnings (Wgted)	15.2	21.5	30.6	43.2	52.1
1981	Firm	Employees	22	26	38	73	169
1981	Indiv.	Earnings	9.46	18.2	31.9	51.7	73.8
1981	Indiv.	Earnings/Firm Avg	0.43	0.724	1.05	1.45	2.06
1981	Indiv.	Employees	42	127	1153	12418	62718
2013	Firm	Earnings (Unwgt)	13.8	19.3	30.5	43.8	61.4
2013	Firm	Earnings (Wgted)	15.3	21.4	35.8	52.1	73.6
2013	Firm	Employees	22	26	39	79	189
2013	Indiv.	Earnings	9.82	19.2	36	63.2	104
2013	Indiv.	Earnings/Firm Avg	0.421	0.681	1.03	1.5	2.22
2013	Indiv.	Employees	45	157	1381	14197	78757

Notes: Values indicate various percentiles for the data for individuals or firms. All dollar values are in thousands and are adjusted for inflation using the PCE deflator. Only firms and individuals in firms with at least 20 employees are included. Firm statistics are based on mean earnings at firms and are either unweighted or weighted by number of employees, as indicated. Only employed individuals aged 20 to 60 are included in all statistics, where "employed" is defined as earning the equivalent of minimum wage for 40 hours per week in 13 weeks. Individuals and firms in public administration or educational services are not included.

3 Earnings Inequality within and between Firms

3.1 Rising Inequality in Average Firm Earnings

Our first key result—that a substantial part of the rise in earnings inequality took place due to a rising dispersion in earnings between firms rather than within firms—can be seen graphically in a number of ways. First, we start with a simple variance decomposition. We then look at earnings percentiles; this includes focusing on key percentiles of the earnings distribution and looking at long-run changes in earnings—between 1981 and 2013—for each percentile by worker and their firms. Finally, we perform a counterfactual analysis that analyzes how the entire distribution of inequality would have changed if only within-firm inequality had varied or only inequality in average earnings between firms had widened. As will become clear, all four approaches show the same substantive result: rising earnings inequality in the United States has been strongly associated with rising inequality in average firm earnings. Until Section 4, we make no distinction between changes in the variance of firm pay premiums, net of worker composition, and changes in worker composition between firms, both of which could be driving our findings in the descriptive analysis that follows.

3.1.1 Simple Variance Decomposition

One straightforward approach is to decompose the overall (cross-sectional) variance of log earnings into within- and between-firm components. In particular, let $y_t^{i,j}$ be the log earnings of worker i employed by firm j in period t.[10] This can be broken down into two components:

$$y_t^{i,j} \equiv \overline{y}_t^j + \left[y_t^{i,j} - \overline{y}_t^j\right], \tag{1}$$

where $\overline{y}_t^j$ is the firm average earnings for firm j, enabling us to simply define the decomposition of variance:

$$\mathrm{var}(y_t^{i,j}) = \underbrace{\mathrm{var}_j(\overline{y}_t^j)}_{\text{Between-firm dispersion}} + \underbrace{\mathrm{var}(y_t^{i,j}|i \in j)}_{\text{Within-firm-}j\text{ dispersion}}. \tag{2}$$

This equation provides a straightforward way to decompose the total earnings dispersion in the economy into (i) between-firm dispersion (in firm average earnings across firms) and (ii) the within-firm dispersion in employee earnings. The latter is computed for each firm and averaged by weighing each firm by its employment share.

The components of equation (2) are plotted separately in Figure 2a. Of the 19 log points rise in overall variance of log earnings between 1981 and 2013, about 13 log points arise from the between-firm component and 6 log points from the within-firm one. Hence, by this simple metric, 69% of the rise in earnings inequality happened across firms.

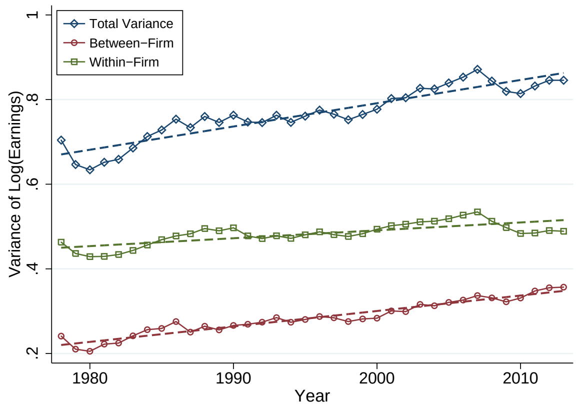
3.1.2 Coworkers of Individuals in Select Percentiles

While the variance decomposition is a useful (and widely employed) tool, it can mask differential trends in inequality across the earnings distribution. To obtain a different perspective on rising between- versus within-firm inequality, we begin in Figure 3a by first plotting selected percentiles—99th, 90th, 50th, and 25th—of the overall (log) earnings distribution in each year, expressed as a deviation from their 1981 values. Our baseline sample covers about 55 million workers in 1981 and 85 million workers in 2013, for an average of 70 million over the sample period, so each one of these percentiles contains around 700,000 workers per year. These percentiles clearly spread out over time, both confirming the rise in inequality revealed by the variance analysis and showing that it reflected a pervasive phenomenon across the income distribution.

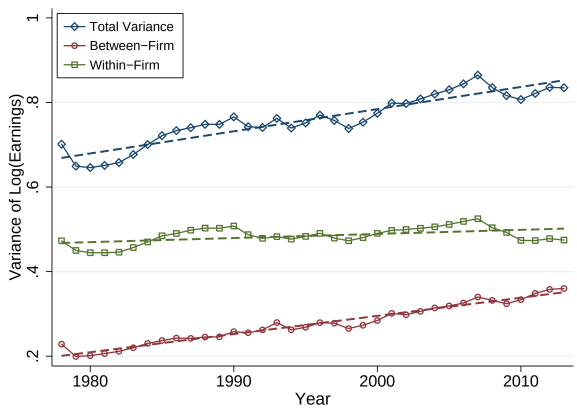
[10] For notational convenience, we suppress the dependence of the subscript j on worker i.

Figure 2 – Decomposition of Variance in Annual Earnings within and between Firms: All, Smaller, and Larger Firms

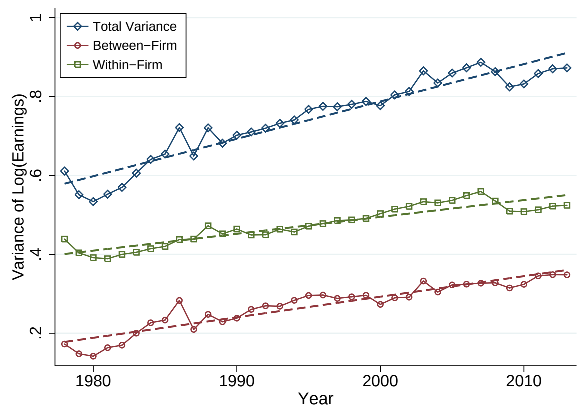
(a) Overall decomposition



(b) Workers at Firms with 20 to 10,000 employees



(c) Workers at Firms with 10,000+ employees



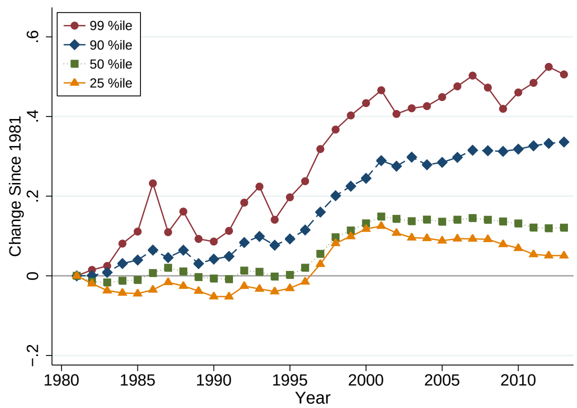
Notes: See variance decomposition in equation (2). Only firms and individuals in firms with at least 20 employees are included. Only employed individuals aged 20 to 60 are included in all statistics, where "employed" is defined as earning the equivalent of minimum wage for 40 hours per week in 13 weeks. Individuals and firms in public administration or educational services are not included. Firm variance is calculated using mean log earnings and weighted by number of employees. Within-firm variance is calculated based on the difference between individual log earnings and firm mean log earnings.

Next, in Figure 3b we plot the average earnings per worker of employers of workers in each percentile of the worker distribution as a deviation from its value in 1981 (shown in Figure 3a).[11] So, for example, the 99th percentile point reports the increase in average earnings per worker for the colleagues of the individuals in the 99th percentile line of

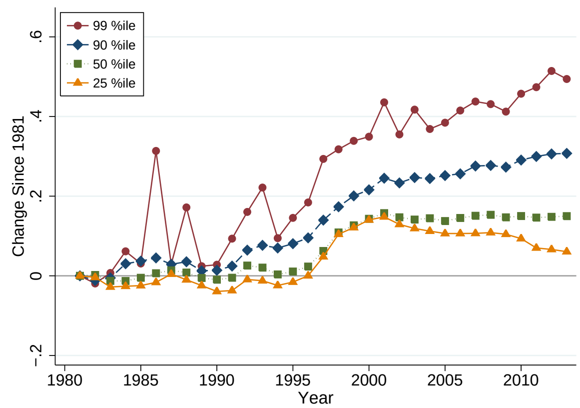
[11] For each percentile of the worker distribution, we average over all firms employing workers in that bin. Clearly, a firm will appear as many times across various percentiles as its number of employees.

FIGURE 3 – Change in Percentiles of Annual Earnings within and between Firms Relative to 1981

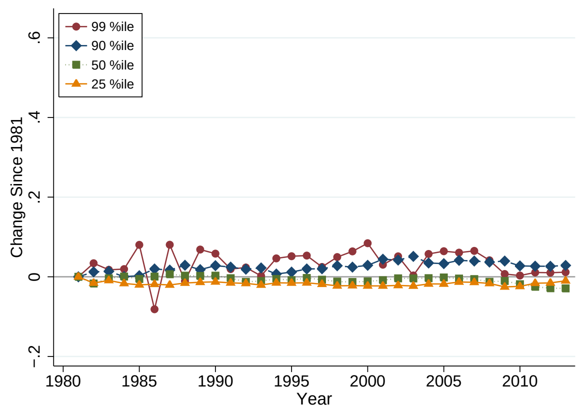
(A) Individuals



(B) Their Firms



(C) Individuals/Their Firms



Notes: Only firms and individuals in firms with at least 20 employees are included. Only employed individuals aged 20 to 60 are included in all statistics, where "employed" is defined as earning the equivalent of minimum wage for 40 hours per week in 13 weeks. Individuals and firms in public administration or educational services are not included. Firm statistics are based on the average of mean log earnings at the firms for individuals in that percentile of earnings in each year. Data on individuals/their firms are based on individual log earnings minus firm mean log earnings for individuals in that percentile of earnings in each year. All values are adjusted for inflation using the PCE price index.

Figure 3a.[12] What is apparent from Figure 3b is that the rise in firm average earnings across percentiles is almost parallel to the changes in the corresponding percentiles of the earnings distribution. This close correspondence indicates that workers' earnings

[12]That is, the line shows $\delta_q^{firm} \equiv E[\bar{y}_{2013}^j | i \in Q_{2013,q}] - E[\bar{y}_{1981}^j | i \in Q_{1981,q}]$, where $Q_{t,q}$ is the set of individuals in the qth percentile in year t, and j refers to the employer of worker i.

and the average earnings of their employer broadly tracked each other in terms of their ranking within the economy.

The flip side of the same conclusion is that the gap between the earnings of workers and their colleagues (i.e., within-firm earnings dispersion) displayed little change over time. This is shown in Figure 3c, which plots the gap between each worker's earnings and the firm average earnings at the worker's employer for each percentile of the worker distribution. While the earnings distribution has spread out over time, the earnings of each worker has been tracked closely by the earnings of the worker's colleagues. So, for example, although the 99th percentile has seen a 51 log point rise in earnings during the whole period, the colleagues of these workers have on average seen a similar rise of 49 log points; thus, the gap between these workers and their colleagues has increased by only 2 log points.

3.1.3 Coworkers of Individuals across the Entire Distribution

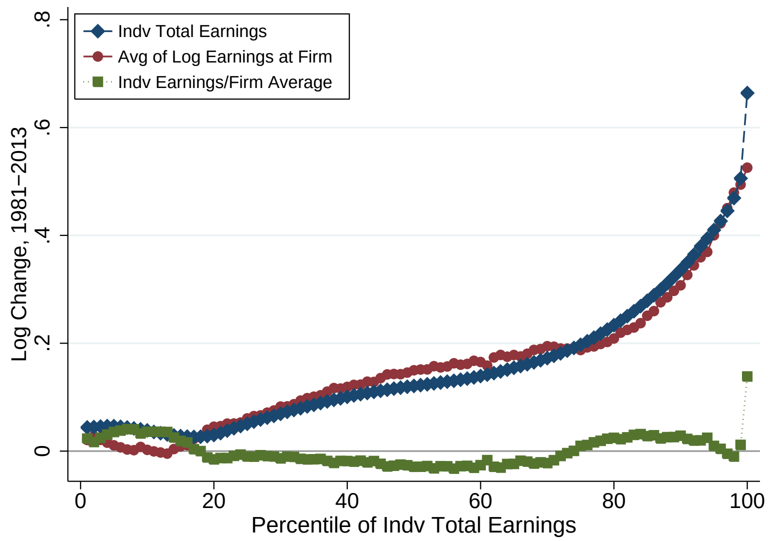
Figure 4 provides information similar to Figure 3 but follows Juhn et al. (1993b) and many related papers in showing the change between 1981 and 2013 for each percentile in the earnings distribution. It is important to realize that this graph, unlike Figure 5 in the next section, is not a counterfactual analysis; instead, it shows how the relationship between individual earnings and coworker earnings changed at different points in the earnings distribution. Understanding the average earnings of coworkers is important for understanding how workers might perceive inequality, among other reasons, but it cannot tell us, for example, how inequality would have been different if between-firm differences in average earnings had been unchanged.

We start with the blue line marked with diamonds (labeled "Indv Total Earnings"), which shows the increase in log earnings between 1981 and 2013 within each percentile of the earnings distribution.[13] So, for example, we see that between 1981 and 2013, the 50th percentile of earnings has increased by 12 log points (13%) from about $31,500 to $35,600. The upward slope of the individual line highlights the rise in individual earnings inequality—earnings at higher percentiles have risen at a faster rate, and this rise grows steadily as you move up the income percentiles.[14]

[13] This graph is closely related to the difference between the 2013 and 1981 lines in Figure 1a, which shows percentiles of earnings in each year. The only difference results from the fact that Figure 1a shows the minimum earnings within each percentile, while Figure 5 is based on average log earnings in each percentile.

[14] This measure does not use any of the panel structure of the data; individuals in the 50th percentile in 1981 are almost certainly different from those in the 50th percentile in 2013. In Section 4, we undertake a type of panel analysis pioneered by Abowd et al. (1999) and reveal that not only has inequality

Figure 4 – Change in Inequality of Annual Earnings across Percentiles from 1981 to 2013



Notes: Only firms and individuals in firms with at least 20 employees are included. Only employed individuals aged 20 to 60 are included in all statistics, where "employed" is defined as earning the equivalent of minimum wage for 40 hours per week in 13 weeks. Individuals and firms in public administration or educational services are not included. Firm statistics are based on the average of mean log earnings at the firms for individuals in that percentile of earnings in each year. Data on individuals/their firms are based on individual log earnings minus firm mean log earnings for individuals in that percentile of earnings in each year. All values are adjusted for inflation using the PCE price index.

To assess how average earnings per worker of employers of workers in each percentile of the earnings distribution has changed, we repeat an exercise similar to that for Figure 3b. For a given percentile, we take firm average earnings and average it across all the employers of workers in that percentile separately in both 1981 and 2013, and then take the difference between the years (shown in Figure 4 as a red line marked with circles, labeled "Avg of Log Earnings at Firm"). The upward slope of this red line indicates that the firms of high-earnings individuals now have higher average earnings than firms of high-earnings individuals in 1981, while firms of low-earnings individuals had roughly the same average earnings as firms of low-earnings individuals in 1981.

Finally, the green line marked with squares (labeled "Indv Earnings/Firm Average") reports changes in the ratio of own log earnings to firm average log earnings for those at different points in the individual distribution.[15] Particular care should be given to

increased in the cross section, but the inequality of the persistent worker component of earnings has also experienced a substantial increase.

[15]Note that this "Individual/Firm" line will be mechanically equal to the difference between the

the interpretation of this line, which is almost flat across all percentiles. Taken together, this graph indicates that although highly paid individuals are now being paid much more than highly paid individuals were in 1981 (as evidenced by the blue line), they are also at firms where their coworkers are being paid better (the red line). Thus their earnings relative to that of their coworkers has barely changed since 1981. (For poorly paid individuals, own earnings and their firm's average earnings changed little in the past few decades, so the ratio is also mostly unchanged.)

3.2 A More Formal Decomposition

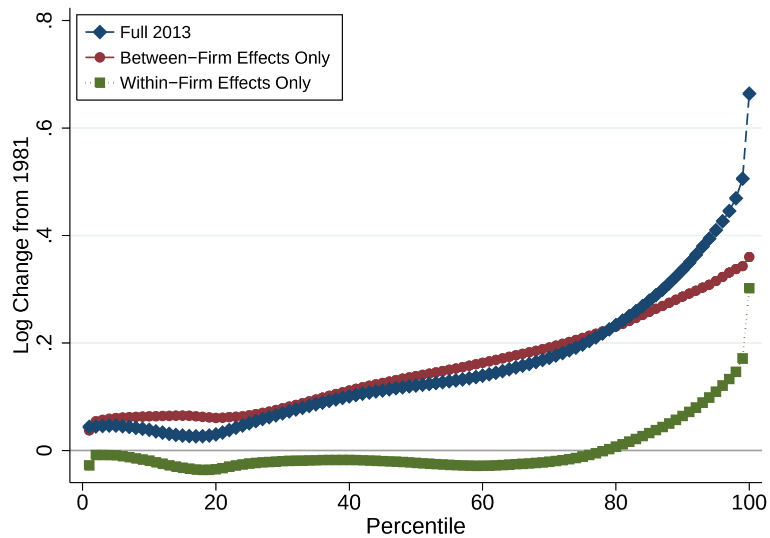
Figure 4 allows one to make statements about how the average earnings of an individual's coworkers has evolved throughout the earnings distribution. However, Figure 4 does not allow us to make a statement on how the distribution of earnings would have evolved, had there been only a rise in the dispersion of average firm earnings. To make such counterfactual statements, we estimated a counterfactual for the entire distribution of earnings shown in Figure 5 using a straightforward simulation exercise. This exercise is based on standard techniques in the inequality literature developed by Machado and Mata (2005) and Autor et al. (2005) but is adapted slightly for our purposes. The approach is described in detail in Appendix Section D, but we briefly explain it here.

We start by calculating two sets of statistics each for 1981 and 2013. First, we obtain the percentiles of the distribution of firms' average log earnings, weighted by firm size; second, within each percentile of the distribution of firm average log earnings, we calculate 500 quantiles of the distribution of the difference between individual earnings and average earnings in that firm-based percentile. These two sets of bins are then used to produce the counterfactual distributions shown in Figure 5 in the following way.

The red "Between-Firm Effects Only" line calculates the counterfactual individual earnings distribution if the firm percentiles had changed to 2013 values but the 50,000 quantiles of deviation *within* each firm-based percentile (500 quantiles within each of 100 firm-based percentiles) had remained at 1981 levels. Conversely, the green "Within-Firm Effects Only" line displays the counterfactual earnings distribution with 1981 values for firm-based percentiles but 2013 values for the distribution of earnings within quantiles. As before, the blue line (labeled "Full 2013") shows the basic change in average earnings from 1981 to 2013 for a given percentile (and is the same as the line labeled "Indv Total Earnings" in Figure 4).

"Individual" line and the "Firm" line. Also, the green line's average taken over all percentiles must be zero.

Figure 5 – Counterfactual Rise in Inequality with between- or within-Firm Effects Only



Notes: Only firms and individuals in firms with at least 20 employees are included. Only employed individuals aged 20 to 60 are included in all statistics, where "employed" is defined as earning the equivalent of minimum wage for 40 hours per week in 13 weeks. Individuals and firms in public administration or educational services are not included. Each point shows the difference in average log earnings within that percentile between actual earnings in 1981 and another distribution. The "Full 2013" line shows the 1981 distribution to the distribution of earnings in 2013. The red "Between-Firm Effects Only" line (green "Within-Firm Effects Only" line) compares the 1981 distribution to the distribution that would have prevailed if the distribution of firm average log earnings (within-firm distribution of earnings) had changed to 2013 levels but the distribution of within-firm earnings (distribution of average firm log earnings) had stayed at 1981 levels, as simulated using the counterfactual procedure discussed in Section 3.2.

The results of this counterfactual calculation in Figure 5 are striking. Holding within-firm changes in earnings constant, the rise in the dispersion of average firm earnings (the "Between-Firm Effects Only" line) can explain the majority of the rise in inequality across almost all earnings percentiles. This confirms our first main finding from our variance decomposition (Figure 2) that a rise in the dispersion of average firm earnings can explain a substantial part of the rise in earnings inequality. However, consistent with the findings of the variance decomposition, increases in the dispersion of earnings within firms do explain some rising inequality above the 80th percentile, with more explained at higher percentiles. In fact, by this decomposition, about half of the rise in earnings among the top 1% is due to changes in within-firm variance.

The difference between the results of Figures 5 and 4 points to another core result of the paper. As discussed in detail in Section 4, the fact that the average earnings of coworkers throughout the distribution has increased proportionally to the rise in individual earnings is partly explained by the fact that higher-wage workers are increasingly working at higher-wage firms and are increasingly working with other higher-wage workers.

3.3 Inequality at the Top of the Earnings Distribution

3.3.1 The Top 1% of Earners, Relative to their Firms

Much of the recent policy and media attention around inequality has focused on the rising share of earnings going to the top 1%. One interesting question in this context is to what extent these very top earners have pulled away from their coworkers in the same firm as opposed to experiencing rising earnings together with the rest of their firm (i.e., the between versus within question). To shed light on this question, in Figure 6 we plot the analog of Figure 4, but this time focusing entirely on the top 1% and splitting it into 100 quantiles of 0.01% each. (With about 70 million people in the full sample per year, each 0.01% represents about 7,000 people on average.)

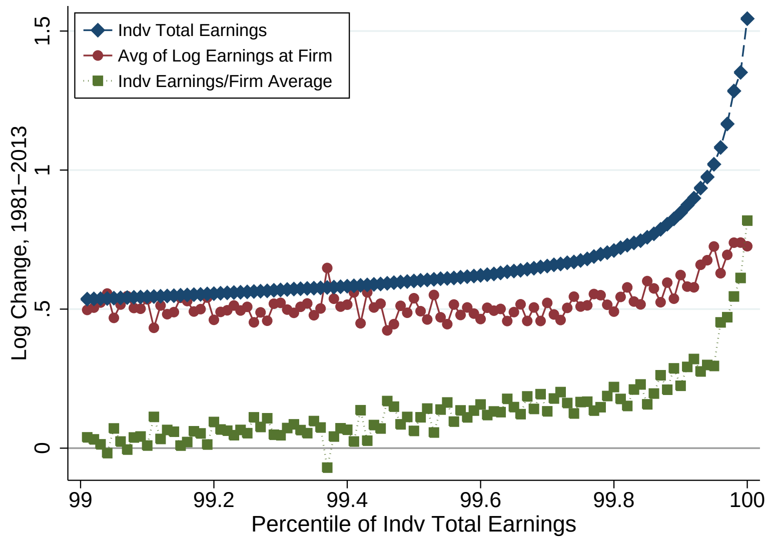
We see in Figure 6 that up until about the 99.5% point—which is an earnings threshold of around $450,000 in 2013 (see Figure 1b)—increases in individual earnings from 1981 to 2013 within each percentile point have been matched almost fully by the increases in earnings of their coworkers. However, in the top 0.5% and particularly the top 0.1%, there is such a steep increase in earnings between 1981 and 2013 that these rises have outpaced those of their colleagues. For example, the 99.95th percentile reveals individual earnings growth of 102 log points (178%), while the firms these employees work for have increased their average earnings by 73 log points (107%), generating a 30 log point gap.[16] Thus, according to this metric, earners in the top 0.5% have seen substantial earnings increases over and above those of their colleagues. This group likely includes the chief executive officers of some very large companies, but also a far wider group of individuals including physicians, finance professionals, lawyers, and engineers, among others (Guvenen et al. (2014a)).

3.3.2 Top Earnings Share

In fact, our data allow us to speak about the share of earnings going to individuals at the top of their firms. Piketty and Saez (2003) describe the increasing fraction of income that is going to the top few percentiles of the income distribution. In this section, we

[16]Most of this divergence between top workers and their firms occurred between 1981 and about 1988; since then, earnings of even those at the top of the top 1% have risen similarly to their firms' earnings.

FIGURE 6 – Rise in Inequality of Annual Earnings between 1981 and 2013 among Top 1% of Earners



Notes: Only firms and individuals in firms with at least 20 employees are included. Only employed individuals aged 20 to 60 are included in all statistics, where "employed" is defined as earning the equivalent of minimum wage for 40 hours per week in 13 weeks. Individuals and firms in public administration or educational services are not included. Firm statistics are based on the average of mean log earnings at the firms for individuals in that percentile of earnings in each year. Data on individuals/their firms are based on individual log earnings minus firm mean log earnings for individuals in that percentile of earnings in each year. All values are adjusted for inflation using the PCE price index.

TABLE 2 – Percentage of Top 1% Earnings in the Economy Going to Those at the Top of Their Firms

	1981	2013
Top-paid person at firm	23%	17%
Among top five at firm	42%	37%
Among top 1% at firm	55%	50%

Notes: Statistics are reported for all people who are in firms with at least 20 employees. Only employed individuals aged 20 to 60 are included in all statistics, where "employed" is defined as earning the equivalent of minimum wage for 40 hours per week in 13 weeks. Individuals and firms in public administration or educational services are not included. Statistics show, of all earnings going to the top 1% overall, how much went to the top-paid person at firms; those who are among the top five top-paid employees at their firm; and those who are among the top 1% at their firm.

note that, while those at the top of their firms are earning a greater fraction of earnings in the overall economy, their share within the top 1% and top 0.1% of economy-wide earnings has changed little in the past three decades.

Table 3 – Percentage Who Are Top-Paid Person at Firm

	1981	2013
All individuals	0.71%	0.62%
Top 1%	18%	11%
Top 0.1%	36%	20%

Notes: The percentage of people who are the top-paid person in their firm, among all individuals in firms with at least 20 employees. Only employed individuals aged 20 to 60 are included in all statistics, where "employed" is defined as earning the equivalent of minimum wage for 40 hours per week in 13 weeks. Individuals and firms in public administration or educational services are not included. Rows show the fraction who are top paid among all individuals; those who are in the top 1% of top earners; and those in the top 0.1% overall.

People at the top of their firms in 2013 generally receive a greater share of economy-wide earnings than those at the top in 1981. In firms with at least 20 employees, the top 1% within each firm took home 8.4% of total earnings, an increase from 4.7% in 1981. (In firms with at least 10,000 employees, the top 1% took home 7.1% in 2013 and 4.7% in 1981.) However, these gains generally match those of other high earners, as shown in Table 2. For example, of all earnings that went to those in the top 1% overall, those who were the top-paid person at their firm (most likely the CEOs) earned 23% in 1981 but only 17% in 2013.

Indeed, high earners are now less likely to be the top-paid person at their firms, as shown in Table 3. The fraction of the top 1% who were the top-paid person at their firm declined from 18% in 1981 to 11% in 2013, while the fraction of those in the top 0.1% who were the top-paid person declined from 36% to 20%. This decline is only partially due to the increasing size of firms: for comparison, the total fraction of people who are the top-paid person at their firm decreased from 0.71% to 0.62%. Rather, it is because highly paid employees are more likely to work with other highly paid employees.

These results mirror those found by Bakija et al. (2012). Using IRS tax data, they found that, although nonfinancial executives, managers, and supervisors in the top 1% and 0.1% earned an increasing fraction of overall income, their total income relative to others in the top 1% was mostly flat.

3.4 Robustness of Results

The results above show that, perhaps rather surprisingly, the majority of the increase in earnings inequality among workers is associated with a rise in the dispersion of mean earnings among firms and their employees. To investigate the robustness of these results,

Table 4 – Robustness Checks on Variance Decomposition

	Total Var, 1981	Between-Firm Var, 1981	Total Var, 2013	Between-Firm Var, 2013	Total Var Increase	Frac Increase Between
Baseline sample	0.652	0.222	0.846	0.357	0.194	0.694
20-10k workers	0.651	0.206	0.835	0.36	0.184	0.837
10k+ workers	0.552	0.164	0.873	0.348	0.32	0.577
Demean: county	0.611	0.181	0.8	0.311	0.189	0.687
Demean: 4-digit SIC	0.517	0.088	0.705	0.216	0.187	0.684
Demean: gender	0.564	0.166	0.819	0.337	0.256	0.668
Demean: person year of birth	0.568	0.186	0.695	0.26	0.127	0.578
Age 20-29	0.556	0.178	0.62	0.241	0.063	0.993
Age 30-39	0.601	0.219	0.72	0.316	0.119	0.807
Age 40-49	0.631	0.255	0.791	0.348	0.16	0.583
Age 50-60	0.617	0.253	0.789	0.338	0.173	0.491

Notes: Only firms and individuals in firms with at least 20 employees are included. Only employed individuals aged 20 to 60 are included in all statistics, where "employed" is defined as earning the equivalent of minimum wage for 40 hours per week in 13 weeks. Individuals and firms in public administration or educational services are not included. "Total Var" indicates total variance of earnings in a given year, and "Between-Firm Var" indicates total between-firm variance in that year. "Total Var Increase" denotes the increase in variance between 1981 and 2013, while "Frac Increase Between" denotes the fraction of that increase in variance accounted for by an increase in between-firm variance. Statistics in rows labeled "Demean:" include earnings that are demeaned within a given group—firm's county, firm's 4-digit SIC industry, individual's gender, or year of birth—before all variances are calculated. Statistics in rows showing numbers of employees are limited to individuals in firms with that number of employees.

we reran the analysis in Section 3.1.1 in several different ways. The basic result—that the rise in the variance of average firm earnings accounts for most of the rise in earnings inequality—remains true for each such analysis. Results for some breakdowns are presented in Table 4. Results for a much larger set of breakdowns are presented in Appendix Tables A.1 and A.2.

First, given the different trends in rents and amenities identified by Moretti (2013) and Diamond (2016), could this increase in between-firm inequality simply reflect regional variation? To investigate this question, we reran our analysis of earnings variance by first subtracting the mean of earnings within each county; any remaining variation represents within-county variation. As can be seen in Table 4, most of the increase in variance still occurred between firms. Another possible driver could be variations by industry; perhaps differential trends arising from trade, technology, or other industry factors are driving the firm results (e.g., Autor et al. (2013) and Pierce and Schott (2016)). However, the results are similar within narrow 4-digit SIC categories. In case these trends reflect changes in demographics, we demean by year of birth and by gender, with again more than half of the increased variance being accounted for by increasing dispersion between firms. (Because somewhat less of the rise in variance is between-firm when demeaning by year of birth, we also present results in Table 4 for each decade of age; the rise in within-firm variance seems to be higher for older workers.)

Another possible concern would be if the increase in earnings inequality within firms is driven by differences across establishments. Using the Census Longitudinal Business Database (LBD), which covers all establishments in the United States, we decompose the variance in average earnings differences across establishments into a between-firm and a within-firm component. We see in Figure A.4 that for the same sample as our main SSA analysis (firms with 20+ employees in all sectors excluding public and education), the increase in the variance of the average of log earnings across establishments has been 12 log points, with the bulk of this rise (10 log points) across firms. So in our overall sample, inequality is primarily a between-firm phenomenon (rather than a within-firm but between-establishment phenomenon). Of course, this sample contains many smaller firms, so it might be expected that the majority of the increase in inequality is across rather than within firms. But in Figure A.5, we examine the sample of establishments in firms with 10,000+ employees and find similarly that of the 15 log point increase in earnings inequality, the large majority (11 log points) was between firms. Hence, examining the rising inequality across firms is capturing the large majority of the rising inequality across workplaces in the United States.[17]

We also considered other robustness issues around health care, self-employment income, and business income. On health care, perhaps rising firm earnings inequality is offset by an increase in the generosity of firm health care insurance that, as a flat entitlement to all employees, provides a progressive compensation component. In fact, as Burkhauser and Simon (2010) show, *employer-provided* (but not government) health insurance is about as unequally distributed as earnings among the bottom eight income deciles. Kaestner and Lubotsky (2016) show that *employer-provided* health insurance actually increases inequality. Higher-paid employees are more likely to be in firms offering generous health care packages, have higher firm coverage rates, pay lower premiums, and are more likely to enroll.[18]

[17] Barth et al. (2016) and Abowd et al. (2018) come to a similar conclusion.

[18] The part of health care that has reduced inequality is Medicaid and Medicare, programs that are strongly progressive and have increased in generosity (Burkhauser and Simon, 2010). However, conditional on total earnings, this part of health care is independent of the employee-firm match itself and does not influence our analysis.

Regarding self-employment, the IRS Statistics of Income reports that in 2012, 16.5% of individuals reported self-employment income on Schedule C and 1099 forms, while it accounted for only 3.2% of all income, most of which is concentrated in employees of smaller firms. Hence, in our 20+ employee sample, self-employment income is too small to play a major role in shaping inequality. Additionally, because this self-employment income is not generally connected to a particular firm, it is beyond the scope of this study on firms and inequality. To the extent that self-employment income is connected to particular firms—for example, in the increasing use of freelancers and independent contractors, as discussed by Weil (2014) and others—including that income would likely lead to higher estimates of sorting and segregation as previously diverse workforces shed all but a core group of likely similar employees.

We also unfortunately do not have data on business income; as noted by Smith et al. (2017), this income can be related to labor performed by firm owners and can be an important contributor to inequality at the very top of the income distribution. However, Smith et al. (2017) find that the firms owned by top business owners are often highly profitable rather than just large; indeed, these may be the same firms that pay other employees well, which would only amplify our results on between-firm inequality.

Overall, then, the basic result that the majority of increasing inequality is related to changes in firm average earnings seems to be broadly robust. One group that is a partial exception, as discussed in Section 3.3.2, is the top 1%. Another setting where the rise in earnings inequality is driven to a large degree by increases in within-firm inequality is among workers employed at very large firms. Figures 2b and 2c plot the decomposition of variance for firms with less than and greater than 10,000 workers. We see in Table 4 that in firms with fewer than than 10,000 workers—which contain over 70% of employees and over 99% of firms—inequality is almost entirely (84%) due to between-firm variation. In comparison, increases in inequality in the 10,000+ worker firms—which account for about 30% of employees and only about 700 firms—is still mostly (58%) between firms but also has a large (42%) within-firm component. We also find that the rise in within-firm earnings inequality among the top 1% of earners discussed in Section 3.3 is more pronounced at very large employers. We discuss the phenomenon of rising within-firm inequality among very large employers and its potential sources in more depth in Section 4 and especially in Section 5.

4 The Role of Worker and Firm Effects

The rise in the dispersion in average earnings between employers we document in Section 3 could come from two different sources. First, a "widening firm premium" story: firms may be increasingly unequal in their earnings because some firms had become economic "winners" and are sharing the increased profits with their workers, whereas other "loser" firms are not. Second, a "worker composition" story: high-wage workers may be increasingly sorted into high-wage firms, or workers may be increasingly segregating among firms (so that high-ability workers are clustering in some firms and low-ability workers in others). As we show below, the second "worker composition" story—including both worker sorting and segregation—appears to jointly account for almost the entire increase in between-firm inequality in average earnings we documented in Section 3.

4.1 Econometric Model of Worker and Firm Effects

To analyze the worker and firm movements in earnings, we follow the Card et al. (2013) [henceforth CHK] implementation of the model introduced by Abowd et al. (1999) [henceforth AKM] and solved by Abowd et al. (2002).[19] We will divide our time period into five seven-year periods, as discussed further below, and estimate a separate model for each period p. The regression model we estimate in each period is

$$y_t^{i,j} = \theta^{i,p} + X_t^i \beta^p + \psi^{j,p} + \epsilon_t^{i,j}, \tag{3}$$

where $\theta^{i,p}$ captures earnings related to fixed worker characteristics (such as returns to formal schooling or to innate ability), β^p captures the effect of time-varying worker characteristics (in our case, a polynomial in age and year effects), and $\psi^{j,p}$ captures persistent earnings differences related to firm j (such as sharing of rents or compensating differentials). The residual, $\epsilon_t^{i,j}$, captures purely transitory earnings fluctuations. In addition, the residual will also contain any worker-firm specific (match) components in earnings, which we will denote by $m^{i,j}$.

The AKM model has proven to be an empirically successful extension of the standard human capital earnings function and has developed into the workhorse model for incorporating firm components into traditional earnings regressions. We confirm that

[19] To simplify notation, we leave the dependence of the identity of the firm on the worker implicit, such that $j \equiv j(i)$. Note that while most of the literature uses the model to analyze daily or hourly wages, we follow an increasing number of papers that analyze earnings. We discuss the potential role of labor supply differences below.

the model appears to summarize a range of key patterns in our data surprisingly well. Hence, despite well-known limitations we discuss below and in Appendix C, we believe that there is sufficient support for the model to treat it as a useful diagnostic device to better understand the patterns underlying the stark changes in the between-firm component over time.

The estimates of the parameters of the econometric model in equation (3) can be used to further decompose the within- and between-firm components of the variance. Ignoring time-varying worker characteristics $X_t^i \beta^p$ for now and variation across periods (dropping superscript p), the standard approach to decompose the variance into components related to worker effects and firm effects used in AKM, CHK, and related work is

$$\text{var}(y_t^{i,j}) = \text{var}(\theta^i) + \text{var}(\epsilon_t^{i,j}) + \text{var}(\psi^j) + 2\text{cov}(\theta^i, \psi^j), \tag{4}$$

where the moments in the last two components are weighted by the number of worker-years in the respective interval.

In this decomposition, the rise in the first two components accounts for the role of worker-related factors in explaining earnings inequality. As we further discuss below, the variance of worker fixed effects in particular is typically associated with increases in the variance of skills and its returns. The last two components account for the variance of firm-related components in earnings inequality. To use our findings to assess the role of changes in worker composition for explaining our descriptive findings pertaining to the rise in the variance of average earnings between firms in Section 3 ("Between-firm component"), we further rewrite the standard variance decomposition as follows:

$$\text{var}(y_t^{i,j}) = \underbrace{\text{var}(\theta^i - \overline{\theta}^j) + \text{var}(\epsilon_t^{i,j})}_{\text{Within-firm component}} + \underbrace{\text{var}(\psi^j) + 2\text{cov}(\overline{\theta}^j, \psi^j) + \text{var}(\overline{\theta}^j)}_{\text{Between-firm component}}, \tag{5}$$

where the moments in the between-firm component are again weighted by the number of worker-years.[20]

Equation (5) shows how the between-firm component discussed in Section 3.1.1 can be decomposed into three pieces: a part deriving from the variance of firm effects, $\text{var}(\psi^j)$, a part deriving from the covariance of worker and firm effects, $\text{cov}(\overline{\theta}^j, \psi^j)$, and a part deriving from the variance of the average worker effect in each firm, $\text{var}(\overline{\theta}^j)$.

[20]Note that one can rewrite the within-firm component as $var(\theta^i - \overline{\theta}^j) = E_j\{var(\theta^i | i \in j)\}$, that is, as the worker-weighted mean of the firm-specific variances of the worker effect (and similarly for $var(\epsilon_t^{i,j})$).

The first component is the "widening firm premium" part, measuring whether the variance of firm pay premiums has increased. The second component reflects the "worker sorting" story—high-paid workers are increasingly sorting into high-paying firms. The third part is the "worker segregation" story—lower- and higher-paid workers are segregating into different firms. Splitting the worker component into the sorting covariance and segregation variance terms allows us to better characterize the role of firms in accounting for earnings inequality, since sorting increases aggregate inequality, whereas segregation does not.

4.2 Implementation of Regression Model Using SSA Data

We estimate equation (3) separately for five adjacent seven-year intervals beginning in 1980 and ending in 2013.[21] As is well known, firm fixed effects are identified by workers moving between firms and hence can only be estimated relative to an omitted firm. Estimation of equation (3) is done on the largest set of firms connected by worker flows. We impose similar restrictions on the data as in our descriptive analysis, with one major exception: because of limitations in computing power, we present worker and firm effects only for men in the main text; results for women only, which are substantively similar, are presented in Appendix C. All other restrictions, including restricting to firms with 20+ total (male and female) employees; dropping workers in education and public administration; and imposing a minimum earnings threshold, are the same as described in Section 2.[22]

Although our implementation of AKM follows CHK, an important difference is that

[21]The choice of intervals trades off limitations in computational power and the desire to analyze changes in the variance over time with the sampling error in estimates of the worker and firm effects and the resulting bias in the variance and covariance terms, which depend on the number of movers between firms. We experimented with intervals up to ten years and found that our results did not change substantially.

[22]To maximize the number of observations in the connected set, when we estimate the model we do not impose a restriction on firm size and do not exclude the education and public sector; those observations are excluded after firm and worker effects have been estimated. (The only exceptions are Tables A.3 and A.4, which report summary statistics based on all observations used to calculate fixed effects.) One more minor difference between results in this section and other results is that these results impose a minimum earnings threshold of 520 times the 2013 hourly minimum wage, adjusted for inflation to the given year with the PCE. Other results impose a threshold of 520 times the contemporaneous minimum wage. Results are similar with both definitions, but due to limits on the number of results disclosures, we have had to keep this different definition. There are also two figures in the current version with slightly different samples: Figure 7, and Figure A.13 include men who earn more than 520 times the contemporaneous minimum wage, regardless of industry or firm size. Those two figures will be updated to match the rest of this section in the next version. For clarity, all tables and figures include sample definitions.

we have data on annual earnings for all workers, not daily wages for full-time workers. This means that our estimates of worker and firm effects may capture systematic differences in labor supply between workers and firms.[23] Given the nature of our data, such differences can arise because of variation at both the intensive margin (i.e., hours worked) and the extensive margin (i.e., days worked in a year). In principle, these differences could affect the level and change of the moments in our variance decomposition.[24] However, it is worth noting that under the plausible assumption that job moves occur randomly within a year, there is no mechanical reason why labor supply effects should introduce a bias into our estimates of firm effects.

We tried various ways to address the potential effects of systematic labor supply differences in our findings. We have experimented by imposing increasingly stringent lower earnings restrictions. Using retrospective data from the CPS, one can show that this approach tends to eliminate part-time or part-year workers. Our results are robust to variation in this restriction; see the "Full-time" sample in the last column of Table A.5. Since our analysis based on the CPS also shows that more stringent earnings cutoffs eliminate low-wage full-time or full-year workers, we use a less stringent restriction in our main sample. CPS data do not reveal any trend in the aggregate variance of weekly hours worked or weeks per year worked over time. Given the robustness of our findings and the stability in trends in the variance of time worked, we are confident that our main results are mainly driven by changes in the variance of wages, not hours or days worked.[25]

Estimating the model requires a set of identification assumptions, which given the prior literature on this, we do not discuss in detail in the paper but rather relegate to Appendix C. Since the estimated firm effects will capture any systematic differences in earnings of movers before and after the job move, to associate estimated firm effects with true underlying firm-specific differences in pay, we have to assume that conditional on

[23] In that sense, our implementation is comparable to Abowd et al. (2018), who implement this model using quarterly earnings. **?** implement the AKM model with data on hours worked from the state of Washington and find only moderate systematic differences in firm effects due to hours variation.

[24] For example, systematic differences in the propensity to take part-time jobs or to be unemployed would load onto the worker fixed effect. If firms offer different hours packages or offer seasonal work, this could load onto the firm effect as well. If high-hour workers (or stable workers) are increasingly sorted into high-hour firms (or stable firms), labor supply can also affect the nature of sorting. If job moves are partly triggered by changes in hours worked, labor supply effects could also contribute to a failure of the conditional random mobility (CRM) assumption.

[25] If one compares the number of observations in our final sample with the number of workers, one obtains that the average worker is in the sample for about five of seven years in each period. This number is very similar to numbers reported by CHK (Table I) for full-time male workers in Germany.

worker and firm effects, job moves do not depend systematically on other components, in particular worker-firm specific job match effects (the conditional random mobility (CRM) assumption). After reviewing the evidence, we join an increasing number of papers whose results indicate that the AKM model can be estimated without too much systematic bias (e.g., AKM, CHK, and Abowd et al. (2018)).

In particular, we do not find that an increasing dispersion in worker-firm match effects plays a role in explaining rising inequality. To check whether adding a match-specific component would substantially increase the fit of the model, we indirectly included a match effect (m_{ij}) in the model. Although, not surprisingly, allowing for a match effect reduces the root mean squared error (RMSE) and raises the adjusted R^2, the standard deviation of match effects declines somewhat over time. Similarly, we also find that the goodness of fit of the model without a match component has increased over time from an R^2 of 74% (1980-1986) to an R^2 of 81% (2007–2013), driven by both a reduction in the RMSE and an increase in the variance of earnings. If the rise in the sorting of workers to firms that we find had resulted from an increasing role of match effects, we would have expected the RMSE to rise and the goodness of fit of the model without match effects to decline over time (see Appendix Table A.4).[26]

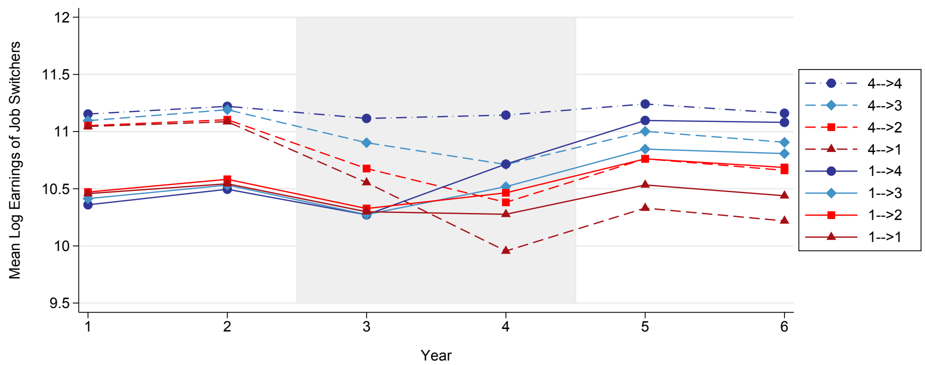
Finally, if the model is correctly specified, on average workers changing from one firm to another should experience earnings changes corresponding to the estimated firm effects. To implement this comparison, we used our data to perform event-study analyses of the effect of job mobility on earnings akin to those shown in CHK (see their Figure VII). In Figure 7, we divided firms into quartiles according to their estimated firm effects and recorded the mean earnings of workers moving between the four firm-type classes in the years before and after the job change.[27] On average, the patterns of earnings changes are approximately symmetric for switches between firm groups, and there are no signs of systematic earnings declines or increases before or after job changes, both

[26] Since violations of the separability assumptions in the AKM model would likely cause large mean residuals for certain matches (say, where highly skilled workers are matched to low-wage establishments), we directly examined the distribution of average residuals by 100 cells of estimated firm and worker effects. For most cells, the mean residual is very small, below 0.02, and shows few systematic patterns (see Appendix Figure A.10).

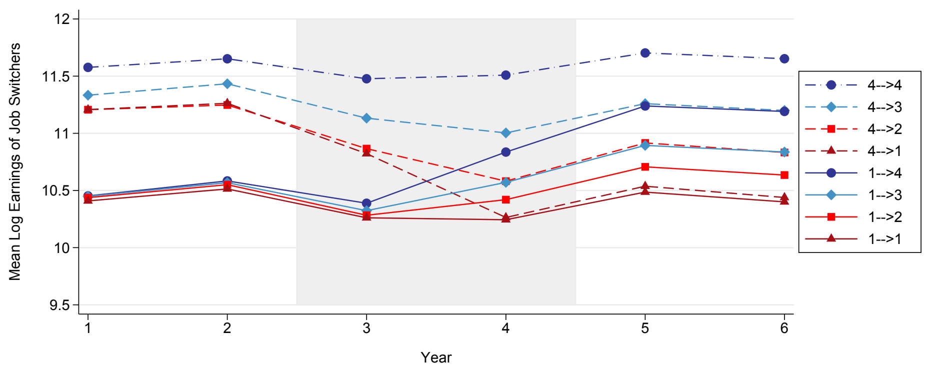
[27] To deal with the fact that we do not know the specific time of the move, we followed workers from two years before the year t in which we observe the move (i.e., from year $t-2$ to $t-1$) to two years after the year succeeding the move (from year $t+2$ to $t+3$). To try to further approximate the transition between "full-time" jobs, we only look at workers who remained at the firm in the two years before and two years after the move. Since we are following workers for six years, we adjust earnings for flexible time trends. In Appendix C, Figure A.13, we show a version of the figure in which the four firm classes are generated based on average earnings within the firm.

Figure 7 – Event Study of Change in Mean Firm Fixed Effects for Job Changers

(a) Firms ranked by fixed effect: 1980-1986



(b) Firms ranked by fixed effect: 2007-2013



Notes: Calculations based on SSA data. Only men are included in these statistics. Men are included regardless of industry or firm size. Only employed individuals aged 20 to 60 are included in all statistics, where "employed" is defined as earning the equivalent 520 times the contemporaneous minimum wage. For an explanation of the methodology, see Section 4.2 and Appendix C.2. For all observations, the main job is the same in years 1, 2, and 3 and then switches to a new main job for years 4, 5, and 6. The shaded region marks the possible years of the job switch. Firm fixed effect quartiles are weighted by worker-years and calculated in years 2 and 5. Log earnings are detrended by subtracting the time-varying observable AKM component from each observation.

of which are consistent with the CRM assumption. Overall, despite being an obvious abstraction from reality, we conclude that our model constitutes a useful tool for a better understanding of trends in earnings inequality in our data.[28]

[28] In Appendix C we provide further discussion of our implementation and sensitivity analysis; among other objectives, to assess the potential role of labor supply differences, we show that our results are not affected by excluding the year of the move or by strengthening our restriction on earnings to isolate full-time workers (Table A.5). We also show that the estimated firm effects are correlated over time (Table A.11) and that there is unlikely to be differential selection between movers and stayers once we condition on age and firm effects (Table A.10).

4.3 Decomposing the Change in the Variance of Earnings

The main implications of our statistical analysis for understanding the role of firms in explaining the evolution of earnings inequality are shown in Tables 5 and 6. Table 5 shows the components of the standard decomposition of variance in equation (4) for our five periods, as well as for the change from period 1 (1980-1986) to period 5 (2007-2013). The first variance decomposition yields two key findings. First, as found by others, in all periods, about half of the *level* of the variance of men's log annual earnings is explained by the variance of worker effects, which at 46% to 52% is by far the biggest component. On the other hand, firm fixed effects, and the covariance between firm and worker fixed effects, together explain about 20% of the total variance in each period.

The second finding shown in Table 5 is that the rising dispersion of worker fixed effects is the biggest single factor in rising wage inequality, accounting for 68% of the rise in inequality of earnings for men from the period 1980-1986 to the period 2007-2013 (column 12). The second biggest component is the change in the covariance of worker and firm effects, which alone explains 35%. In contrast, the contribution of the variance in firm effects declines somewhat over time.

These changes contrast with CHK's results from a similar exercise in Germany. CHK found that approximately equal shares of the rise in variance were explained by worker fixed effects (39%), establishment fixed effects (25%), and their covariance (34%). (The larger role for a rising dispersion of worker fixed effects in the United States could have many causes, but one potential explanation is the role of rising returns to skill, discussed in more detail in Section 5.1.) On the other hand, it is interesting that the covariance explains a similar proportion of the rise in inequality in both countries. Indeed, the rise in correlation between worker effects and firm/establishment effects is similar in the United States (.10 to .38) and Germany (.03 to .25).

To better understand these patterns and to connect them to our descriptive analysis in Section 3, Table 6 presents results for the more detailed variance decomposition of earnings shown in equation (5). Again, the table shows results separately for our five periods, as well as for the change from period 1 (1980-1986) to period 5 (2007-2013). As shown in the final column of Table 6, consistent with our results in Section 3, the sum of the firm components explains 74% of the rise in the overall variance.[29]

[29]This number is quite close to the corresponding statistic reported in Section 3.1.1. However, statistics in this section may differ from those in Section 3.1.1 because of differences in the sample selection (including the fact that these statistics involve men only) and time periods analyzed.

Table 5 – Basic Decomposition of the Rise in Inequality of Annual Earnings

		Interval 1 (1980-1986)		Interval 2 (1987-1993)		Interval 3 (1994-2000)		Interval 4 (2001-2007)		Interval 5 (2007-2013)		Change from 1 to 5	
		Comp (1)	Share (2)	Comp (3)	Share (4)	Comp (5)	Share (6)	Comp (7)	Share (8)	Comp (9)	Share (10)	Comp (11)	Share (12)
Total Variance	Var(y)	0.708	-	0.776	-	0.828	-	0.884	-	0.924	-	0.216	-
Components of variance	Var(WFE)	0.330	46.6	0.375	48.3	0.422	51.0	0.452	51.2	0.476	51.5	0.146	67.6
	Var(FFE)	0.084	11.9	0.075	9.7	0.067	8.1	0.075	8.5	0.081	8.7	-0.003	-1.6
	Var(Xb)	0.055	7.8	0.065	8.4	0.079	9.5	0.061	6.9	0.059	6.4	0.004	1.8
	Var(residual)	0.154	21.7	0.148	19.1	0.146	17.6	0.149	16.8	0.136	14.7	-0.018	-8.2
	2*Cov(WFE,FFE)	0.033	4.7	0.057	7.3	0.076	9.2	0.094	10.6	0.108	11.7	0.075	34.8
	2*Cov(WFE,Xb)	0.028	3.9	0.029	3.7	0.013	1.6	0.028	3.1	0.036	3.9	0.009	4.1
	2*Cov(FFE,Xb)	0.022	3.1	0.025	3.3	0.023	2.7	0.024	2.7	0.027	2.9	0.005	2.2
Sum of firm components	Cov(y,FFE)	0.112	15.8	0.116	14.9	0.117	14.1	0.134	15.1	0.148	16.0	0.037	16.9
Counterfactuals	1.) No rise in Corr(WFE,FFE)	0.708		0.750	96.7	0.784	94.6	0.826	93.4	0.854	92.4	0.146	67.5
	2.) No fall in Var(FFE)	0.708		0.788	101.4	0.854	103.1	0.898	101.6	0.929	100.6	0.221	102.4
	3.) Both 1 and 2	0.708		0.763	98.3	0.807	97.4	0.838	94.8	0.859	92.9	0.150	69.7

Notes:

Var(y) - variance of annual earnings, Var(WFE) - variance of worker fixed effects, Var(FFE) - variance of firm fixed effects, Var(Xb) - variance of covariates.

Sum of firm related components is equal to var(FFE)+Cov(WFE,FFE)+Cov(FFE,Xb).

Only men are included in these statistics. Only firms and individuals in firms with at least 20 employees are included. Only employed individuals aged 20 to 60 are included in all statistics, where "employed" is defined as earning the equivalent of 2013 minimum wage, adjusted for inflation with the PCE for 40 hours per week in 13 weeks. Individuals and firms in public administration or educational services are not included. Raw decomposition refers to the between- and within-firm variance composition simply on log wages, rather than using the CHK components.

TABLE 6 – Detailed Decomposition of the Rise in Earnings Inequality between and within Firms

		Interval 1 (1980-1986)		Interval 2 (1987-1993)		Interval 3 (1994-2000)		Interval 4 (2001-2007)		Interval 5 (2007-2013)		Change from 1 to 5	
		Comp (1)	Share (2)	Comp (3)	Share (4)	Comp (5)	Share (6)	Comp (7)	Share (8)	Comp (9)	Share (10)	Comp (11)	Share (12)
Total var	Var(y)	0.708	-	0.777	-	0.828	-	0.884	-	0.924	-	0.216	-
Between-firm var	Var(m_y)	0.210	29.6	0.253	32.6	0.287	34.7	0.323	36.5	0.370	40.0	0.160	74.2
	Var(m_WFE)	0.053	7.5	0.070	9.0	0.091	11.0	0.101	11.4	0.120	13.0	0.067	30.9
	Var(FFE)	0.084	11.9	0.075	9.7	0.067	8.1	0.075	8.5	0.081	8.7	-0.003	-1.6
	Var(m_Xb)	0.006	0.8	0.008	1.0	0.008	1.0	0.007	0.8	0.007	0.8	0.001	0.6
	2Cov(m_WFE,FFE)	0.033	4.7	0.057	7.3	0.076	9.2	0.094	10.6	0.108	11.7	0.075	34.8
	2Cov(m_WFE,m_Xb)	0.012	1.7	0.018	2.3	0.022	2.6	0.022	2.5	0.028	3.0	0.016	7.3
	2Cov(FFE,m_Xb)	0.022	3.1	0.025	3.3	0.023	2.7	0.024	2.7	0.027	2.9	0.005	2.2
Within-firm var	Var(diff_y)	0.499	70.4	0.524	67.4	0.541	65.3	0.562	63.5	0.554	60.0	0.056	25.8
	Var(diff_WFE)	0.277	39.1	0.305	39.3	0.331	39.9	0.351	39.7	0.356	38.6	0.079	36.7
	Var(diff_Xb)	0.049	6.9	0.058	7.4	0.071	8.5	0.055	6.2	0.052	5.6	0.003	1.2
	Var(r)	0.154	21.7	0.148	19.1	0.146	17.6	0.149	16.8	0.136	14.7	-0.018	-8.2
	2Cov(diff_WFE,diff_Xb)	0.016	2.2	0.010	1.4	-0.008	-1.0	0.005	0.6	0.009	1.0	-0.007	-3.2
	2Cov(diff_WFE,r)	0.002	0.3	0.002	0.3	0.002	0.2	0.001	0.2	0.001	0.1	-0.001	-0.6
	2Cov(diff_Xb,r)	0.000	0.0	0.000	0.0	0.000	0.0	0.000	0.0	0.000	0.0	0.000	-0.1
Segregation Index	Var(m_WFE)/Var(WFE)	0.161		0.186		0.216		0.223		0.252		0.091	
	N (millions)	221.62		256.22		285.57		304.45		302.77		81.15	

Notes:
y - natural log of annual earnings

m_y - firm average log earnings

m_WFE - firm average of worker fixed effect

FFE - firm fixed effect

m_Xb - firm average of its employees' Xb component

diff_y - difference of a worker's log earnings from m_y for its employer

diff_WFE - difference of a worker's WFE from m_WFE for its employer

diff_Xb - difference of Xb from m_Xb for its employer

r - AKM residual

Only men are included in these statistics. Only firms and individuals in firms with at least 20 employees are included. Only employed individuals aged 20 to 60 are included in all statistics, where "employed" is defined as earning the equivalent of 2013 minimum wage, adjusted for inflation with the PCE for 40 hours per week in 13 weeks. Individuals and firms in public administration or educational services are not included.

The main new finding of Section 4 is that the entire rise in the combined between-firm component of the variance is due to a change in worker composition (see column 12). This comes about equally from a rise in the variance of the average worker effect (31%) and the covariance of worker and firm effects (35%). In contrast, the worker-weighted variance of firm fixed effects does not rise and in fact declines early during our sample. Hence, the entire rise in the variance of average firm earnings found in Section 3 is due to a change in worker decomposition. Therefore, only about half of this change in worker composition is related to firm pay premiums as we measure them here (i.e., the firm effect).

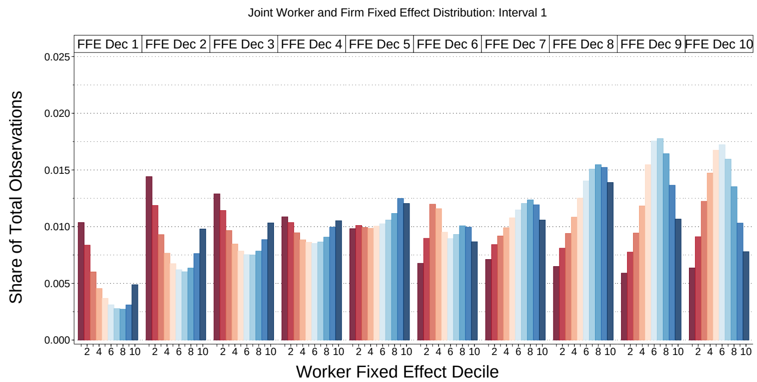
To reveal more about the rise in the covariance of worker and firm effects, the first two panels of Figure 8 display the joint distribution among deciles of worker and firm effects in 1980-1986 and 2007-2013, while the third panel shows the difference between them. The change in the pattern of sorting is striking. Over time, there has been a substantial shift of middle-decile individuals toward middle- and lower-decile firms, whereas the top-two-decile individuals have shifted toward top-decile firms. Hence, this increased sorting of workers has occurred across the entire firm and worker distribution. The figure also indicates an apparent shift in employment away from high-wage firms. This partly helps to explain the decline in the worker-weighted variance of the firm fixed effect we found in Table 6.

Table 7 replicates these findings by firm size, which we discuss further in Section 5 below. First, we see in columns (1) to (6) that once we drop firms with 10,000 employees or more, the share of inequality accounted for by the between-firm component rises to 90% (row labeled "Between-firm var"). Breaking this figure down, we see that about half of this share (37%) comes from the increased dispersion of average individual effects, and the other half mostly comes from increased employee sorting across firms (39%), with some small additional contributions from the covariance of individual characteristics at the firm level ($7.4\% + 3.7\% = 11.1\%$ in total). If we drill down further into this group of firms in the right panel, keeping only firms with 1,000 employees or fewer (columns 7 to 12), we find that the increase in inequality is entirely (105%) explained by a rise in the between-firm component. This comes about equally from two sources: the increased variance of the average worker effect (45%) and the increasing covariance of worker and firm effects (41%), plus small additional contributions from the firm effects (4.3%) and employee characteristics $8.5\% + 5.6\% = 14.1\%$.

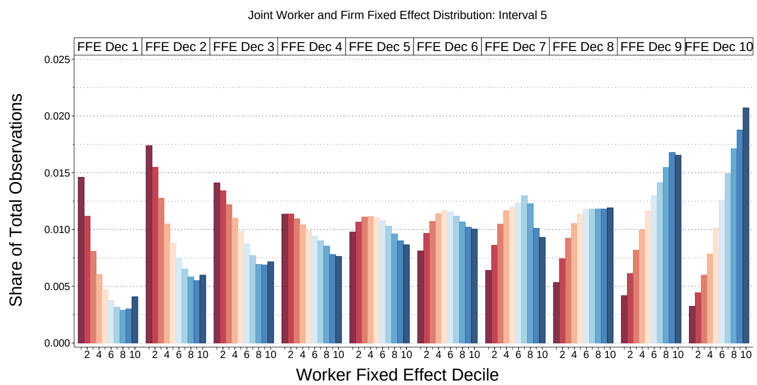
Finally, Table 7 also shows that larger firms experienced more substantial growth in inequality inside the firm (an increase of 5.6 log points with all firm sizes but a reduction

Figure 8 – Distribution of Workers among Deciles of Worker and Firm Fixed Effects

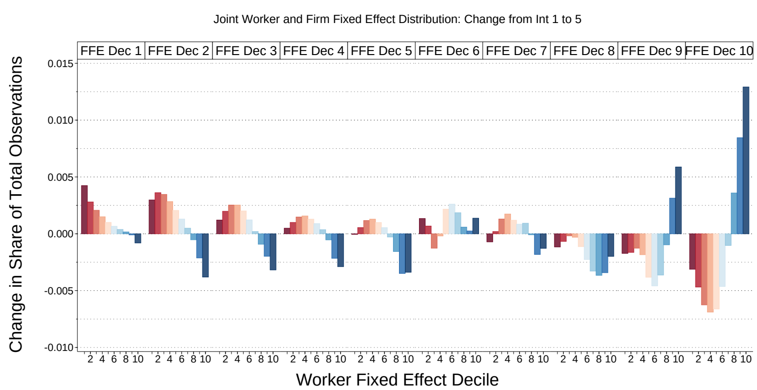
(a) 1980-1986



(b) 2007-2013



(c) Change from 1980-1986 to 2007-2013



Notes: Calculations based on SSA data. Only men are included in these statistics. Only firms and individuals in firms with at least 20 employees are included. Only employed individuals aged 20 to 60 are included in all statistics, where "employed" is defined as earning the equivalent of 2013 minimum wage, adjusted for inflation with the PCE for 40 hours per week in 13 weeks. Individuals and firms in public administration or educational services are not included. Firm and worker fixed effects from our AKM estimation are sorted into deciles. Since higher fixed-effect firms are larger, there are more employees in the higher firm fixed-effect deciles. Firm fixed-effect deciles are computed with respect to the distribution of firms. Within each firm FE decile group, worker FE deciles are ordered from left to right from 1 to 10.

Table 7 – Decomposition of the Rise in Earnings Inequality between and within Firms by Firm Size

		Excluding Firms with over 10,000 Employees						Excluding Firms with over 1,000 Employees					
		Interval 1 (1980-1986)		Interval 5 (2007-2013)		Change from 1 to 5		Interval 1 (1980-1986)		Interval 5 (2007-2013)		Change from 1 to 5	
		Comp	Share	Comp	Share	Comp	Share	Comp	Share	Comp	Share	Comp	Share
		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Total var	Var(y)	0.736	-	0.920	-	0.184	-	0.762	-	0.903	-	0.141	-
Between-firm var	Var(m_y)	0.204	100.0	0.370	100.0	0.166	90.4	0.205	100.0	0.353	100.0	0.148	104.9
	Var(m_WFE)	0.060	29.3	0.128	34.6	0.068	37.1	0.069	33.8	0.133	37.5	0.063	44.8
	Var(m_FFE)	0.073	35.6	0.078	21.0	0.005	2.9	0.068	33.0	0.074	20.9	0.006	4.3
	Var(m_Xb)	0.006	2.9	0.007	1.8	0.001	0.4	0.006	3.1	0.007	1.9	0.000	0.3
	2Cov(m_WFE,m_FFE)	0.037	18.2	0.108	29.3	0.071	38.8	0.036	17.8	0.095	26.8	0.058	41.2
	2Cov(m_WFE,m_Xb)	0.012	5.8	0.026	6.9	0.014	7.4	0.012	5.7	0.024	6.7	0.012	8.5
	2Cov(m_FFE,m_Xb)	0.017	8.3	0.024	6.4	0.007	3.7	0.014	6.6	0.022	6.1	0.008	5.6
Within-firm var	Var(diff_y)	0.532	260.9	0.550	148.6	0.018	9.6	0.557	271.7	0.550	155.7	-0.007	-4.9
	Var(diff_WFE)	0.300	147.1	0.356	96.2	0.056	30.5	0.317	154.8	0.355	100.7	0.038	27.1
	Var(diff_Xb)	0.052	25.3	0.050	13.5	-0.002	-0.9	0.054	26.3	0.050	14.3	-0.004	-2.5
	Var(diff_r)	0.163	80.1	0.141	38.1	-0.022	-12.2	0.171	83.6	0.145	41.0	-0.027	-18.9
	2Cov(diff_WFE,diff_Xb)	0.014	6.9	0.003	0.8	-0.011	-6.1	0.011	5.5	0.000	0.1	-0.011	-7.7
	2Cov(diff_WFE,diff_r)	0.003	1.5	0.000	0.0	-0.003	-1.8	0.003	1.6	-0.001	-0.3	-0.004	-3.1
	2Cov(diff_Xb,diff_r)	0.000	-0.1	0.000	0.0	0.000	0.1	0.000	-0.2	0.000	0.0	0.000	0.3
Segregation Index	Var(m_WFE)/Var(WFE)	0.166		0.264		0.098		0.179		0.272		0.093	
	N (millions)	159.19		220.79		61.60		108.07		146.55		38.48	

Notes: See notes to Table 6. Only men are included in these statistics. Only firms and individuals in firms with at least 20 employees are included. Only employed individuals aged 20 to 60 are included in all statistics, where "employed" is defined as earning the equivalent of 2013 minimum wage, adjusted for inflation with the PCE for 40 hours per week in 13 weeks. Individuals and firms in public administration or educational services are not included. Raw decomposition refers to the between- and within-firm variance composition simply on log wages, rather than using the CHK components.

of 0.7 log points in firms with less than 1,000 employees). Given a similar absolute increase in between-firm inequality, this implies that larger firms experienced stronger increases in overall earnings inequality than smaller firms. (The same fact could also be seen by comparing the panels of Figure 2, which plot the entire time series during this period.) Interestingly, large firms initially appear to have had *lower* within-firm inequality than smaller firms. This is consistent with the view that large firms may have compressed wages, at least for the bottom end of their workforce. Yet, by the end of our sample period, there is no difference in earnings inequality between large and small firms (row 1).[30]

We also examined to what extent our main findings in Table 6 can be explained by employment shifts between industries. While there are some interesting differences in the time trends in the variance components across industries, our three main patterns of a rise in sorting, a rise in the variance of worker effects, and a stagnation (or small reduction) in the variance of firm effects occur within major sectors. Hence, most of our findings are driven by changes within sectors, and changes in sector composition have only a moderate effect.

Figure 9 shows the evolution of the correlation between worker and firm fixed effects by major industries for five seven-year time periods covering the period 1980 to 2013. Each industry generally sees strong increases in correlations beginning in the early 1980s that are slowing down over time; an exception is education and public administration, in which the correlation has been flat (those sectors are dropped from other analyses that aggregate all industries). Table 8 shows the corresponding values of the correlation, the covariance, and the variances of worker and firm effects, respectively.

We also performed a simple counterfactual exercise that recalculated the variances and the correlation, holding constant the share of 1-digit and 4-digit industries (not shown). Secular sectoral employment shifts cannot explain any of the increase in the correlation of worker and firm effects at the aggregate level. The only component of the composition of the variance in earnings that is affected by industry shifts is the rise in the variance of the worker fixed effect, about one-third of which is explained by industry employment shifts. This component can explain the entire impact of sectoral shifts on the increase in the total variance of earnings that we find (not shown) and that has been documented elsewhere.

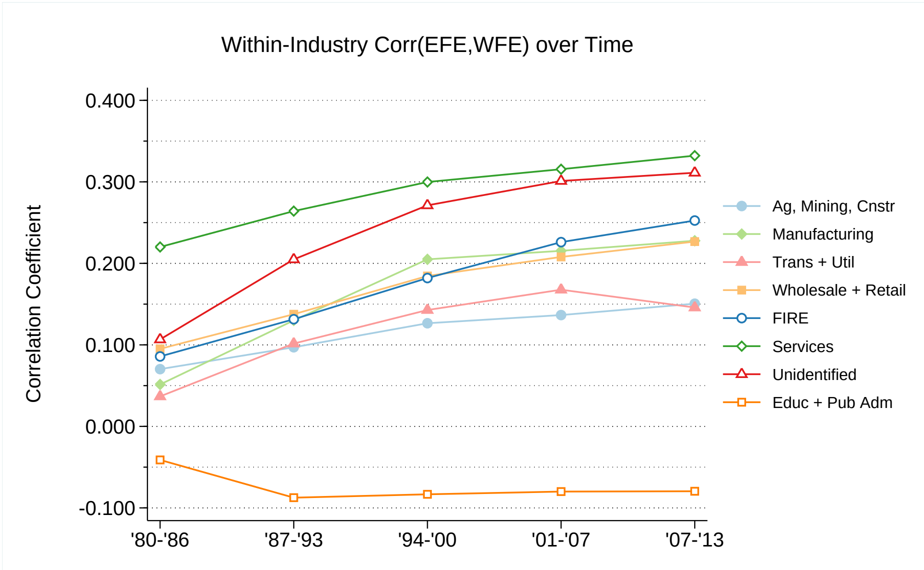
[30] It is worth noting that even smaller firms experience an increase in the average within-firm variance of worker effects. However, this is largely offset by a reduction in the variance of the residual, and in the reduction in the covariance of worker effects and time-varying worker characteristics within firms.

Table 8 – Variation in the Distribution and Correlation of Worker and Firm Fixed Effects by Major Industry from 1980 to 2013

	Interval 1: 1980-1986				Interval 5: 1980-1986				Change from Interval 1 to 5			
	Emp. Share (1)	Var(WFE) (2)	Var(FFE) (3)	Corr(WFE,FFE) (4)	Emp. Share (5)	Var(WFE) (6)	Var(FFE) (7)	Corr(WFE,FFE) (8)	Emp. Share (9)	Var(WFE) (10)	Var(FFE) (11)	Corr(WFE,FFE) (12)
Agriculture, Forestry, & Fishing	2.03	0.201	0.032	0.135	1.35	0.312	0.047	0.165	-0.67	0.111	0.015	0.030
Mining	1.97	0.304	0.071	0.005	0.72	0.398	0.047	0.200	-1.25	0.094	-0.025	0.195
Construction	6.33	0.401	0.053	0.100	4.90	0.414	0.035	0.102	-1.42	0.013	-0.018	0.003
Manufacturing	31.43	0.279	0.068	0.051	13.00	0.412	0.052	0.228	-18.43	0.133	-0.016	0.176
Transportation & Public Utilities	9.35	0.244	0.063	0.037	6.54	0.342	0.069	0.146	-2.81	0.099	0.006	0.109
Wholesale Trade	5.09	0.363	0.045	0.051	4.62	0.434	0.045	0.186	-0.46	0.071	0.000	0.135
Retail Trade	8.82	0.389	0.036	0.097	8.74	0.429	0.033	0.164	-0.08	0.040	-0.004	0.067
Finance, Insurance, & Real Estate	5.57	0.427	0.075	0.086	5.52	0.636	0.077	0.253	-0.06	0.209	0.002	0.167
Services	14.04	0.383	0.094	0.220	23.46	0.524	0.082	0.332	9.42	0.140	-0.012	0.112
Education	2.54	0.400	0.059	-0.094	4.43	0.495	0.042	-0.104	1.89	0.095	-0.017	-0.011
Public Administration	9.87	0.215	0.075	0.057	8.69	0.303	0.041	0.024	-1.18	0.088	-0.034	-0.033
Unidentified	2.96	0.327	0.099	0.107	18.02	0.483	0.094	0.311	15.06	0.156	-0.005	0.204

Notes: Variance and correlation of fixed effects estimated by AKM model as explained in Section 4. Only men are included in these statistics. Only firms and individuals in firms with at least 20 employees are included. Only employed individuals aged 20 to 60 are included in all statistics, where "employed" is defined as earning the equivalent of 2013 minimum wage, adjusted for inflation with the PCE for 40 hours per week in 13 weeks. Individuals and firms in public administration or educational services are not included. Raw decomposition refers to the between- and within-firm variance composition simply on log wages, rather than using the CHK components.

FIGURE 9 – Correlation of Worker and Firm Effects by Period by Major Industry from 1980 to 2013



Notes: Only men are included in these statistics. Only firms and individuals in firms with at least 20 employees are included. Only employed individuals aged 20 to 60 are included in all statistics, where "employed" is defined as earning the equivalent of 2013 minimum wage, adjusted for inflation with the PCE for 40 hours per week in 13 weeks. Individuals and firms in public administration or educational services are not included. Raw decomposition refers to the between- and within-firm variance composition simply on log wages, rather than using the CHK components. The 7-year periods are 1980-1986, 1987-1993, 1994-2000, 2001-2007, and 2007-2013.

5 Explaining Trends in within- and between-Firm Inequality

In this section, we first establish that increasing returns to skills alone could mechanically explain part of the rise in sorting and segregation we find, but also that it is unlikely to explain all of it. We then discuss factors that could underlie the rise in sorting and segregation we document, and then turn to changes in within-firm inequality, especially within larger firms.

5.1 Rising Returns to Skill, Segregation, and Sorting

We found in Section 4.3 that worker fixed effects diverged substantially over the last three decades. A substantial literature provides evidence of a rising skill premium as a key driver of rising income inequality.[31] The same rise in skill premium could mechanically explain part of the observed rise in segregation and sorting. In this subsection, we discuss how such an effect could arise and present some simple calculations to estimate its potential importance.

Define s^i as individual i's skill level, and r^p as the return to skill in period p, so that the worker fixed effect can be written as $\theta^{i,p} = r^p s^i$. Suppose that the distribution of worker skill is fixed over time, while returns to skill are allowed to vary. In that case, we can calculate the changing return to skill between periods 1 and 5 as

$$\frac{r^5}{r^1} = \sqrt{\frac{\text{var}(\theta^{i,5})}{\text{var}(\theta^{i,1})}} = \sqrt{\frac{0.476}{0.330}} \approx 1.20, \tag{6}$$

where the values for the variances are from columns 1 and 9 of Table 5.

Now, suppose the distribution of worker skill across firms had not changed. In that case, average worker effects within each firm would be expected to change by a factor of r^5/r^1.[32] Thus, if only skill prices changed, we would expect

$$\frac{2\text{cov}(\overline{\theta}^{j,5}, \psi^{j,5})}{2\text{cov}(\overline{\theta}^{j,1}, \psi^{j,1})} = \frac{r^5}{r^1}, \tag{7}$$

or an increase of 20%. Instead, we find that $2\text{cov}(\overline{\theta}^{j}, \psi^{j})$ increased by 227%, so rising skill returns explain only 9% of the rise we find in sorting.

Segregation, however, is more affected by changes in returns to skill. It is straightforward to show that the rise in segregation ($\text{var}(\overline{\theta}^{j,p})$) is

$$\frac{\text{var}(\overline{\theta}^{j,5})}{\text{var}(\overline{\theta}^{j,1})} = \left(\frac{r^5}{r^1}\right)^2, \tag{8}$$

so using the 1.20 value obtained above for r^5/r^1 implies a 44% rise in segregation ($1.2^2 - 1$) due to rising skill returns. In the data, we found a 126% increase in the segregation measure, implying that the mechanical effect of returns to skill can account for about 35% ($= .44/1.26$) of the observed increase.

Of course, these estimates are sensitive to assumptions about the unchanging distribution of skills, both in the economy as a whole and within firms. Additionally, our

[31] For detailed reviews of the evidence on the rising skill premium, see, for example, Katz and Autor (1999) and Acemoglu and Autor (2011).

[32] To see this, note that, for firm j with size N_j, $\overline{\theta}^{j,p} = \frac{1}{N_j} \sum_{i|j(i)=j} \theta^{i,p} = r^p \frac{1}{N_j} \sum_{i|j(i)=j} s^i$.

estimates would vary if worker fixed effects do not have the simple form assumed here. In any case, segregation driven by rising returns to skill remains economically interesting, as it implies that top-paid individuals are now likely to work with even higher-paid coworkers, which could affect firm hiring practices and affect workers' beliefs about inequality. The estimates in this section, though, suggest that a substantial fraction of the rise in segregation might be driven by changing returns to skills rather than changes in sorting among coworkers.

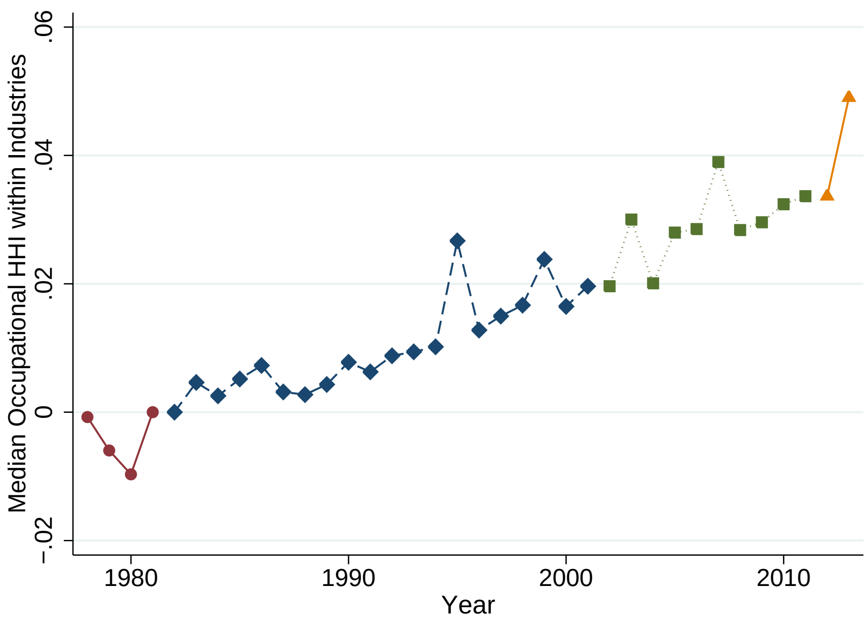
5.2 Accounting for between-Firm Inequality

An important question for understanding the strong rise in inequality in the United States is which mechanisms underlie a rise in sorting of high-wage workers to high-wage firms. Any hypothesis should also be compatible with a stable distribution of ψ^j—firm differences in composition-adjusted pay; a rise in worker sorting and worker segregation; a relatively stable distribution of firm size (see Figure A.6—so this is not simply the atomization of firms; in fact, firm size has grown modestly during this period); and the fact that a rise in sorting and segregation is occurring within industries, regions, and demographic groups. Our finding in Section 4 that the variance of the worker-firm ("match") component is stable over time provides additional discipline on possible models. There are several candidate explanations, including outsourcing, changes in rent sharing, changes in search costs, or technological or organizational innovations that arise in worker-firm or worker-worker complementarities, but it is difficult to fit all of our facts within any basic model.

One explanation is that rising overall inequality is driven by skill-biased technical change, whereas rising outsourcing is constraining the impact on within-firm inequality. Likely drivers of the rise in outsourcing include falling costs of outsourcing (due to improving information-communications technology), a desire to limit the extent of inequality within firms due to concerns over fairness (e.g., Akerlof and Yellen (1990), Dube et al. (2015), and Breza et al. (2018)), and a push by businesses to focus on "core competencies" (Prahalad and Hamel (1990)).[33] (Weil (2014) discusses these and other causes of the increasingly fissured workplace.) This would lead firms to reorganize away from full-service production toward a more focused occupation structure. This is consistent with findings that occupations are increasingly concentrating within industries and firms (Kremer and Maskin (1996), Handwerker (2015)), as shown in Figure 10.

[33] While the concept of "core competencies" may not be well known in economics, it is an extremely popular idea in the business and consulting world; the Prahalad and Hamel (1990) article that coined the term has received almost 30,000 citations as of October 2016.

Figure 10 – Occupational Segregation Has Risen over Time



Notes: This figure plots the median Herfindahl-Hirschman concentration index (HHI) of occupations by industry in the CPS. Because of changes in the occupational classification system in 1982, 2002, and 2012, the figure is spliced across these three years and is normalized to zero in 1981 and 1982. Only individuals aged 20-60; who earn a positive wage income in the given year; who work at least 35 hours per week for 40 weeks; and who are not in education, public administration, or military industries are included.

The rise in outsourcing is also consistent with the increased occupational, educational, and ability segregation of employees found in Sweden by Håkanson et al. (2015), in Germany by Card et al. (2013)), and in the United States by Barth et al. (2016). Goldschmidt and Schmieder (2017) examine German data, finding clear evidence that a rise in outsourcing contributed to increasing inequality. An explanation based on outsourcing could also be compatible with a stable distribution of firm fixed effects and firm size, especially in the United States, where existing low-wage firms could absorb outsourced workers.

Of course, other possible stories can also generate sorting and segregation. One class of models posits that firms pay different wages to workers with the same skills. This idea has a long tradition in labor economics, going back at least to Slichter (1950) and Stigler (1961), and lies at the heart of modern search theory. Several explanations have been put forward for such wage differentials, including that firms share product market rents, the presence of monopsony power in the labor market, or the presence of efficiency wage setting. If high-wage workers are more mobile or have a higher elasticity of labor supply, they will be more likely to work at high-wage employers (e.g., Card et al. (2018)). At a given distribution of firm pay premiums, a rise in relative search efficiency or elasticities of high-wage with respect to low-wage workers will lead to an increase in sorting.

An alternative class of explanations of the presence of sorting rests on complementarities in production between high-wage workers and high-wage firms. In a competitive market, such complementarity would cause high-wage firms to be willing to pay more for high-wage workers than low-wage firms would be willing to pay. The market wages of high-wage workers would then be higher than what low-wage firms would be willing to pay, so that high-wage workers would sort into high-wage firms. This is consistent with our finding in Section 4 that worker-firm interactions contribute to explaining the variance of wages. A growing number of papers suggest that search frictions may prevent the labor market from reaching its optimal allocation of workers to firms. A reduction in search costs, perhaps due to a decline in the cost of acquiring information or a rise in labor market intermediation, could then raise the degree of sorting. At a given type of technology, the increase in the effective supply of high-wage workers would tend to depress the match component, consistent with the stability of its variance we found in Section 4.

A related set of explanations rely on the interaction of fixed technologies with a rising dispersion of worker productivity. Kremer and Maskin (1996) suggest that complementarities in production occurred between low- and high-skilled workers. A similar version of this explanation posits that firms need to limit within-firm inequality for reasons of fairness or because of benefit-related fixed costs. At a given complementarity, a rise in the relative efficiency (or relative supplies) of high- and low-skilled workers implies that firms will hire increasingly homogeneous workers, leading to a pattern of segregation. If firms with higher complementarity also pay higher average wages, such a mechanism could explain an increase in sorting. A model by Acemoglu (1999) features search frictions, and in this model, firms decide what type of job to open before meeting a worker. When worker skills are similar, a pooling equilibrium emerges in which firms create "middling" jobs. With higher skill dispersion, it becomes optimal for firms to open good and bad jobs, suitable for high- and low-skill workers, respectively, leading to a separating equilibrium.

A closely related class of explanations relies on a process of uneven adoption of technological innovations between firms. Insofar as innovating firms require higher-skilled workers, this would imply a rise in the worker-firm complementarity for some firms and could explain an increase in either sorting or segregation. Whether such uneven technological progress would also imply a change in firm pay premiums or a change in worker-firm components in pay depends on the particular wage-setting mechanism. While innovating firms may raise wages to attract high-skilled workers, they may also differentiate themselves or the jobs they offer to high-skilled workers in terms of their benefits. Free food, drinks, and massages at Google or tree houses at Amazon come to mind, as do companies like Starbucks that offer free college tuition and free food (and of course free coffee).

5.3 Accounting for within-Firm Inequality

To investigate within-firm inequality, we focus on larger firms because, as noted in Sections 3.1.1 and 4.3, the within-firm increases in inequality have primarily occurred in large firms. To examine why these mega (10,000+ employee) firms see this much greater increase in inequality, in Figure 11 we plot the change in earnings for employees in various positions in the firm, ranging from the top-paid employee down to the employee in the 10th percentile.

We see two clear differences between larger and smaller firms (here, firms with between 100 and 1,000 employees). First, large firms saw a fall in median log earnings of 7 log points (7%), while smaller firms saw an increase of 27 log points (31%). Second, in larger firms, earnings increases at the top end were far larger: since 1981, the highest-paid employees in larger firms saw their average log earnings increase by 86 log points (137%), while the top-paid employees in smaller firms saw an increase of 37 log points (45%). As a result, the top-to-median employee earnings gap widened by 94 log points (155%) in mega firms (155%) compared with a rise of 10 log points (11%) in smaller firms—a strikingly large difference. We now turn to examining these two changes in large firms.

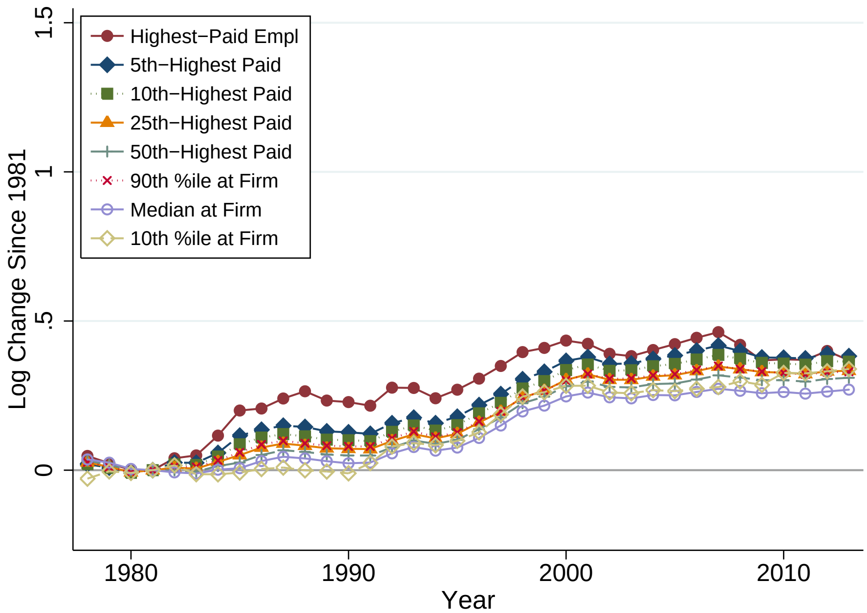
5.3.1 Stagnating Earnings for Lower-Paid Workers in Large Firms

Figure 11 shows that in firms with 10,000+ workers, median earnings has fallen by 7% in real terms between 1981 and 2013 (compared with a rise of 31% in firms with 100 to 1,000 employees). This collapse in earnings in the bottom 50% of large firms accounts for 35% of rising within-firm variance in these firms.[34] The question is, why

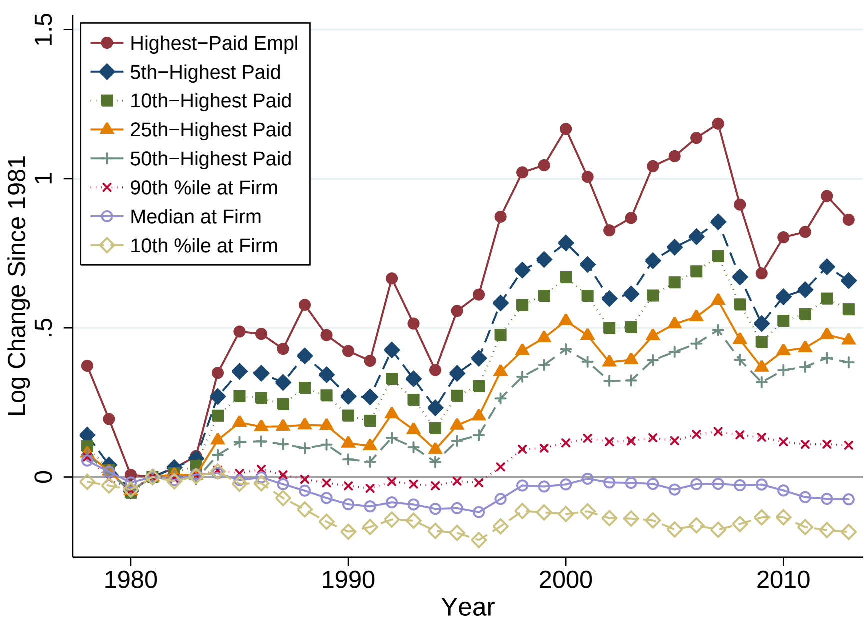
[34] We calculate this by noting that within-firm variance is defined as $\text{var}\left(y_t^{i,j} - \overline{y}_t^j\right) = \frac{1}{N}\sum_i \left(y_t^{i,j} - \overline{y}_t^j\right)^2$. We then define the fraction F_S of variance accounted for by a subset of the population S as $F_S = \sum_{i\in S}\left(y_t^{i,j} - \overline{y}_t^j\right)^2 \Big/ \sum_i \left(y_t^{i,j} - \overline{y}_t^j\right)^2$.

FIGURE 11 – Change in within-Firm Distribution of Annual Earnings: Smaller and Larger Firms

(A) Workers at Firms with 100 to 1,000 employees



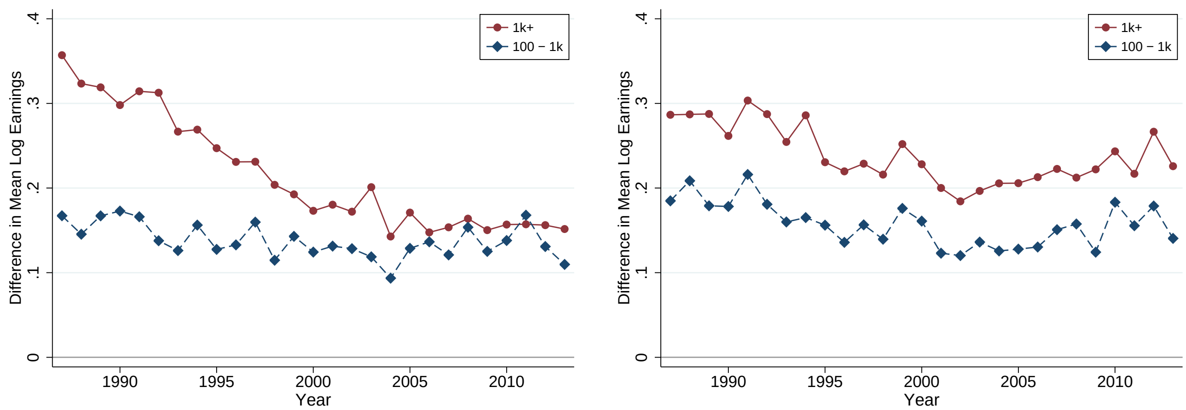
(B) Workers at Firms with more than 10,000 employees



Notes: Only firms and individuals in firms of the listed size are included. Only employed individuals aged 20 to 60 are included in all statistics, where "employed" is defined as earning the equivalent of minimum wage for 40 hours per week in 13 weeks. Individuals and firms in public administration or educational services are not included. Statistics shown are based on the average log earnings among those at the given rank or percentile within their firm. All values are adjusted for inflation using the PCE price index.

Figure 12 – The Earnings Premium in Larger Firms, by Education

(a) High school or less (b) At least some college



Notes: Data are from the Current Population Survey Annual Social and Economic Supplement. Only individuals aged 20-60; who earn a positive wage income in the given year; who work at least 35 hours per week for 40 weeks; and who are not in education, public administration, or military industries are included. "High school or less" refers to those who have no more education than a high school diploma or equivalent. "At least some college" refers to the remainder of the population: those with at least one year of college education. Values shown are the differences in mean log earnings among those in the given firm size bracket, compared with those in firms with fewer than 100 workers.

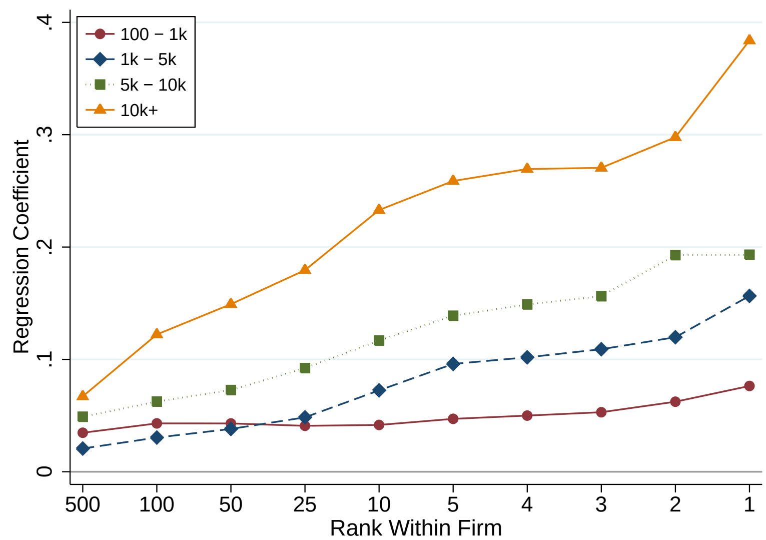
have earnings fallen more in the lower percentiles of large firms compared with small firms?[35]

One fact that helps to explain this inequality is that the lower percentile earnings in large firms have converged *from above* with those in smaller firms. So, for example, in 1981 the median-paid employee in 10,000+ employee firms was paid 40 log points more than its counterpart in firms with 100 to 1,000 employees, but this gap shrunk to only 5 log points by 2013.

To examine this convergence in earnings for lower-earning employees in large firms, we used the CPS, which reports information on firm size since 1987. As shown in Figure 12, the earnings premium for low-skilled employees (high school or less) in large firms (1000+ employees using the CPS definition) compared with small firms (fewer than 100 employees) has fallen by over half, from 36% in 1987 to 15% in 2013. In comparison, higher-skilled employees (the rest of the population, who have at least some college education) have seen this earnings premium fall far less, from 29% in 1987 to 23% in

[35] This is related to the general debate over the collapsing large-firm wage premium (see, e.g., Cobb and Lin (2017)).

FIGURE 13 – Earnings Responsiveness to the S&P 500 Returns



Notes: Only employed individuals aged 20 to 60 are included in all statistics, where "employed" is defined as earning the equivalent of minimum wage for 40 hours per week in 13 weeks. Individuals and firms in public administration or educational services are not included. Each data point represents a regression coefficient; the dependent variable for each regression is the change in average log earnings from year t to $t + 1$ among those at the given rank or percentile within their firm, for firms of given sizes. The coefficient shown is on the log change in the S&P 500 during year t. There are 35 observations in each regression, one per year from 1979 to 2013. The regression includes controls for unemployment in year t and log GDP growth between year t and year $t + 1$. All values are adjusted for inflation using the PCE price index.

2013. Hence, the earnings premium for low-skilled employees in large firms has fallen by 21 percentage points in the last 27 years (1987-2013), potentially accounting for much of the difference in growth in median earnings between the very largest firms and the rest of the firms in the SSA data.

5.3.2 Rising Earnings in the Top 1%

The other striking exception to the between-firm inequality result in Section 3 was the large gap between the earnings growth of the highest-paid employees (e.g., the top 0.5%) and the rest of the employees in the largest (10,000+ employee) firms. To help explain this result, Figure 13 plots the coefficients from regressions of the yearly change in log earnings for top earners at different positions in firms of different sizes on the annual returns on the S&P 500 plus controls for GDP growth and unemployment. For example, the top right point with a triangle marker on the yellow "10k+" line indicates that the highest-paid employees in firms with 10,000 or more employees saw their annual log earnings change in relation to S&P 500 returns with a coefficient of 0.38. That is, for every 10% the S&P 500 rose, their earnings rose by 3.8%. Figure 13 shows that the earnings of the highest-paid employees at the 10,000+ employee firms have very high coefficients: 0.38 for the highest-paid employee (presumably the CEO), 0.3 for the second highest-paid employee (presumably the CFO), down to 0.15 for the 50th highest-paid employee (a very senior manager). In comparison, top-paid employees in firms of 100 to 1,000 employees saw a compensation connection with the returns on the S&P 500 of about 0.08.

One possible explanation for these results is that 10,000+ employee firms often reward their senior executives with stock options and stock grants. Moreover, this stock-based remuneration (which is included in the W-2 earnings figure in the year they vest) has been rising over time. For example, in 2014 the annual compensation of the top-five executives listed in the Execucomp database—which spans roughly the top 1,800 largest U.S. firms by market capitalization—was 48% from stock options and stock awards, up from 15% in 1993 (the first full year of Execucomp data). Alongside this rising stock payment to senior executives, there has been a 19-year stock market bull run, with real returns averaging 9.5% between 1981 and 1999. As Figure 11 shows, the senior executives at the largest firms received extremely generous compensation increases over this 1981-1999 period, and since 2000 (a period of low stock returns), increases have moved roughly in line with the rest of their firm. Thus, it appears that the top 50 or so executives in the largest U.S. firms have experienced rapidly rising earnings—far outstripping their colleagues—in part because of the rising level and generosity of stock-based compensation.[36]

Given this, it is perhaps surprising that the top 50 employees account for only 3% of the increase in within-firm inequality in mega-firms. The reason is that they make up a very small share of employment—accounting for only 35,000 of the 20 million employees in mega-firms—so have little impact on the increasing within-firm variance of log wages. However, the top-earning 10% of employees, a group that contains a much wider group of managers, technicians, and other highly paid individuals in large firms, accounts for 46% of increasing within-firm inequality.

[36]Simply applying the magnitudes of the 680% real increase in the S&P 500 over the period 1981–1999 to the average 0.25 coefficient on the S&P 500 returns in Figure 13 yields a real cumulative earnings increase of 170%, which is similar to the earnings gains of up to 200% that this group made over the same period (see Figure 11). One outstanding question this analysis raises, however, is why these stock-driven compensation rises have been permanent, rather than one-off high earnings payouts during the years of unexpectedly strong S&P 500 performance. One recent paper offering an explanation is Shue and Townsend (2016), who report that S&P 500 firms tend to give executives similar numbers of stock options each year, despite these options rising in value with the firms' stock price. Hence, historic rises in the S&P 500 tend to get locked into future equity compensation levels.

6 Conclusions

Using a massive, matched employer-employee database that we construct for the United States, we documented four stylized facts. First, the rise in earnings inequality between workers over the last three decades has primarily been a between-firm phenomenon. Two-thirds of the increase in the variance of log earnings from 1981 to 2013 can be accounted for by differences in earnings between firms and only one-third by differences between workers within firms.

Second, the distribution of firm fixed effects themselves accounts for essentially none of the rise in inequality. Instead, over three-quarters of the rise in inequality is accounted for by rising variance in individual fixed effects, potentially due to rising returns to skill. The rising covariance between worker and firm fixed effects accounts for the remainder.

Third, examining the sources of the increase in between-firm inequality, we find that it has been driven about equally by increased employee sorting (i.e., high-wage workers are increasingly found at high-wage firms) and segregation (i.e., highly paid employees are increasingly clustering in high-wage firms with other high-paid workers, while low-paid employees are clustering in other firms). Rising returns to skill, which is unrelated to firm wage setting, can account for about a third of rising segregation but very little of rising sorting. These two phenomena also seem to be happening globally, with similar patterns seen in every country for which detailed worker-firm earnings data are available (i.e., Brazil, Germany, Sweden, Japan, and the United Kingdom).

Fourth, the rise in within-firm inequality is concentrated in large firms with 1000+ (and particularly 10,000+) employees. This is driven both by a fall in the earnings premium in large firms for median- and lower-paid employees and by rising earnings for the top 10% of employees.

These results raise the question as to what is driving this dramatic change in worker composition across firms. While our analysis does not provide a definitive answer to this question, a variety of circumstantial evidence indicates that outsourcing could be playing an important role in allowing firms to constrain inequality within firms and focus on core competency activities, spinning off nonessential activities such as cleaning, catering, security, accounting, IT, and HR. Since firm size is only slowly growing over this period, firms are not atomizing; instead they may be reorganizing around a more narrow set of occupations, perhaps leading to greater cross-firm segregation by worker skill level. Studying this and other channels is an important area for further research.

Finally, this increase in between-firm inequality raises a question over its impact on individual welfare. We believe increased worker sorting and worker segregation are potentially worrisome for several reasons. One concern of course is that low-wage workers appear to have lost access to good jobs at high-wage firms, increasing overall aggregate inequality. Another concern is that firms play an important role in providing employee health care and pensions, so rising earnings segregation could very well spill into rising health care and retirement inequality. Indeed, over the last 30 years, as noted by the National Academies of Sciences, Engineering, and Medicine (2015), the correlation between income and life expectancy has increased greatly at the same time as a greater fraction of wealth for those at the top comes from benefits, including health insurance. Moreover, given the importance of work experience for earnings growth, if employees gain experience more rapidly by working alongside higher-ability colleagues, then rising segregation will dynamically increase inequality.

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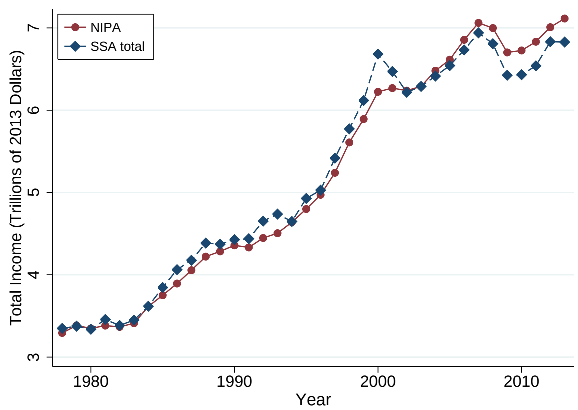
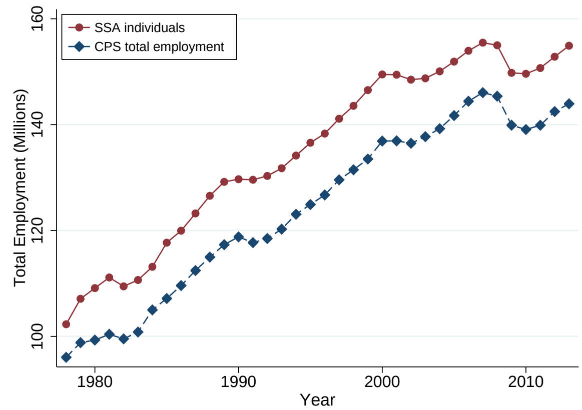
Supplemental Online Appendix

Figure A.1 – Comparing the SSA totals to other records

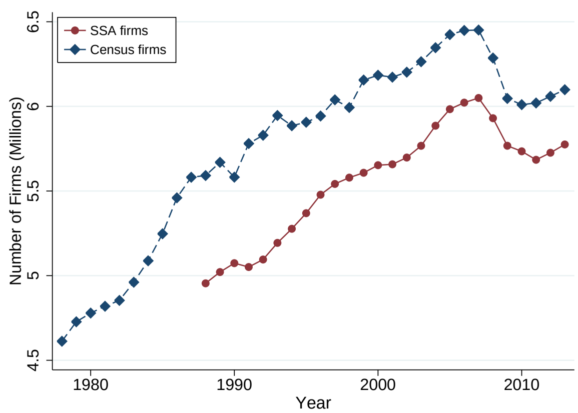
(A) Total earnings



(B) Total employment



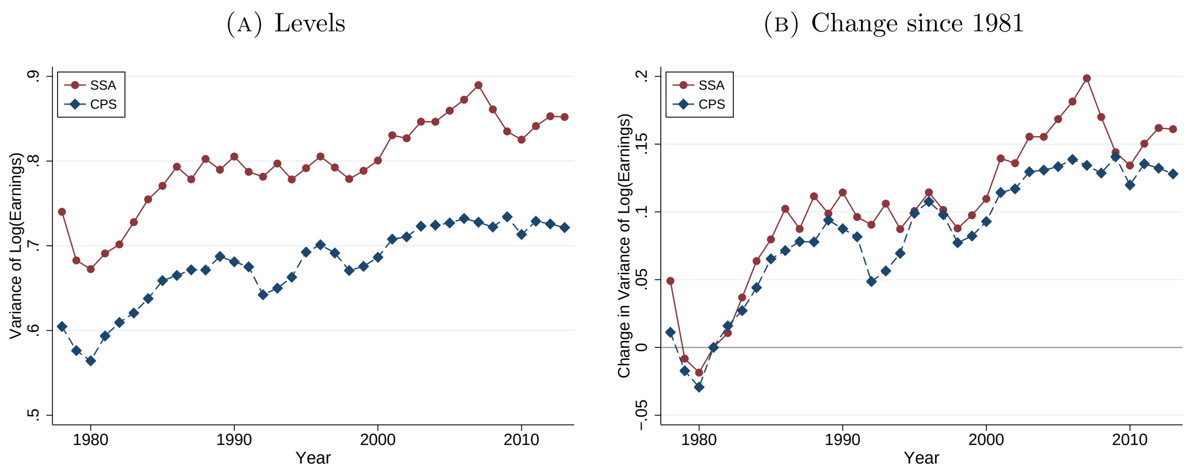
(C) Total firms



Notes: SSA data includes all entries in the MEF. National Income and Product Accounts (NIPA) data is from the St. Louis Federal Reserve Bank's FRED service, series A576RC1, "Compensation of Employees, Received: Wage and Salary Disbursements." Current Population Survey (CPS) total employment shows the yearly average of the monthly employment numbers in the CPS. This data is from the Bureau of Labor Statistics Table LNS12000000. Census firms shows the total number of firms reported by the Census Bureau's Statistics of U.S. Businesses data set, available at http://www.census.gov/econ/susb/historical_data.html. All data are adjusted for inflation using the PCE price index.

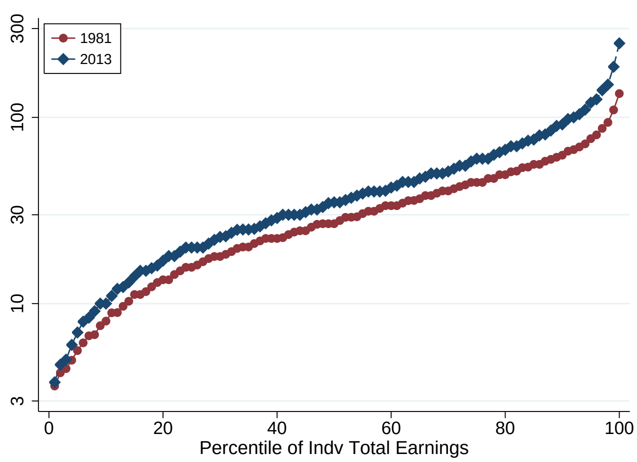
A Appendix: Additional Figures

FIGURE A.2 – Comparing earnings variance in SSA and CPS data



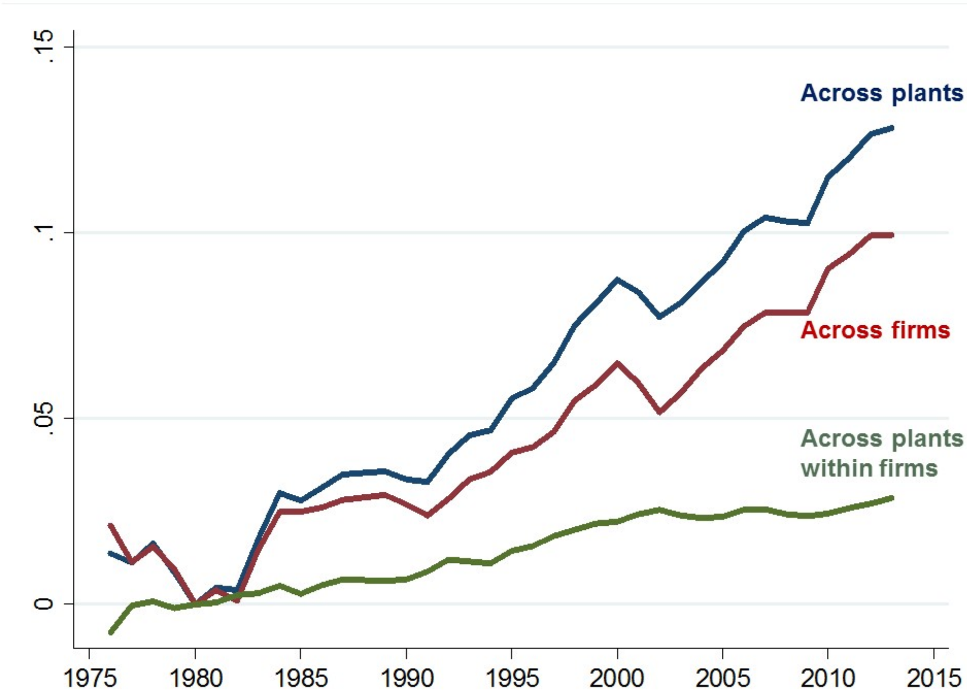
Notes: Only employed individuals aged 20 to 60 are included in all statistics, where "employed" is defined as earning the equivalent of minimum wage for 40 hours per week in 13 weeks. Individuals and firms in public administration or educational services are not included. Only firms and individuals in firms with at least 20 employees are included in SSA data.

FIGURE A.3 – Cumulative distribution of annual earnings in CPS data



Notes: For each percentile, statistics are based on the minimum earnings among individuals in that percentile of earnings in each year. All values are adjusted for inflation using the PCE price index. Only employed individuals aged 20 to 60 are included in all statistics, where "employed" is defined as earning the equivalent of minimum wage for 40 hours per week in 13 weeks. Individuals and firms in public administration or educational services are not included.

Figure A.4 – Variance of log(wages) across establishments and firms - firms with 20+ workers



Notes: Plots the employment weighted variance of log wages normalized to 0 in 1980. Source Census Longitudinal Business Database 1976-2013. All establishments and firms with positive employment and wages. All sectors excluding education (SIC codes 8200 to 8299) and public administration (sic codes 9000 to 9899). Establishments are dropped if their average wage (defined as total wages/employment) is above \$250,000 or below \$12,80 (minimum wage for 35 hours a week for 48 weeks a year) in 2013 dollars. Establishments only from firms with 20+ employees.

B Appendix: Data Procedures

B.1 Social Security Administration Data

As noted in Section 2, this paper uses data from SSA's MEF database. We begin with an extract from this file that includes one observation for each year, for each individual, for each firm that this individual worked for. (For self-employed individuals, the data set also contains these earnings from the IRS as reported in Schedule-SE tax form by the individuals. Because our focus is on firms with employees, we exclude these earnings from our analysis.) For each observation, this file includes the year, a transformation of that individual's Social Security Number, along with the associated sex and date of birth; and the EIN, along with the associated 4-digit SIC code and state.

The first step we take with this data is to exclude individuals who did not have a reasonably strong labor market attachment in a given year from the analysis for that year. More concretely,

Table A.1 – Complete Robustness Checks on Variance Decomposition - Part 1

	Total Var, 1981	Between-Firm Var, 1981	Total Var, 2013	Between-Firm Var, 2013	Total Var Increase	Frac Increase Between
Baseline sample	0.652	0.222	0.846	0.357	0.194	0.694
Any number of empl	0.691	0.272	0.852	0.387	0.161	0.71
20-10k workers	0.651	0.206	0.835	0.36	0.184	0.837
10k+ workers	0.552	0.164	0.873	0.348	0.32	0.577
Avg 5-year earnings	0.69	0.207	0.861	0.314	0.171	0.629
Min earn = 260 x min ‘wage	0.823	0.284	1.03	0.434	0.206	0.73
Min earn = 1040 x min wage	0.479	0.159	0.658	0.272	0.179	0.628
Min earn = 2080 x min wage	0.33	0.101	0.48	0.179	0.151	0.518
Min earn based on 2013 min wage	0.641	0.218	0.846	0.357	0.205	0.676
Excluding top 1%	0.607	0.21	0.771	0.323	0.164	0.694
Excluding top 1% in each firm	0.619	0.227	0.804	0.359	0.185	0.717
Excluding top 5%	0.537	0.183	0.664	0.265	0.127	0.644
Excluding top 5% in each firm	0.577	0.23	0.744	0.36	0.167	0.776
Excluding top-paid person in each firm	0.64	0.228	0.835	0.36	0.195	0.681
Excluding 5 top-paid people in each firm	0.627	0.243	0.815	0.369	0.188	0.67
Women only	0.485	0.164	0.74	0.306	0.255	0.555
Men only	0.619	0.195	0.89	0.389	0.271	0.718
Ag/Mining/Construct/Oth	0.633	0.169	0.822	0.34	0.19	0.905
Manufacturing	0.576	0.191	0.676	0.251	0.1	0.605
Utilities	0.444	0.111	0.611	0.207	0.167	0.577
Trade	0.678	0.173	0.797	0.275	0.119	0.858
FIRE	0.589	0.12	0.848	0.274	0.259	0.593
Services	0.676	0.231	0.832	0.333	0.157	0.652

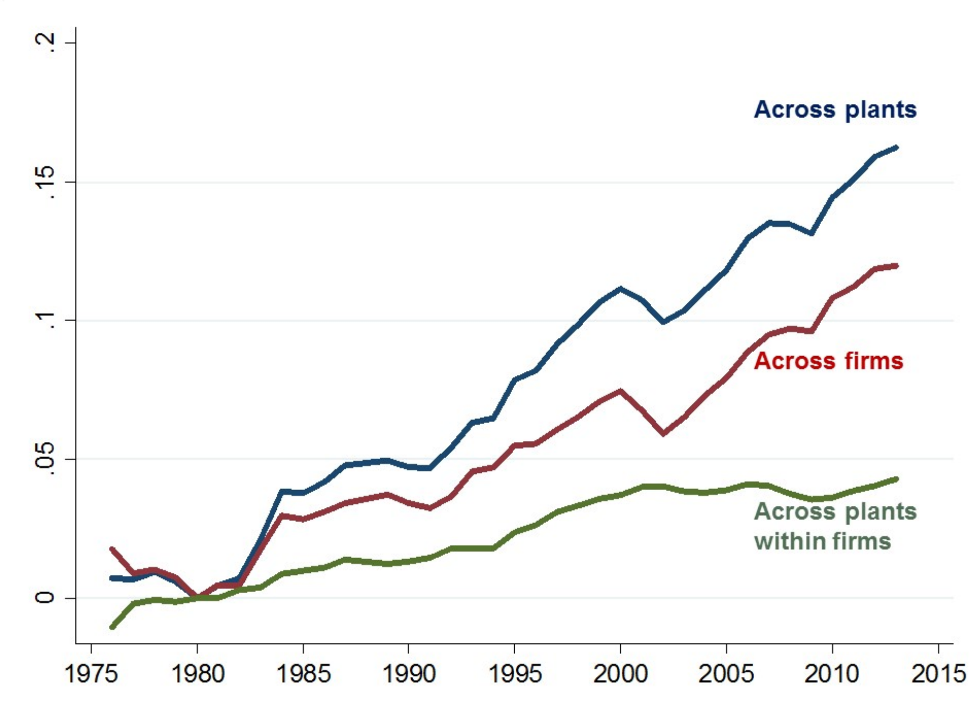
Notes: Only firms and individuals in firms with at least 20 employees are included. Only employed individuals aged 20 to 60 are included in all statistics, where "employed" is defined as earning the equivalent of minimum wage for 40 hours per week in 13 weeks. Individuals and firms in public administration or educational services are not included. “Total Var” indicates total variance of earnings in a given year, and “Between-Firm Var” indicates total between-firm variance in that year. “Total Var Increase” denotes the increase in variance between 1981 and 2013, while “Frac Increase Between” denotes the fraction of that increase in variance accounted for by an increase in between-firm variance. Statistics in rows labeled “Demean by” include earnings that are demeaned within a given group before all variances are calculated. Statistics in rows with showing numbers of employees are limited to individuals in firms with that number of employees. Demeaning by “firm size category” includes each category listed starting with “Size:” in this table. “Avg 5-year earnings” performs the same analysis but uses all earnings over 5 years, 1981-1985 to 2009-2013, to calculate statistics. “Min earn =” uses different minimum earnings thresholds. “Min earn based on 2013 min wage” uses the 2013 minimum wage adjusted for inflation, rather than the minimum wage in the given year. “Excluding top...” exclude top people in the overall economy, or at each firm, from the analysis. Industry groupings are based on SIC divisions. “Continuing firms only” only include firms, and people at firms, that are in the sample in both 1981 and 2013 (though the individuals at those firms are likely different).

Table A.2 – Complete Robustness Checks on Variance Decomposition - Part 2

	Total Var, 1981	Between-Firm Var, 1981	Total Var, 2013	Between-Firm Var, 2013	Total Var Increase	Frac Increase Between
Baseline sample	0.652	0.222	0.846	0.357	0.194	0.694
Age 20-29	0.556	0.178	0.62	0.241	0.063	0.993
Age 30-39	0.601	0.219	0.72	0.316	0.119	0.807
Age 40-49	0.631	0.255	0.791	0.348	0.16	0.583
Age 50-60	0.617	0.253	0.789	0.338	0.173	0.491
Continuing firms only	0.607	0.19	0.783	0.292	0.176	0.577
Midwest	0.632	0.221	0.736	0.281	0.104	0.585
Northeast	0.646	0.212	0.871	0.35	0.225	0.612
South	0.612	0.189	0.775	0.299	0.163	0.678
West	0.704	0.228	0.887	0.384	0.183	0.855
Size: 0-10	0.707	0.383	0.769	0.463	0.062	1.291
Size: 10-20	0.711	0.24	0.794	0.346	0.084	1.257
Size: 20-50	0.692	0.216	0.798	0.331	0.106	1.095
Size: 50-100	0.674	0.205	0.793	0.318	0.119	0.941
Size: 100-200	0.654	0.2	0.775	0.31	0.122	0.904
Size: 200-500	0.631	0.191	0.805	0.341	0.173	0.866
Size: 500-1k	0.599	0.17	0.831	0.362	0.232	0.827
Size: 1k-2k	0.582	0.161	0.838	0.364	0.256	0.795
Size: 2k-5k	0.595	0.174	0.867	0.382	0.272	0.764
Size: 5k-10k	0.602	0.176	0.9	0.395	0.298	0.737
Size: 10k+	0.552	0.164	0.873	0.348	0.32	0.577
Demean: county	0.611	0.181	0.8	0.311	0.189	0.687
Demean: state	0.63	0.2	0.828	0.339	0.198	0.701
Demean: census region	0.638	0.208	0.84	0.351	0.202	0.707
Demean: 2-digit SIC	0.554	0.125	0.75	0.261	0.196	0.697
Demean: 3-digit SIC	0.527	0.097	0.714	0.225	0.187	0.683
Demean: 4-digit SIC	0.517	0.088	0.705	0.216	0.187	0.684
Demean: gender	0.564	0.166	0.819	0.337	0.256	0.668
Demean: firm size category	0.611	0.182	0.838	0.349	0.226	0.738
Demean: person year of birth	0.568	0.186	0.695	0.26	0.127	0.578

Notes: See notes for Table A.1.

FIGURE A.5 – Variance of log (wages) across establishments and firms - establishments in firms with 10,000+ workers



Notes: Plots the employment weighted variance of log wages normalized to 0 in 1980. Source Census Longitudinal Business Database 1976-2013. All establishments and firms with positive employment and wages. All sectors excluding education (SIC codes 8200 to 8299) and public administration (sic codes 9000 to 9899). Establishments are dropped if their average wage (defined as total wages/employment) is above $250,000 or below $12,80 (minimum wage for 35 hours a week for 48 weeks a year) in 2013 dollars. Establishments only from firms with 10,000+ employees.

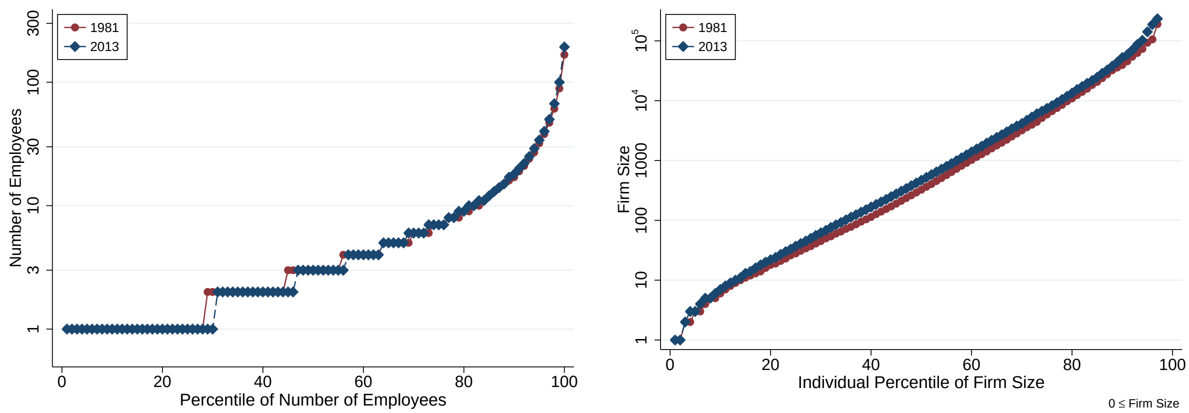
we consider an individual to be employed in a given year and include in the analysis if, summing across all jobs, he/she earns at least the equivalent of 40 hours per week for 13 weeks at that year's minimum wage (so $3,770 in 2013). (As discussed above, we also conducted robustness checks with other threshold levels, which show similar results.)[37] This condition ensures that we are focusing on data about individuals with a reasonably strong labor market attachment, and that our results are comparable to other results in the wage inequality literature, such as Juhn et al. (1993b) and Autor et al. (2008). The data from any individual earning below this threshold in a given year is excluded from all results for both firms and individuals in that year.

We assign workers to firms based on the firm where that worker earned the most money in a given year. Firm earnings statistics are based on total annual earnings of each individual

[37]Note that the worker-firm fixed effect model instead imposes the restriction of 520 hours at the 2013 minimum wage, adjusted for inflation with the PCE.

Figure A.6 – Cumulative firm size distribution

(A) Unweighted (B) Weighted by employment



Notes: Only employed individuals aged 20 to 60 are included in all statistics, where "employed" is defined as earning the equivalent of minimum wage for 40 hours per week in 13 weeks. Individuals and firms in public administration or educational services are not included. Both graphs are inverse cumulative distribution functions. Figure A.6a shows the fraction of firms below a given size; Figure A.6b shows the fraction of individuals at firms below a certain size. For disclosure reasons, Figure A.6b does not report the top 3 percentiles.

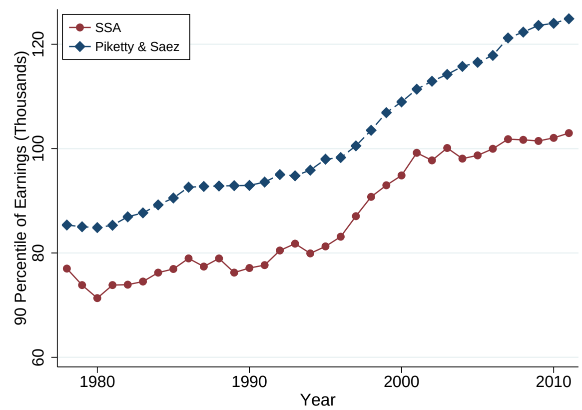
whose primary job is with that firm, even if the worker earned part of that money in a different firm. Where our results analyze the same firm over multiple years, we include a correction to ensure that firms that change EINs are not counted as exiting in one year and entering in the next. We define an EIN in Year 1 as being the same firm as a different EIN in Year 2 if the following conditions are met. First, Year 1 must be the last year in which the original EIN appears, while Year 2 must be the first year that the new EIN appears in our data. Next, more than half of the individuals who worked in each firm must have also worked in the other firm. Finally, to ensure that our results aren't influenced by a few individuals switching companies, we only include EINs in this switching analysis if they employ at least 10 individuals.

Firms are only included in our sample if they have at least 20 employees in a given year to ensure that firm-wide statistics are meaningful; for example, comparing an individual to the mean earnings at their two-person firm may not be a good way to characterize inequality within firms in a given year (though our results are robust to changing this threshold). We also exclude firms in the Educational Services (SIC Codes 8200 to 8299) and Public Administration (SIC Codes 9000 to 9899) industries, as employers in these industries are frequently not what we would consider firms. Finally, we exclude employers with EINs that begin with certain two-digit codes that are associated with Section 218 Agreements, or other issues that may not be handled consistently in the data across years. Individuals whose primary job is with a firm in one of these excluded categories are also dropped from the data in that year.

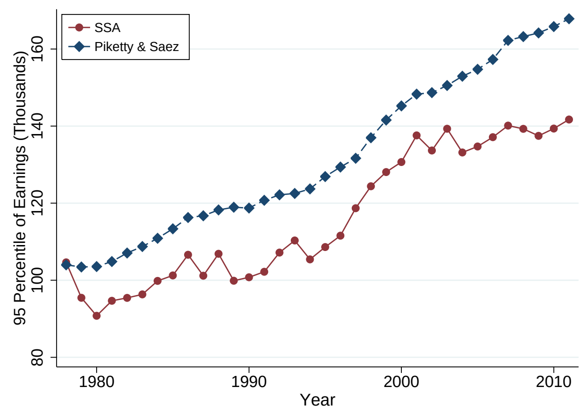
In order to analyze a representative sample of individuals in a computationally feasible way, we analyze a one-eighth representative sample of all U.S. individuals from 1978 to 2013 (except

Figure A.7 – Comparison to Piketty and Saez (IRS data)

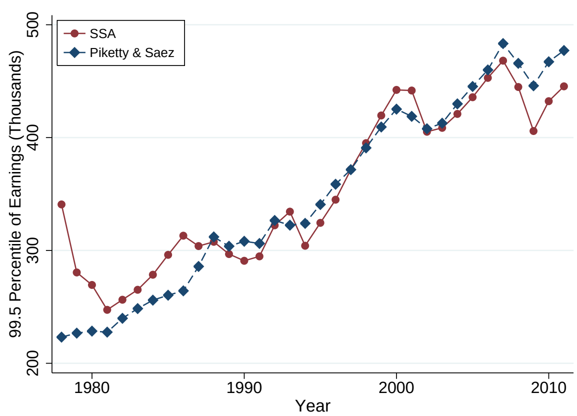
(a) 90th Percentile



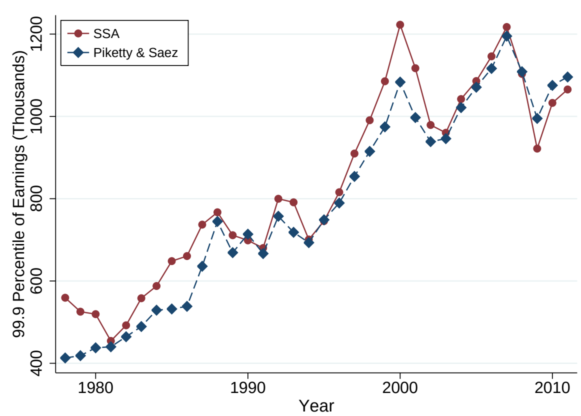
(b) 95th Percentile



(c) 99.5th Percentile



(d) 99.9th Percentile

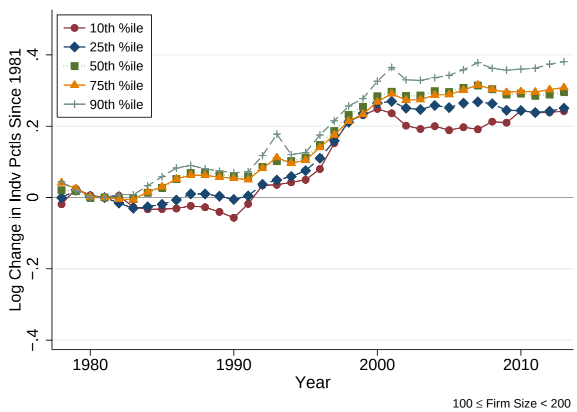


Notes: Piketty and Saez (2003) data is based on Table B3 in http://eml.berkeley.edu/~saez/TabFig2014prel.xls. All values are adjusted for inflation using the PCE price index. For SSA data, only individuals in firms with at least 20 employees are included. Only employed individuals aged 20 to 60 are included in all SSA statistics, where "employed" is defined as earning the equivalent of minimum wage for 40 hours per week in 13 weeks. Individuals and firms in public administration or educational services are not included in SSA data.

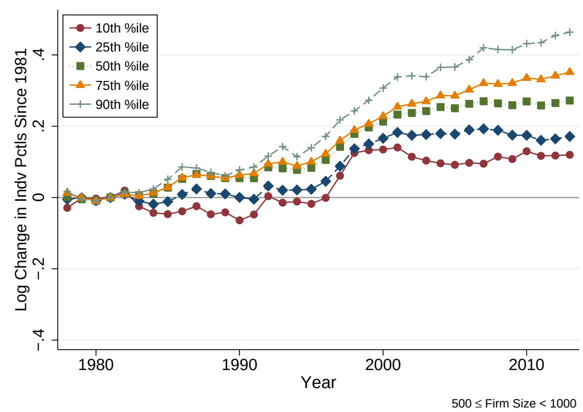
in the firm and worker fixed effects analysis, in which we use a 100% sample). Results are robust to using a 100% sample. The sample is organized as a longitudinal panel, in the sense that once an individual is selected into the sample, he/she remains in the sample until he/she dies. In particular, an individual is in our sample if the MD5 hash of a transformation of their Social Security Number begins with a zero or one; because MD5 hashes are hexadecimal numbers, this will select one in eight individuals. MD5 is a cryptographic algorithm that deterministically turns any string into a number that is essentially random. It is designed so that a slightly different input would lead to a completely different output in a way that is essentially impossible

Figure A.8 – Alternative Version of Figure 11: Change in Percentiles of Annual Earnings Distribution for Workers Grouped by Employer Size. Workers are first assigned to samples defined by their employers' size, and percentiles are computed for each sample separately. Select samples are shown to save space.

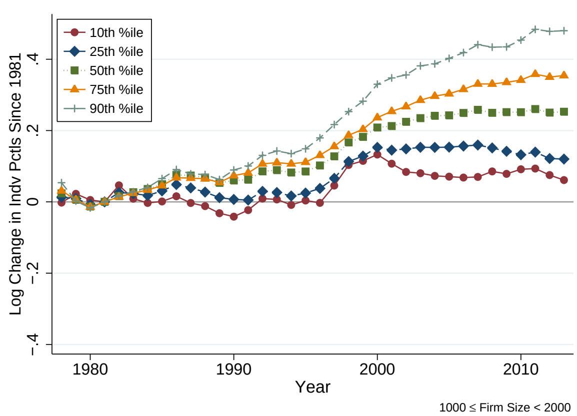
(A) Workers at Firms with 100 to 200 employees



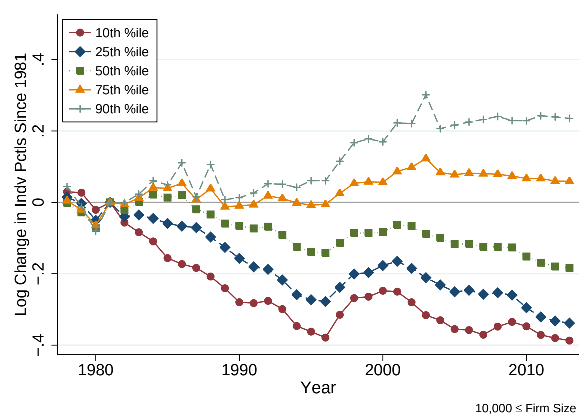
(B) Workers at Firms with 500 to 1000 employees



(C) Workers at Firms with 1,000 to 2,000 employees



(D) Workers at Firms with more than 10,000 employees

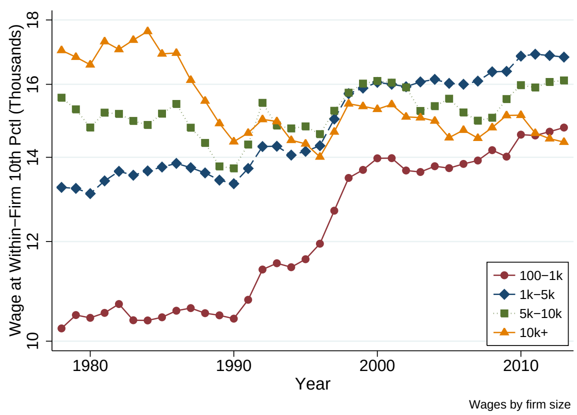


Notes: Only firms and individuals in firms with the given number of employees are included. Only employed individuals aged 20 to 60 are included in all statistics, where "employed" is defined as earning the equivalent of minimum wage for 40 hours per week in 13 weeks. Individuals and firms in public administration or educational services are not included.

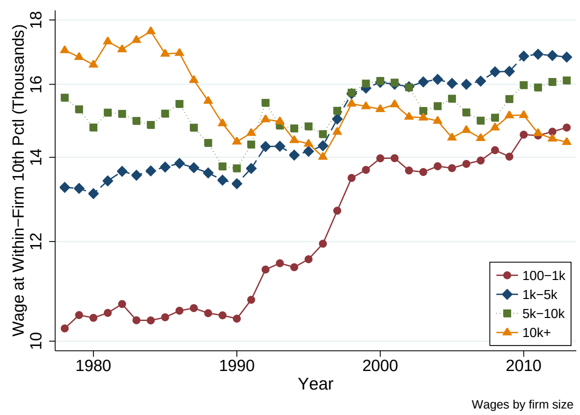
to predict. Because it took cryptographic researchers several years to figure out a way that, under certain circumstances, MD5 is somewhat predictable, this algorithm is certainly random enough for our purposes. Thus whether one individual is included in our sample is essentially independent of whether some other individual is included, regardless of how similar their SSNs are.

FIGURE A.9 – Figure 11, Non-scaled version. Levels of Percentiles in Thousands of Dollars. All other details same as Figure 11.

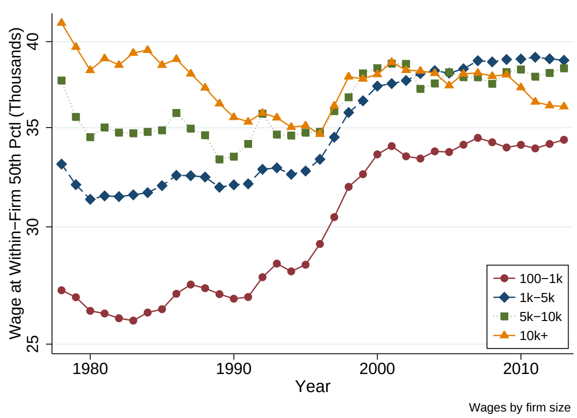
(A) 10th Percentile



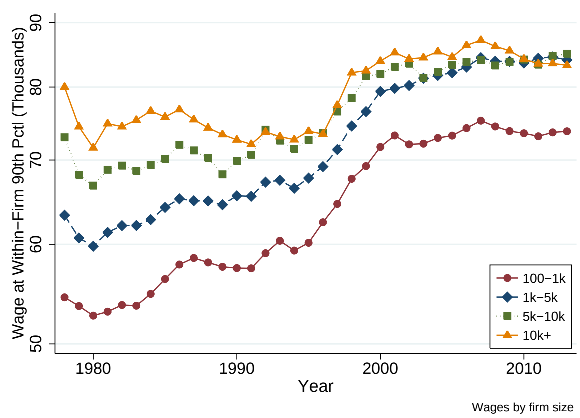
(B) 10th Percentile



(C) 50th Percentile



(D) 90th Percentile



Notes: Only firms and individuals in firms with the given number of employees are included. Only employed individuals aged 20 to 60 are included in all statistics, where ”employed” is defined as earning the equivalent of minimum wage for 40 hours per week in 13 weeks. Individuals and firms in public administration or educational services are not included.

We top-code all variables of interest above the 99.999th percentile to avoid potential problems with disclosure or extreme outliers. Variables are top-coded with the average value (or geometric average value, as appropriate) of all observations within the top 0.001%. Variables are top-coded immediately before analysis. An exception is in analysis of top income ranks within firms, as in Figures 11 and 13, which could be more affected by top-coding; for these analyses, we top-code at the maximum value in Execucomp for the given year (or, before 1992, the average of the maximum values between 1992 and 1994). Top-coding at the 99.999th percentile has no visible effect on the main analysis. Finally, we adjust all dollar values in the data set to be equivalent to 2013 dollars with the Personal Consumption Expenditure (PCE) price index.[38]

There are several differences between the data used in the worker-firm fixed effect model (CHK model) and the rest of the text. The most important difference is that the CHK model only includes data on men. Men are included if they earned the equivalent of at least 520 hours at the 2013 minimum wage, adjusted for inflation with the PCE; in the rest of the text, the minimum earnings threshold was 520 times the contemporaneous minimum wage. To estimate the model, we included men in all firms, regardless of the firm's size or industry. We then report results based on the same sample as the rest of the paper: firms, and people in firms, with at least 20 total (male and female) employees, who are not in public administration. (The only exceptions are Tables A.3 and A.4, which report summary statistics based on all observations used to calculate fixed effects.) Thus if someone moved from a 5-person firm to a 50-person firm, that move would be part of the sample used to calculate fixed effects, but only data from the second year would only be included in our estimation results. If they stayed at the same firm and the firm grew from 5 to 50 people, both years would be included in the sample used to calculate fixed effects, but only data from the second year would be included in estimation results.

B.2 Current Population Survey Data

We use micro data from the Current Population Survey (CPS) Annual Social and Economic Supplement, as made available by Flood et al. (2015). Data for year t is based on the survey from year $t + 1$. The sample is restricted to those aged between 20 and 60; with non-zero, non-missing wage and salary income; and who are not in education, public administration, or military industries. Figures in the text are restricted to those who had at least 35 usual hours of work per week and who worked at least 40 weeks. For comparability with SSA data, data for Figures A.2 and A.3 restrict to those earning at least the equivalent of 40 hours per week for 13 weeks at that year's minimum wage. All statistics are weighted by the person-level supplemental weight. Wherever possible, we use variables that are coded consistently throughout the time period considered. Education data is based on variable EDUC; industry and occupation data are based on variables IND1990 and OCC1990, respectively.

C Appendix: The Abowd, Kramarz and Margolis decomposition

C.1 Identifying Assumption

Estimation of the firm effects in equation (3) crucially relies on earnings changes of workers switching employers. Hence, the estimated firm effects will capture any systematic differences in earnings of movers before and after the job move. This includes the difference in firm effects between the sending and receiving firm, but also potential differences in average fixed worker-firm match effects, or systematic transitory earnings changes leading up to or following a job change. Hence, to associate estimated firm effects with true underlying firm-specific differences

[38] http://research.stlouisfed.org/fred2/series/PCEPI/downloaddata?cid=21

in pay, one has to assume that conditional on worker and firm effects, job moves do not depend systematically on other components. This assumption, often referred to as the conditional random mobility (CRM) assumption, and its relation to economic models of job mobility, is discussed at length in AKM and CHK, among others, and we will not review the theoretical arguments against or in favor here.

On a fundamental level, whether the CRM assumption is conceptually or empirically plausible or not, the estimation of the parameters in equation (3) is done by Ordinary Least Squares, and hence one relies on "random" variation provided by nature, not on known sources of manipulation. To ensure our core assumption and findings are plausible, following CHK, we will provide several pieces of corroborating evidence below. This includes event studies of the effect of worker mobility, the goodness of fit of the model, the value added of allowing for worker-firm match effects, and the properties of the residuals. After a careful review, we conclude from this evidence that there appear to be no large, systematic worker-firm or transitory components influencing job mobility. We thus join an increasing number of papers whose results indicate the AKM model can be estimated without systematic bias (e.g., AKM, CHK, Abowd et al. (2018)). Nevertheless, we are well aware of the limitations of the model, and incorporate them into our overall approach. Among other measurements, we will separately estimate worker-firm component in earnings m_{ij}, and use it to directly assess potential departures from the basic model for our discussion of earnings inequality.

A few additional technical aspects are worth highlighting. The linear age component is not separately identified when worker effects and year effects are present. If one simply drops the linear age effects, the estimated variance of the worker effects is biased. Instead, we follow CHK and normalize age by subtracting and dividing by 40. Since at age 40 the marginal effect of age on earnings is approximately equal to zero, the estimated worker effects and their variance are unbiased.[39] However, as is well known, there is still a finite sample bias in estimates of $\text{var}_j(\psi^j)$ and $\text{var}_i(\theta^i)$ because of sampling error in the estimated worker and firm effects.

In addition, the estimate of the covariance term $(\text{cov}(\theta^i, \psi^j))$ is likely to be downward biased, because the sampling error in the worker and firm effects are negatively correlated. We do not attempt to construct bias-corrected estimates of these components. Instead, we follow the literature and focus on trends in the estimated moments assuming that the bias from sampling errors is similar over time.[40] Finally, firm effects are identified up to the difference with respect to an omitted reference firm. Hence, one can only obtain comparable estimates of firm effects for firms that are connected by worker flows. Following AKM and CHK, we estimate equation (3) on the greatest connected set of workers, which in our case comprises close to 98% of all observations (see Table A.3).

[39]The age-earnings gradient in SSA data flattens out around age 40. The worker effect is biased because it absorbs the time-invariant effect of age (i.e., age at start of the sample, which is effectively a cohort effect). Note that for the analysis of changes in the variance of worker effects over time, the normalization has no effect on the trend as long as the age distribution of the population and the return to age are roughly stable over time. The firm effects are not affected by the normalization. The covariance of worker and firm effects may be affected insofar as workers are sorted into firms by age.

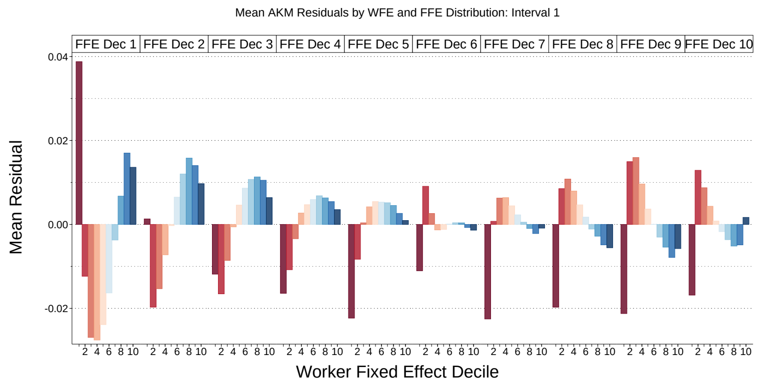
[40]Andrews et al. (2008) show that the degree of negative correlation declines with the number of movers that is used to identify firm effects. We indeed find that the level of the covariance rises with our sample size. However, the gradient over time is unaffected.

C.2 Model Fit

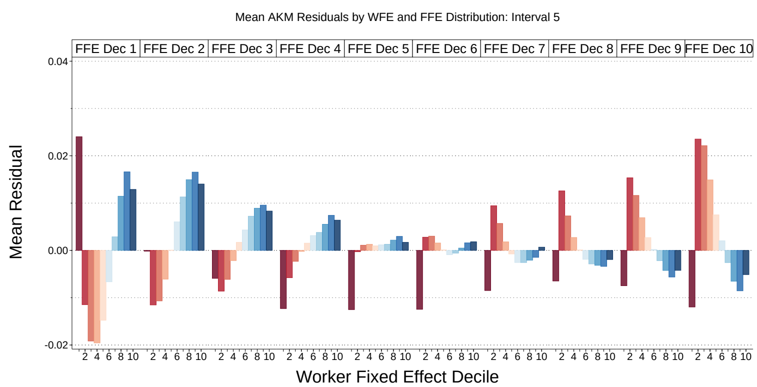
Table A.3 shows basic characteristics for the full sample of men as well as for observations of men in the connected set, separately for each of our five time periods. In the following, we will focus our discussion on men. Unless otherwise noted, the results for women are similar. (For space reasons, the results for women are in Appendix Tables A.6 and A.7.) Table A.3 shows that in all five periods, approximately 98% of workers are in in the greatest connected set. As a result, the mean, median, and standard deviation of earnings in the connected set are very similar to the overall sample. If one compares the number of observations with the number of workers, one obtains that the average worker is in the sample about 5 of 7 years in each period. This number is very similar to numbers reported by CHK (Table I) for full-time men in Germany.

FIGURE A.10 – Regression residuals by firm fixed effect decile

(A) 1980-1986



(B) 2007-2013

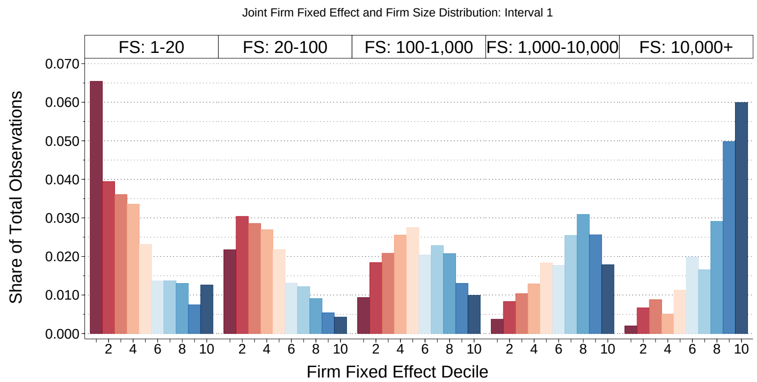


(C) Change from 1980-1986 to 2007-2013

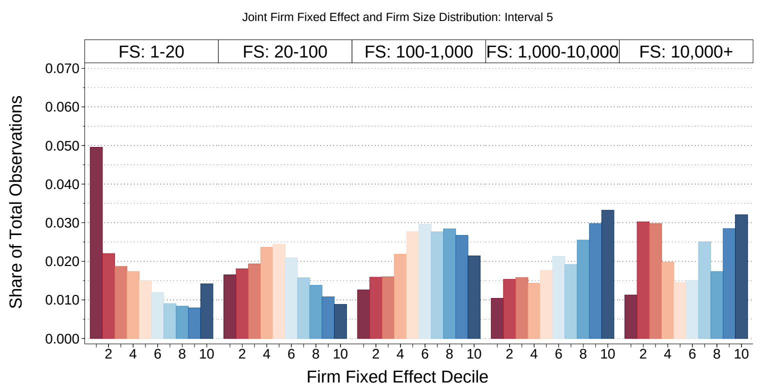
Notes: Calculations based on SSA data. Only men are included in these statistics. Only firms and individuals in firms with at least 20 employees are included. Only employed individuals aged 20 to 60 are included in all statistics, where "employed" is defined as earning the equivalent of 2013 minimum wage, adjusted for inflation with the PCE for 40 hours per week in 13 weeks. Individuals and firms in public administration or educational services are not included. Within each firm FE decile group, worker FE deciles are order from left to right from 1 to 10.

Figure A.11 – Distribution of workers among firm FE deciles, by firm size

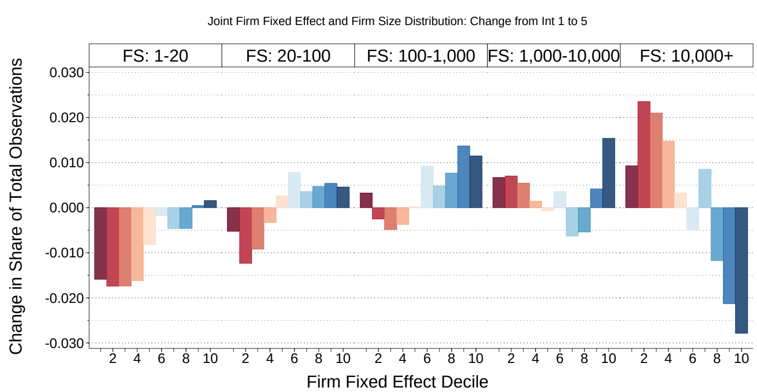
(a) 1980-1986



(b) 2007-2013



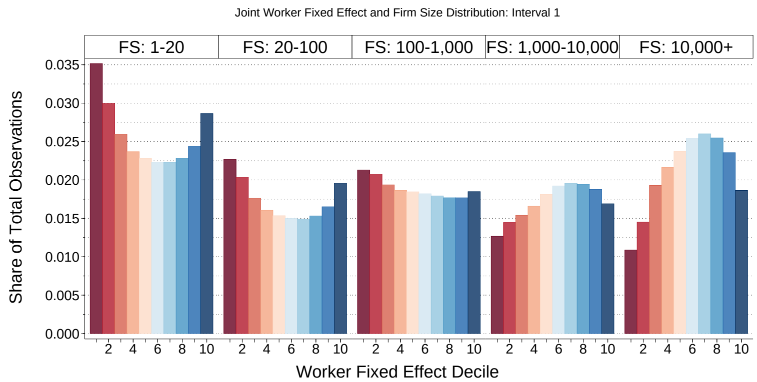
(c) Change from 1980-1986 to 2007-2013



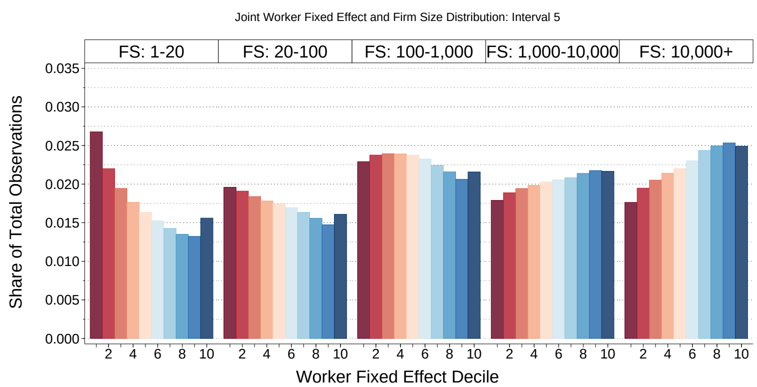
Notes: Calculations based on SSA data. Only men are included in these statistics. Only firms and individuals in firms with at least 20 employees are included. Only employed individuals aged 20 to 60 are included in all statistics, where "employed" is defined as earning the equivalent of 2013 minimum wage, adjusted for inflation with the PCE for 40 hours per week in 13 weeks. Individuals and firms in public administration or educational services are not included. Within each firm size group, firm FE deciles are order from left to right from 1 to 10.

Figure A.12 – Distribution of workers among worker FE deciles, by firm size

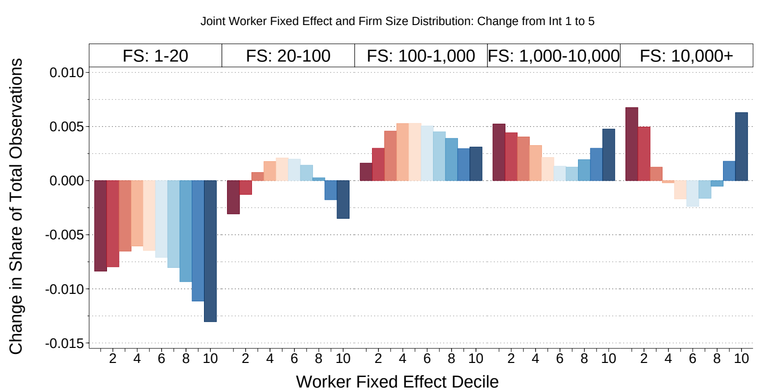
(a) 1980-1986



(b) 2007-2013



(c) Change from 1980-1986 to 2007-2013



Notes: Calculations based on SSA data. Only men are included in these statistics. Only firms and individuals in firms with at least 20 employees are included. Only employed individuals aged 20 to 60 are included in all statistics, where "employed" is defined as earning the equivalent of 2013 minimum wage, adjusted for inflation with the PCE for 40 hours per week in 13 weeks. Individuals and firms in public administration or educational services are not included. Within each firm size group, worker FE deciles are order from left to right from 1 to 10.

Table A.3 – Summary Statistics for Overall Sample and Individuals in Largest Connected Set

7-year Interval	All employed men, age 20-60						Individuals in largest connected set					
				Log real annual earnings						Log real annual earnings		
	Number of worker/yr. obs.	Number of workers	Number of firms	Mean	Median	Std. dev.	Number of worker/yr. obs.	Number of workers	Number of firms	Mean	Median	Std. dev.
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
1980-1986	334,147,424	65,942,723	5,964,555	10.397	10.514	0.854	330,634,861	64,987,602	5,165,584	10.396	10.515	0.851
							(98.9)	(98.6)	(86.6)	(100.0)	(100.0)	(99.6)
1987-1993	372,145,155	71,152,434	6,541,630	10.394	10.493	0.892	367,763,450	70,062,879	5,627,188	10.393	10.494	0.888
							(98.8)	(98.5)	(86.0)	(100.0)	(100.0)	(99.5)
1994-2000	405,222,444	76,179,038	6,873,943	10.445	10.527	0.910	399,981,325	74,930,695	5,822,056	10.444	10.528	0.907
							(98.7)	(98.4)	(84.7)	(100.0)	(100.0)	(99.7)
2001-2007	427,033,756	81,260,292	7,134,061	10.514	10.593	0.935	420,186,588	79,688,393	5,816,098	10.514	10.595	0.932
							(98.4)	(98.1)	(81.5)	(100.0)	(100.0)	(99.8)
2007-2013	421,150,246	82,515,998	6,735,729	10.496	10.572	0.951	413,228,494	80,665,231	5,232,154	10.498	10.575	0.949
							(98.1)	(97.8)	(77.7)	(100.0)	(100.0)	(99.8)
Change from first to last interval				0.099	0.057	0.096				0.102	0.060	0.099

Notes: Ratio of largest connected set to all observations in parentheses. Only men are included in these statistics. Individuals are included regardless of industry or firm size. Only employed individuals aged 20 to 60 are included in all statistics, where "employed" is defined as earning the equivalent 520 times the contemporaneous minimum wage.

Table A.4 – Estimation Results for AKM Model, Fit by Interval

		Interval 1 1980-1986 (1)	Interval 2 1987-1993 (2)	Interval 3 1994-2000 (3)	Interval 4 2001-2007 (4)	Interval 5 2007-2013 (5)
Sample	# Worker effects	64,987,602	70,062,879	74,930,695	79,688,393	80,665,231
Summary	# Firm effects	5,165,584	5,627,188	5,822,056	5,816,098	5,232,154
Statistics	Sample size	330,634,861	367,763,450	399,981,325	420,186,588	413,228,494
	sd(log(y))	0.851	0.888	0.907	0.932	0.949
Summary of	sd(WE)	0.587	0.624	0.657	0.677	0.693
AKM Parameter	sd(FE)	0.338	0.323	0.305	0.319	0.326
Estimates	sd(Xb)	0.239	0.261	0.282	0.249	0.243
	corr(WE,FE)	0.028	0.078	0.117	0.130	0.145
	corr(WE,Xb)	0.106	0.087	0.031	0.076	0.102
	corr(FE,Xb)	0.123	0.126	0.109	0.123	0.141
	rmse(residual)	0.431	0.427	0.421	0.428	0.411
	Adj R^2	0.743	0.768	0.784	0.789	0.812
Comparison	rmse(match residual)	0.365	0.363	0.354	0.360	0.346
Match Model	Adj R^2	0.816	0.833	0.848	0.851	0.867
	sd(match effect)	0.254	0.250	0.255	0.256	0.241

Notes: Only men are included in these statistics. Individuals are included regardless of industry or firm size. Only employed individuals aged 20 to 60 are included in all statistics, where "employed" is defined as earning the equivalent 520 times the 2013 PCE-deflated minimum wage.

Table A.4 displays basic statistics from the estimation. The table delivers a snapshot of the basic findings, as well as important diagnostic checks. In terms of basic findings, the table shows how the standard deviation of worker effects has risen over time, especially in the early 1980s. The standard deviation of firm effects has remained stable. In contrast, the correlation of worker and firm effects rose almost five fold from our first period, 1980-1986, to our last period, 2007-2013.[41] The table also shows that the RMSE has remained stable, and has at best declined somewhat over time. If the rise in sorting of workers to firms had resulted from an increasing role of complementarities (i.e., match effects), we would have expected the goodness of fit of the model without match effects to decline over time. Instead, the RMSE drops at the same time as the variance of earnings increases. As a result, the adjusted R^2 increases from 74% in 1980-1986 to 81% in 2007-2013.

While the goodness of fit based on worker and firm effects and age is quite high, at around 80%, there is room left for additional components. To check whether adding a match-specific component would substantially increase the fit of the model, the bottom of the table shows basic statistics of a model that also allows for a match effect (m_{ij}). Not surprisingly, allowing for a match effect reduces the RMSE and increases the adjusted R^2, by about the same amount

[41] The correlation of observable worker characteristics (mainly age) with worker and firm effects has a U-shaped pattern—declining to a low point during the economic book of the late 1990s, and returning to similar levels by the end of the period.

each period, to $81 - 87\%$. However, the standard deviation of match effects declines somewhat over time. As noted by CHK, this is consistent with an interpretation of the match effects as uncorrelated random effects. If instead they were specification errors caused by incorrectly imposing additivity of the person and establishment effects, one would expect the standard deviation of match effects to rise and the relative fit of the AKM model to deteriorate over time as the covariance of worker and firm effects increases in magnitude.

As additional check on the appropriateness of the basic AKM specification of model (3), we examined average regression residuals for different groups of worker and firm effects. Violations of the separability assumptions in the AKM model would likely cause large mean residuals for certain matches, say, where highly skilled workers are matched to low-wage establishments. To search for such potential interactions, we followed CHK and divided the estimated person and establishment effects in each interval into deciles, and computed the mean residual in each of the 100 person firm decile cells.

Figure A.10b shows the mean residuals from the cells using data from period 2007–2013. For most cells, the mean residual is very small, below 0.02, and shows few systematic patterns; because the dependent variable is in logs, this means that the predicted value and actual average generally differ by under 2%. Only for cells with either low worker effects or low firm effects do residuals appear larger. It is interesting to note that this pattern is quite similar to those found by CHK (Figure VI), who report larger mean residuals for the lowest worker and firm effect groups. Hence, in both Germany and the U.S. separability appears a good description for all worker and firm groups but for the bottom end.[42] Figure A.10c shows the change in mean residuals within cells over time. The changes are of opposite signs of the deviations in A.10b, implying that the absolute magnitude of deviations has declined over time. Hence, overall, the goodness of fit of the model has improved from the first to the last period in our sample.

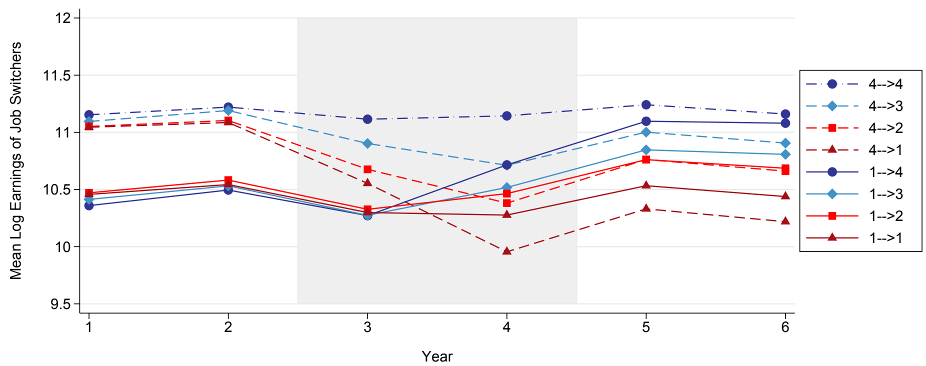
Another diagnostic assesses the ability of the model to explain earnings changes at job changes. If the model is correctly specified, on average workers changing from one firm to another should experience earnings changes corresponding to the estimated firm effects. To implement this comparison, we used our data to perform event-study analyses of the effect of job mobility on earnings akin to those shown in CHK (Figure VII). As in CHK, we divided firms into quartiles according to both their average wage and their firm effects, and recorded the mean earnings of workers moving between the four firm-type classes in the years before and after the job change. One complication is that we do not observe when in a given year a worker leaves his initial employer, and whether he joins his new employer in the same year or at some point in the adjacent year. To deal with the fact that we do not know the specific time of the move, we followed workers from two years before the year t in which we observe the move (i.e., from year $t-2$ to $t-1$), to two years after the year succeeding the move (from year $t+2$ to $t+3$). To further try to approximate transition between "full-time" jobs, we only look at workers who remained at the firm in the two years before and two years after the move. Since we are following workers for six years, we adjust earnings for flexible time trends. The results are shown in Figures 7 and A.13, for firm classes based on firm fixed effects and firm average wages, respectively. The results are discussed in the main text in Section 4. Overall, we conclude that despite the fact we are modeling information on annual earnings rather than

[42] Not surprisingly given the presence of labor supply effects, the mean residuals in Figure A.10 are on average larger than those shown CHK (Figure VI).

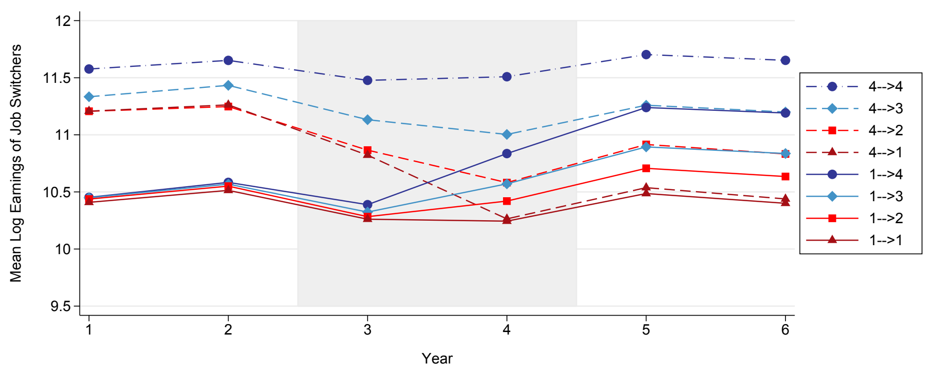
daily or hourly wages, our model delivers a good approximation of the underlying earnings process.

Figure A.13 – Event study of change in mean earnings for job changers

(a) Firms ranked by earnings: 1980-1986



(b) Firms ranked by earnings: 2007-2013



Notes: Calculations based on SSA data. Only men are included in these statistics. Men are included regardless of industry or firm size. Only employed individuals aged 20 to 60 are included in all statistics, where "employed" is defined as earning the equivalent 520 times the contemporaneous minimum wage. For an explanation of the methodology see Section4.2 and Appendix C.2. For all observations main job is the same in years 1, 2, and 3 and then switches to a new main job for years 4, 5, and 6. The shaded region marks the possible years of the job switch. Mean earning quartiles are weighted by worker-years and calculated in years 2 and 5. Mean earnings are computed as "leave-out" means, i.e. for each individual, mean firm earnings are computed over all employees except the reference employee. Log earnings are detrended by subtracting the time-varying observable AKM component from each observation.

Several other robustness checks are shown in Table A.5, all of which show fairly similar results. The second column shows that the main results are similar when restricting the sample to women only, rather than men only. For the third column, We construct a "sandwich sample" to include only observations on either side of a job move: that is, we drop an observation for an individual in year t if that individual's primary EIN in year t is different from their EIN in years $t-1$ or $t+1$. This sandwich sample helps ensure that our results are not driven by changes in labor supply caused by the process of switching jobs. In the last column, we restrict our sample to those with at least the equivalent of 2000 hours at the 2013 minimum wage. The similarity of the main results to the results of the specifications with labor supply restrictions suggest that our results are being driven more by wage differences than by differences in hours or weeks of work.

Finally, Tables A.6 and A.7 show more details on our main results for the women-only sample. Women see somewhat less rising between-firm variance than men. However, for women as well as men, rising between-firm variance still accounts for most of rising inequality; rising dispersion of individual fixed effects accounts for most of rising variance in the basic decomposition; and, in the detailed decomposition, sorting and segregation dominate the between-firm component.

Table A.10 shows detailed descriptive statistics on the characteristics of job movers. The first row shows the average number of moves per interval. The table shows a slight decline in the average number of job moves per worker. However, we suspect that this is due to the effect of the Great Recession in 2007-2013 as prior to this interval the series shows no trend. We also include average age, earnings, worker fixed effect, firm size, and firm fixed effect of job movers versus job stayers. As expected, job movers tend to be younger, come from smaller firms, and have lower average earnings. Job movers also on average have lower firm fixed effects than job stayers. In addition, if we disaggregate job movers by the number of switches per interval, we find a negative, monotonic relationship between the number of switches and the average firm fixed effect. This in turn implies a positive relationship between match duration and firm fixed effects. What is important for our purposes is that the average years in the sample of movers and stayers is similar and has remained similar over time, suggesting that differential selection into the sample is unlikely to affect our estimates.

Table A.11 reports the correlation of estimated firm effects across intervals. The estimated firm fixed effects are significantly correlated across intervals and this correlation drops only slightly as the time period is extended to a three interval difference. In particular, the firm fixed effects of large firms are highly correlated over time.

TABLE A.5 – Sensitivity of AKM Results

	Main Sample: Male				**Main Sample: Female**				**Sandwich Sample: Male**				**"Full-time" Sample: Male**			
	Int 1 (1)	Int 5 (2)	Change (3)	Share (4)	Int 1 (5)	Int 5 (6)	Change (7)	Share (8)	Int 1 (9)	Int 5 (10)	Change (11)	Share (12)	Int 1 (13)	Int 5 (14)	Change (15)	Share (16)
Total Var	0.71	0.92	0.22	-	0.53	0.75	0.22	-	0.39	0.61	0.22	-	0.36	0.53	0.17	-
Between Firm Var	0.21	0.37	0.16	74.2	0.17	0.28	0.12	53.5	0.12	0.26	0.14	63.7	0.09	0.19	0.10	57.9
Var(m_wfe)	0.05	0.12	0.07	30.9	0.04	0.09	0.05	21.4	0.06	0.12	0.07	30.5	0.04	0.09	0.06	34.9
Var(m_ffe)	0.08	0.08	0.00	-1.6	0.07	0.07	0.00	-0.4	0.08	0.10	0.02	7.4	0.04	0.03	0.00	-2.2
Var(m_xb)	0.01	0.01	0.00	0.6	0.00	0.01	0.00	1.5	0.00	0.00	0.00	0.0	0.00	0.00	0.00	-0.2
2Cov(m_wfe,m_ffe)	0.03	0.11	0.08	34.8	0.05	0.09	0.04	18.2	-0.03	0.01	0.05	21.2	0.01	0.05	0.04	23.3
2Cov(m_wfe,m_xb)	0.01	0.03	0.02	7.3	0.00	0.02	0.01	6.6	0.00	0.01	0.01	2.7	0.00	0.01	0.00	2.0
2Cov(m_ffe,m_xb)	0.02	0.03	0.00	2.2	0.01	0.02	0.01	6.1	0.01	0.01	0.00	1.8	0.00	0.00	0.00	0.1
Within Firm Var	0.50	0.55	0.06	25.8	0.36	0.47	0.10	46.5	0.27	0.35	0.08	36.3	0.27	0.34	0.07	42.1
Var(diff_wfe)	0.28	0.36	0.08	36.7	0.21	0.30	0.09	42.4	0.19	0.29	0.10	45.0	0.17	0.26	0.08	51.0
Var(diff_xb)	0.05	0.05	0.00	1.2	0.03	0.04	0.01	5.3	0.02	0.02	0.00	-0.1	0.02	0.02	0.00	0.3
Var(diff_r)	0.15	0.14	-0.02	-8.2	0.13	0.12	-0.01	-4.8	0.05	0.03	-0.02	-8.5	0.08	0.07	-0.01	-5.9
2Cov(diff_wfe,diff_xb)	0.02	0.01	-0.01	-3.2	-0.01	0.00	0.01	3.7	0.01	0.01	0.00	0.0	0.00	0.00	-0.01	-3.4
Segregation index	0.16	0.25	0.09		0.16	0.22	0.07		0.23	0.30	0.07		0.18	0.27	0.09	
Corr(wfe,ffe)	0.10	0.28	0.18		0.18	0.27	0.09		-0.12	0.03	0.15		0.06	0.23	0.17	
N (millions)	221.62	302.77	81.15		159.45	268.25	108.80		127.45	152.84	25.39		188.83	253.38	64.55	
Adj R_2	0.743	0.812	0.07		0.694	0.796	0.10		0.835	0.882	0.05		0.753	0.840	0.09	
Adj R_2 - match model	0.816	0.867	0.05		0.772	0.857	0.09		0.845	0.920	0.08		0.791	0.875	0.08	

Notes: Variance and correlation of fixed effects estimated by AKM model as explained in Section 4. Only firms and individuals in firms with at least 20 employees are included. Only employed individuals aged 20 to 60 are included in all statistics. Individuals and firms in public administration or educational services are not included, and only those aged 20 to 60 are included. The first column includes the usual sample restrictions: men only, and employed is defined as earning the equivalent of 2013 minimum wage, adjusted for inflation with the PCE for 40 hours per week in 13 weeks. The second column includes women only. The third column (the "sandwich sample") drops observations for individuals in years that are not preceded and succeeded by observations with the same primary EIN. The fourth column restricts the analysis to "full-time" workers, defined as earning the equivalent of the 2013 minimum wage for 2000 hours.

TABLE A.6 – Basic Decomposition of the Rise in Inequality of Annual Earnings: Women Only

		Interval 1 (1980-1986)		Interval 2 (1987-1993)		Interval 3 (1994-2000)		Interval 4 (2001-2007)		Interval 5 (2007-2013)		Change from 1 to 5	
		Comp (1)	Share (2)	Comp (3)	Share (4)	Comp (5)	Share (6)	Comp (7)	Share (8)	Comp (9)	Share (10)	Comp (11)	Share (12)
Total Variance	Var(y)	0.530	-	0.594	-	0.657	-	0.719	-	0.751	-	0.222	-
Components of variance	Var(WFE)	0.245	46.2	0.288	48.5	0.330	50.3	0.365	50.7	0.386	51.4	0.142	63.8
	Var(FFE)	0.070	13.1	0.062	10.4	0.058	8.8	0.067	9.3	0.069	9.1	-0.001	-0.4
	Var(Xb)	0.030	5.6	0.035	5.9	0.055	8.4	0.046	6.4	0.045	6.0	0.015	6.9
	Var(residual)	0.135	25.5	0.137	23.0	0.139	21.2	0.140	19.4	0.124	16.5	-0.011	-4.8
	2*Cov(WFE,FFE)	0.047	8.8	0.055	9.3	0.062	9.5	0.074	10.3	0.087	11.6	0.040	18.2
	2*Cov(WFE,Xb)	-0.003	-0.6	0.007	1.2	-0.001	-0.2	0.011	1.5	0.020	2.6	0.023	10.4
	2*Cov(FFE,Xb)	0.007	1.3	0.010	1.6	0.014	2.1	0.017	2.3	0.020	2.7	0.014	6.1
Sum of firm components	Cov(y,FFE)	0.096	18.2	0.094	15.8	0.096	14.6	0.112	15.6	0.122	16.3	0.026	11.8
Counterfactuals	1.) No rise in Corr(WFE,FFE)	0.530		0.586	98.7	0.644	98.1	0.701	97.5	0.723	96.2	0.193	87.1
	2.) No fall in Var(FFE)	0.530		0.606	102.0	0.676	103.0	0.724	100.7	0.753	100.2	0.224	100.8
	3.) Both 1 and 2	0.530		0.597	100.6	0.662	100.8	0.705	98.0	0.724	96.4	0.195	87.7

Notes: Results for women only; otherwise, see notes for Table 5.

Table A.7 – Detailed Decomposition of the Rise in Earnings Inequality between and within Firms: Women Only

		Interval 1 (1980-1986)		Interval 2 (1987-1993)		Interval 3 (1994-2000)		Interval 4 (2001-2007)		Interval 5 (2007-2013)		Change from 1 to 5	
		Comp (1)	Share (2)	Comp (3)	Share (4)	Comp (5)	Share (6)	Comp (7)	Share (8)	Comp (9)	Share (10)	Comp (11)	Share (12)
Total var	Var(y)	0.530	-	0.594	-	0.657	-	0.719	-	0.751	-	0.222	-
Between-firm var	Var(m_y)	0.166	31.4	0.190	32.0	0.216	32.9	0.248	34.6	0.285	37.9	0.119	53.5
	Var(m_WFE)	0.038	7.2	0.053	8.9	0.065	9.9	0.073	10.1	0.086	11.4	0.047	21.4
	Var(m_FFE)	0.070	13.1	0.062	10.4	0.058	8.8	0.067	9.3	0.069	9.1	-0.001	-0.4
	Var(m_Xb)	0.003	0.5	0.004	0.6	0.006	0.9	0.005	0.7	0.006	0.8	0.003	1.5
	2Cov(m_WFE,m_FFE)	0.047	8.8	0.055	9.3	0.062	9.5	0.074	10.3	0.087	11.6	0.040	18.2
	2Cov(m_WFE,m_Xb)	0.003	0.5	0.007	1.2	0.011	1.7	0.013	1.8	0.017	2.3	0.015	6.6
	2Cov(m_FFE,m_Xb)	0.007	1.3	0.010	1.6	0.014	2.1	0.017	2.3	0.020	2.7	0.014	6.1
Within-firm var	Var(diff_y)	0.363	68.6	0.404	68.0	0.440	67.1	0.470	65.4	0.466	62.1	0.103	46.5
	Var(diff_WFE)	0.207	39.0	0.235	39.6	0.265	40.3	0.292	40.6	0.301	40.0	0.094	42.4
	Var(diff_Xb)	0.027	5.2	0.032	5.3	0.049	7.5	0.041	5.7	0.039	5.2	0.012	5.3
	Var(diff_r)	0.135	25.5	0.137	23.0	0.139	21.2	0.140	19.4	0.124	16.5	-0.011	-4.8
	2Cov(diff_WFE,diff_Xb)	-0.006	-1.1	0.000	0.0	-0.012	-1.9	-0.002	-0.2	0.003	0.3	0.008	3.7
	2Cov(diff_WFE,diff_r)	0.000	0.1	0.000	0.1	0.000	0.0	0.000	0.0	0.000	0.0	-0.001	-0.3
	2Cov(diff_Xb,diff_r)	0.000	-0.1	0.000	0.0	0.000	-0.1	0.000	0.0	0.000	0.0	0.000	0.1
Segregation Index	Var(m_WFE)/Var(WFE)	0.156		0.183		0.198		0.199		0.221		0.066	
	N (millions)	159.45		206.46		239.43		263.02		268.25		108.80	

Notes: Results for women only; otherwise, see notes for Table 6.

Table A.8 – Basic Decomposition of the Rise in Inequality: All Firm Sizes, All Industries

		Interval 1 (1980-1986)		Interval 2 (1987-1993)		Interval 3 (1994-2000)		Interval 4 (2001-2007)		Interval 5 (2007-2013)		Change from 1 to 5	
		Comp (1)	Share (2)	Comp (3)	Share (4)	Comp (5)	Share (6)	Comp (7)	Share (8)	Comp (9)	Share (10)	Comp (11)	Share (12)
Total Variance	Var(y)	0.724	-	0.788	-	0.822	-	0.869	-	0.901	-	0.177	-
Components of variance	Var(WFE)	0.345	47.6	0.390	49.4	0.431	52.4	0.458	52.7	0.480	53.2	0.135	76.1
	Var(FFE)	0.114	15.8	0.104	13.2	0.093	11.3	0.102	11.7	0.106	11.8	-0.008	-4.5
	Var(Xb)	0.057	7.9	0.068	8.6	0.080	9.7	0.062	7.1	0.059	6.5	0.002	1.0
	Var(residual)	0.147	20.3	0.145	18.4	0.141	17.2	0.146	16.8	0.134	14.9	-0.013	-7.2
	2*Cov(WFE,FFE)	0.011	1.5	0.031	4.0	0.047	5.7	0.056	6.5	0.065	7.3	0.054	30.6
	2*Cov(WFE,Xb)	0.030	4.1	0.028	3.6	0.011	1.4	0.026	2.9	0.034	3.8	0.005	2.6
	2*Cov(FFE,Xb)	0.020	2.7	0.021	2.7	0.019	2.3	0.020	2.2	0.022	2.5	0.002	1.4
Sum of firm components	Cov(y,FFE)	0.130	17.9	0.131	16.6	0.126	15.3	0.140	16.1	0.150	16.7	0.020	11.4
Counterfactuals	1.) No rise in Corr(WFE,FFE)	0.724		0.768		0.787		0.825		0.848		0.125	70.3
	2.) No fall in Var(FFE)	0.724		0.801		0.851		0.886		0.912		0.189	106.4
	3.) Both 1 and 2	0.724		0.780		0.811		0.840		0.858		0.134	75.6

Notes: Only men are included in these statistics. Individuals are included regardless of industry or firm size. Only employed individuals aged 20 to 60 are included in all statistics, where "employed" is defined as earning the equivalent of 520 times the 2013 PCE deflated minimum wage.

Table A.9 – Detailed Decomposition of the Rise in Inequality between and within Firms: All Firms, All Industries

		Interval 1 (1980-1986)		Interval 2 (1987-1993)		Interval 3 (1994-2000)		Interval 4 (2001-2007)		Interval 5 (2007-2013)		Change from 1 to 5	
		Comp (1)	Share (2)	Comp (3)	Share (4)	Comp (5)	Share (6)	Comp (7)	Share (8)	Comp (9)	Share (10)	Comp (11)	Share (12)
Total var	Var(y)	0.724	-	0.788	-	0.822	-	0.869	-	0.901	-	0.177	-
Between-firm var	Var(m_y)	0.250	34.5	0.287	36.4	0.307	37.3	0.332	38.2	0.369	41.0	0.120	67.4
	Var(m_wfe)	0.081	11.2	0.100	12.7	0.117	14.3	0.126	14.5	0.142	15.8	0.062	34.7
	Var(m_ffe)	0.114	15.8	0.104	13.2	0.093	11.3	0.102	11.7	0.106	11.8	-0.008	-4.5
	Var(m_xb)	0.009	1.2	0.011	1.4	0.011	1.3	0.009	1.0	0.009	0.9	0.000	-0.1
	2Cov(m_wfe,m_ffe)	0.011	1.5	0.031	4.0	0.047	5.7	0.056	6.5	0.065	7.3	0.054	30.6
	2Cov(m_wfe,m_xb)	0.015	2.0	0.020	2.5	0.020	2.4	0.020	2.3	0.024	2.7	0.010	5.4
	2Cov(m_ffe,m_xb)	0.020	2.7	0.021	2.7	0.019	2.3	0.020	2.2	0.022	2.5	0.002	1.4
Within-firm var	Var(diff_y)	0.474	65.5	0.501	63.6	0.515	62.7	0.537	61.8	0.532	59.0	0.058	32.6
	Var(diff_wfe)	0.264	36.5	0.290	36.8	0.314	38.1	0.333	38.2	0.337	37.4	0.073	41.4
	Var(diff_xb)	0.048	6.7	0.057	7.3	0.069	8.3	0.053	6.1	0.050	5.6	0.002	1.1
	Var(diff_r)	0.147	20.3	0.145	18.4	0.141	17.2	0.146	16.8	0.134	14.9	-0.013	-7.2
	2Cov(diff_wfe,diff_xb)	0.015	2.1	0.009	1.1	-0.008	-1.0	0.006	0.6	0.010	1.1	-0.005	-2.8
	2Cov(diff_wfe,diff_r)	0.000	0.0	0.000	0.0	0.000	0.0	0.000	0.0	0.000	0.0	0.000	0.0
	2Cov(diff_xb,diff_r)	0.000	0.0	0.000	0.0	0.000	0.0	0.000	0.0	0.000	0.0	0.000	0.0
Segregation index	Var(m_wfe)/Var(wfe)	0.234		0.256		0.272		0.274		0.297		0.062	
	N (millions)	331		368		400		420		413		82	

Notes: Only men are included in these statistics. Individuals are included regardless of industry or firm size. Only employed individuals aged 20 to 60 are included in all statistics, where "employed" is defined as earning the equivalent of 520 times the 2013 PCE deflated minimum wage.

Table A.10 – Descriptive Statistics for Job Movers versus Job Stayers

	Type of worker	Interval 1 (1980-1986) (1)	Interval 2 (1987-1993) (2)	Interval 3 (1994-2000) (3)	Interval 4 (2001-2007) (4)	Interval 5 (2007-2013) (5)	Change from 1 to 5 (6)
Mean number of job moves	*All workers*	1.02	1.03	1.14	1.06	0.91	-0.11
	Job mover	1.82	1.89	1.97	1.91	1.79	-0.03
	Job stayer	0.00	0.00	0.00	0.00	0.00	0.00
	One year in sample	-	-	-	-	-	-
Percent of observations	*Job mover*	55.97	54.49	58.03	55.55	50.68	-5.29
	Job stayer	34.95	37.16	33.52	35.62	39.37	4.41
	One year in sample	9.08	8.35	8.45	8.83	9.95	0.88
Mean years in sample	*Job mover*	5.55	5.67	5.80	5.74	5.62	0.07
	Job stayer	5.43	5.67	5.69	5.64	5.52	0.10
	One year in sample	1.00	1.00	1.00	1.00	1.00	0.00
Mean age	*Job mover*	31.34	31.53	33.00	33.86	34.07	2.73
	Job stayer	36.89	37.54	39.12	40.04	40.40	3.50
	One year in sample	33.37	34.05	34.17	34.94	35.87	2.50
Mean firm size (thousands)	*Job mover*	294.1	271.9	232.0	309.9	369.9	75.84
	Job stayer	723.3	675.3	527.0	569.7	669.4	-53.90
	One year in sample	373.6	282.8	257.6	352.2	424.8	51.15
Mean log earnings	*Job mover*	10.08	10.00	10.12	10.16	10.15	0.07
	Job stayer	10.59	10.60	10.65	10.71	10.67	0.08
	One year in sample	9.37	9.26	9.34	9.34	9.40	0.03
Mean worker FE	*Job mover*	10.39	10.23	9.67	10.64	10.53	0.14
	Job stayer	10.73	10.63	10.07	11.05	10.93	0.20
	One year in sample	9.95	9.79	9.22	10.13	10.09	0.14
Mean firm FE	*Job mover*	-0.05	0.08	0.67	-0.21	-0.09	-0.04
	Job stayer	0.08	0.19	0.73	-0.14	-0.03	-0.11
	One year in sample	-0.15	-0.02	0.56	-0.32	-0.21	-0.07

Notes: "One year in sample" refers to workers workers who are in the sample only a single year and hence cannot be classified as movers or stayers. Statistics are computed at the worker-interval level. For each individual in each interval we compute number of years in the sample, number of job switches, average age, average earnings, average firm size, worker fixed effect, and average firm fixed effect. Then we compute descriptive statistics based on the worker-level variables. Only men are included in these statistics. Individuals are included regardless of industry or firm size. Only employed individuals aged 20 to 60 are included in all statistics, where "employed" is defined as earning the equivalent of 520 times the contemporaneous minimum wage.

Table A.11 – Correlation of Firm Fixed Effects across Time

	All firms (1)	Large firms (2)	Medium firms (3)	Small firms (4)
A. Correlation across one interval				
1980-1986 to 1987-1993	0.67	0.92	0.75	0.39
1987-1993 to 1994-2000	0.67	0.88	0.80	0.40
1994-2000 to 2001-2007	0.66	0.84	0.80	0.40
2001-2007 to 2007-2013	0.72	0.90	0.87	0.46
B. Correlation across two intervals				
1980-1986 to 1994-2000	0.60	0.80	0.67	0.33
1987-1993 to 2001-2007	0.60	0.72	0.74	0.36
1994-2000 to 2007-2013	0.64	0.84	0.78	0.36
C. Correlation across three intervals				
1980-1986 to 2001-2007	0.57	0.68	0.63	0.32
1987-1993 to 2007-2013	0.61	0.77	0.74	0.33

Notes: Fixed effects are weighted by the average number of observations across intervals. Large firms have more than 10,000 employees, medium firms have 101 to 10,000 employees, small firms have 1 to 100 employees. Employment is counted in terms of males aged 20-60 years. Only men are included in these statistics. Individuals are included regardless of industry or firm size. Only employed individuals aged 20 to 60 are included in all statistics, where "employed" is defined as earning the equivalent of 520 times the contemporaneous minimum wage.

C.3 Patterns of Sorting By Firm Earnings, Firm Size, and Industry

Tables 5 and 6 have shown that the substantial between-firm component of the rise in earnings inequality in the United States from the early 1980s to today can be attributed almost entirely to sorting (a rise in the correlation of worker and firm effects) and segregation (a rise in the variance of mean worker effects between firms). We have also found that these patterns are particularly pronounced for moderately sized firms (i.e., for employment size less or equal to 1000). In this section, we will use our estimated worker and firm effects from implementing equation (3) to assess how workers are sorted into high-wage firms and large firms, and how this has changed over time. We will also describe the changing patterns of firm and worker effects by firm size and industry.

To learn more about the pattern of sorting, the first two panels of Figure 8 display the joint distribution among deciles of worker and firm effects in 1980-1986 and 2007-2013. The cross-sectional sorting patterns displayed in the figure are striking. Consider first the early 1980s shown in Figure 8a. One can see that most workers are in medium to high fixed-effect firms. Yet, lower fixed-effect workers are over-represented at lower fixed-effect firms; workers with fixed effects in the middle range are over-represented at middle to high fixed-effect firms; and high fixed-effect workers are over-represented at high fixed-effect firms. However, one also sees that low to medium fixed-effects firms have modes at both low and high fixed effects workers, presumably reflecting a distribution of lower-skilled production workers and managerial employees.

The distribution for the years 2007–2013 displayed in Figure 8b show these patterns have changed substantially over time. Figure 8c shows the net change of density of the two distributions at corresponding deciles.[43] Overall, there has been a substantial shift in the distribution away from the two highest firm categories towards middle to lower fixed-effect firms. Yet, this shift did not occur uniformly across worker groups. It is the middle of the worker fixed-effect distribution that predominantly left high-wage firms, such that high-wage workers are now over-represented at the top firms. This pattern is augmented by a move of the highest fixed-effect workers to higher-paying firms.

The figures confirm the evidence from the variance decomposition that sorting has increased, and show which workers and firms appear most affected. A striking finding is that the incidence and composition of workers at high-wage firms has been changing substantially. Since high-wage firms are likely to be in part large firms, and we have found large firms to play a special role in the evolution of inequality, we use our data to examine the incidence of worker and fixed effects separately by firm size. These results are shown in Figures A.11 and A.12 for three firm size groups (firms with number of workers in range $1-100$, $101-9999$, and $10,000+$).

From Figure A.11 it is clear that on average, high-wage firms tend to be larger. However, over time, Figure A.11c shows that large employers have experienced a substantial shift out of high-wage firms to middle and lower-wage firms. Figure A.12 shows that among larger firms, the decline was accompanied by an *increase* in the incidence of high wage workers at larger firms. In addition, especially employers with more than 10,000 employees saw a reduction in

[43] Note that the definition of the deciles differ between the two time periods. Yet, since the distribution of firm effects has changed little, the deciles of firm effects are roughly comparable over time.

workers in the middle of the worker fixed-effects distribution. Hence, this confirms that larger firms have become, on average, workplaces that pay less and employ a more unequal set of workers.

To examine potential differences in sorting patterns, we have also examined the joint distribution of firm and worker fixed effects within each size class. These figures can be produced upon request. The results show that the pattern of sorting is quite similar among our two larger firm size classes, and reflects the pattern shown in Figure 8 – there is a substantial net shift in the mass of workers from high-wage firms to middle-wage firms. The bulk of this shift is comprised of middle-wage workers. In contrast, high-wage workers have left middle-wage firms to move to the top firms. In contrast, the distribution of low-wage workers has changed less. These results corroborate our finding from Table 6 that the differences in the sources of inequality growth by firm size is not the between-firm component, whose levels evolve similarly, but rather the within-firm component of inequality.

We have also examined the pattern of marginal distributions of firm and worker effects by one-digit industry. These figures can also be produced upon request. The results show that the large decline in the incidence of employment in higher wage deciles tends to be concentrated in manufacturing. Employment at high-wage manufacturing firms is increasingly replaced by employment in middle-wage service firms. In terms of workers, middle-wage workers have again shifted out of manufacturing, and moved to services. Yet, services has also received an increasing proportion of high-wage workers, with low-wage workers increasingly moving to firm with unknown industry affiliation. These are likely to be disproportionately new employers, which might be likely to have low firm fixed effects.

Overall, the findings from the figures corroborate and strengthen our core results from the detailed variance composition in Table 6. There is a clear pattern of increasing sorting of higher-wage workers into higher-wage firms over time. In particular, from the early 1980s to today, high-wage firms appear to lose middle-wage workers to middle-wage firms, and in turn gain more high-wage workers. These patterns partly correspond to shifts between firm-size classes. Fewer middle-wage workers work at very large employers, at the same time as these employers are increasingly composed of lower-wage firms. Yet, within firm-size classes the patterns of sorting are similar to the full sample, and characterized by a substantial shift between firm-size classes and substantial redistribution of workers. Overall, these findings hint at a substantial reorganization of U.S. businesses over the last 40 years. This reorganization has had profound consequences for both the level and the nature of earnings inequality.

D Non-Parametric Counterfactual Decomposition: Technical Details

In this appendix section, we describe the technical details underlying the counterfactual decomposition presented in Section 3.2. This methodology was developed by Machado and Mata (2005) and Autor et al. (2005), but is adapted slightly for our purposes.

We start with one observation per person in a given year. For each person, we make note of their log earnings in that year, and their firm's mean log earnings in the same year. Individuals are then sorted into 100 firm-based bins with equal numbers of people, denoted f, on the basis of their firm's mean log earnings. (Thus, except when a firm is right on the border between bins, all people within a given firm are in the same firm-based percentile.) Next, people in each firm-based percentile are sorted into 500 individual-based bins, denoted i on the basis of their own log earnings. There are then 50,000 firm-individual bins, denoted fi, and each person is placed in one of them. So, for example, if $f = 60$ and $i = 400$, that indicates that the bins includes everyone between the 59th percentile and 60th percentile, among all people, in terms of their firm's mean log earnings; and, within that bin, they are between the 79.8th percentile and the 80th percentile by their own earnings.

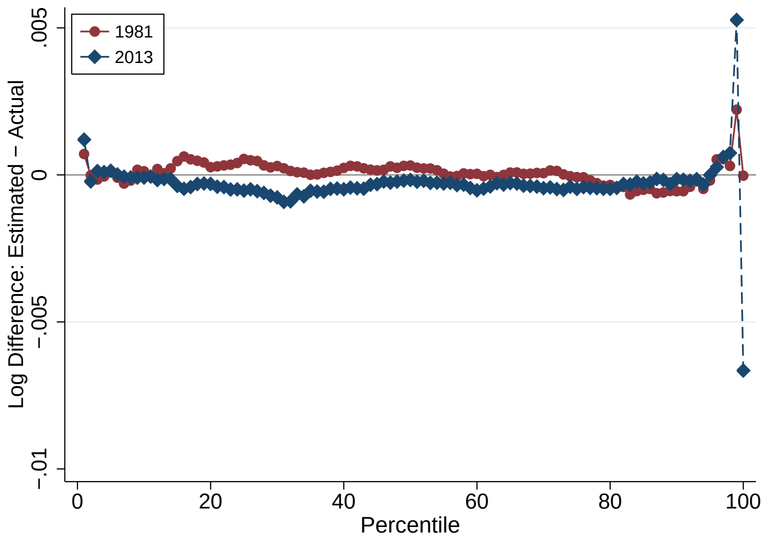
In year t, the mean log earnings in a firm-individual bin is denoted as $\bar{w}_{tfi}$, while the mean log earnings for the entire firm-based bin is denoted by $\bar{w}_{tf}$. Then, a statistic d_{tfi} is calculated for each of the firm-individual bins: deviation from firm bin average, $d_{tfi} = \bar{w}_{tfi} - \bar{w}_{tf}$.

We can now simulate various counterfactuals with the 50,000 bin-level observations. First, we can simulate the actual data for year t with 50,000 data points: each point in this counterfactual is calculated as $c_{fi}^{t,t} = d_{tfi} + \bar{w}_{tf}$ for all fi. (Note that in this case, $c_{fi}^{t,t} = \bar{w}_{tfi}$.) Once we have these 50,000 data points, we then sort them into 100 percentiles, we and calculate the average value of $c_{fi}^{t,t}$ within each percentile, as with the blue-diamond line in Figure 5. The "change" (in this case just due to the binning procedure) can then be calculated as the difference between the values in these percentiles, minus the average earnings within actual percentiles of the earnings distribution in year t. These changes, calculated based on 1981 data and 2013 data, are shown in Figure A.14. If the binning procedure were perfect, each point would be at zero; in fact, except for some small deviations at the top, they are very close to zero. For example, in 1981, the average log earnings for those in the 99th percentile was 11.9634 (corresponding to \$156,906). Using our counterfactual procedure, the average of $c_{fi}^{1981,1981}$ within the 99th percentile of that statistic was 11.9656 (\$157,251); the difference of 0.0022, the largest such difference for 1981, is plotted in Figure A.14 at the 99th percentile point along the red "1981" line.

More interestingly, these statistics allow us to simulate what the distribution would be if between-firm inequality stayed constant at levels from year t, but within-firm inequality changed to the levels observed in year s. To do this, we would use 50,000 data points made up of $c_{fi}^{t,s} = d_{tfi} + \bar{w}_{sf}$ for all fi. Alternatively, we can simulate the distribution if within-firm inequality stayed constant at levels from year t but between-firm inequality changed to the levels observed in year s by using 50,000 data points made up of $c_{fi}^{s,t} = d_{sfi} + \bar{w}_{tf}$ for all fi. In either case, we can compare this to the true distribution in year t or s by sorting these 50,000 data points into percentiles by their value, calculating the average in each percentile, and then comparing the values in these bins to the percentiles of the actual distribution in year t or s.

The results of these counterfactuals are shown in Figure 5. For example, the average of $c_{fi}^{2013,1981}$ within the 99th percentile of that statistic is 12.31; the difference between that value and the average log earnings within the 99th percentile in 1981 (11.96, as noted above) is 0.34; that difference is plotted in Figure 5, on the red "Between-Firm Effects Only" line, at the 99th percentile point. Similarly, the average of $c_{fi}^{1981,2013}$ within the 99th percentile of that statistic is 12.13; the difference of 0.17 is plotted on the green "Within-Firm Effects Only" line, at the 99th percentile point.

FIGURE A.14 – "Counterfactual" difference in distribution due to binning procedure



Notes: Each point shows the difference in average log earnings within that percentile between actual earnings in that year, and earnings simulated in that year using the counterfactual procedure discussed in Appendix Section D. Only firms and individuals in firms with at least 20 employees are included. Only employed individuals aged 20 to 60 are included in all statistics, where "employed" is defined as earning the equivalent of minimum wage for 40 hours per week in 13 weeks. Individuals and firms in public administration or educational services are not included. Each point shows the difference in average log earnings within that percentile between actual earnings in 1981, and another distribution.