Firming Up Inequality*

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June 17, 2016

Abstract

Using a massive, new, matched employer-employee database that we construct for the United States, we show that the rise in earnings inequality between workers over the last three decades has primarily been a between-firm phenomenon. Over two-thirds of the increase in earnings inequality from 1981 to 2013 can be accounted for by the rising variance of earnings between firms and only one-third by the rising variance within firms. This rise in between-firm inequality was particularly strong in smaller and medium-sized firms (explaining 84% for firms with fewer than 10,000 employees). In contrast, in the very largest firms with 10,000+ employees, almost half of the increase in inequality took place within firms, driven by both declines in earnings for employees below the median and sharp rises for the top 50 or so best-paid employees. Finally, examining the mobility of employees across firms, we find that the increase in between-firm inequality has been driven by increased employee segregation—high- and low-paid employees are increasingly clustering in different firms.

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

JEL Codes: E23, J21, J31

*Special thanks to Gerald Ray at the Social Security Administration for his help and support. We thank seminar participants at the AEA, ASU, Berkeley, CEA, Chicago, Dartmouth, Drexel, FRBs of Atlanta, New York, and Philadelphia, Harvard, MIT, Michigan, NBER SI, Northwestern, NYU, Rand, Stanford, TNIT, and Yale for helpful comments. Benjamin Smith 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. wage inequality since the 1970s has been well documented. An enormous body of theoretical and empirical research has been conducted over the past two decades in an attempt to understand the causes of this trend.[1] While much has been learned from these analyses, several major questions remain unanswered. An important set of open questions concerns the link between wage inequality on the worker side to trends in the behavior of the firms and industries that employ these workers. A major difficulty with studying questions of this sort has been the lack of a comprehensive, matched employer-employee data set in the United States that covers the period of rising inequality, beginning with the 1970s.

In the absence of comprehensive evidence on wages paid by firms, a frequent assertion is that inequality within the firm is a driving force leading to an increase in overall inequality. For example, according to Mishel and Sabadish (2014), "a key driver of wage inequality is the growth of chief executive officer earnings and compensation." Piketty (2013) agrees, noting that "the primary reason for increased income inequality in recent decades is the rise of the supermanager" (p. 315). And he adds that "wage inequalities increased rapidly in the United States and Britain because U.S. and British corporations became much more tolerant of extremely generous pay packages after 1970" (p. 332).

Two related strands of literature on inequality also have potential implications for the role of firms in affecting inequality. The classic explanation for increases in inequality has been a rise in the returns to skills and evolving tasks, possibly associated with technological change (e.g., Katz and Murphy (1992), Berman et al. (1994), Machin and Van Reenen (1998), or Autor et al. (2008)). Another strand of literature has sought to explain increases in inequality with changes in institutions, such as declining values in the minimum wage or the clout of unions, especially in the 1980s (e.g., DiNardo et al. (1996) and Card and DiNardo (2002)). To what extent the effects of changing tasks, technological developments, or institutional changes on inequality are mediated by firms are central but open questions.

To help address these questions, we use earnings data from W-2 records held by the Social Security Administration (SSA) for the universe of U.S. employees between 1978 and 2013, which has a number of advantages. Wage earnings in this data set are recorded at the

[1] For detailed reviews of these trends as well as the theoretical models designed to study them, see, among others, Katz and Autor (1999) and Acemoglu and Autor (2011).

individual level (rather than household) and are not capped (top or bottom coded), which allows us to examine both the bottom and top of the individual earnings distribution. Because it is an administrative records database, there is little measurement error, and our sample size of about 100 million individuals per year enables us to do detailed analysis of industry, demographic, and regional groups.

Our main—and somewhat surprising—result is that between-firm inequality accounts for the majority of the total increase in income inequality during the period we study. For example, examining one measure of inequality—the variance of log earnings—we show that the 19 log point increase between 1981 and 2013 is driven by a 13 point increase between firms and a 6 point increase within firms. The reason is that the higher earnings percentiles which have seen large earnings increases, have seen similar pay increases among their coworkers. For example, during this period the 50th percentile of the income distribution saw an increase in real earnings of 12 log points (13%), while the top 1% saw an increase of 66 log points (94%). But the colleagues of those in these earnings percentiles saw very similar earnings increases of 15 log points and 53 log points, respectively. So, of the 56 log point greater increase in earnings of the top 1% compared with the median, 44 log points (79%) is accounted for by the difference in their employers' average pay.

Our second result is that this dominance of between-firm inequality in explaining overall inequality trends is also seen in very fine subsets of the overall economy. It holds true within broad—as well as very narrow—industry groups, within different firm size groups (with the exception of very large firms—discussed in a moment), within U.S. regions and counties, for different demographic groupings (age and gender), and by different measures of inequality (variance of log earnings and long differences of income percentiles). It also holds true for the sample of continuing firms only and using five-year average measures of earnings.

Our third result is that the 30% of the increase in total variance that occurs within firms comes mainly from large firms. The increase in the variance of log earnings in firms with 10,000+ employees (a group comprising around 800 firms that employ about 20% of the workers in the U.S. economy) is 58% between firms and 42% within firms (whereas the change in the variance of log earnings in firms with fewer than 10,000 workers is 84% between and 16% within firms). This much higher rise in within-firm inequality in large firms comes from two sources. First, the lower half of the earnings distribution fell in large firms. For example, median workers within 10,000+ employee firms saw their earnings fall by an average of 7% between 1981 and 2013, while the 90th percentile within those firms rose by an average of 11%. Second, in the largest firms the top 100 or so managers—about the top 0.25% of employees at large firms—have seen substantial pay increases. For example, the average 50th highest-paid manager in large firms has seen real earnings rise by 47% between 1981 and 2013, while the average top paid employee (presumably the CEO) has seen real earnings rise by 137% over the same period.

An obvious question is why has inequality risen so much between firms? One explanation is the *widening firm premium* story. The rising between-firm inequality could arise from a rising dispersion in earnings premiums that a firm pays all of its workers—for example, if some firms have been increasingly successful and paid all their employees well while others have not and have cut employee wages. An alternative explanation is the *worker segregation*, whereby high-paid workers could be increasingly clustering in some firms and lower-paid workers in others.

To investigate this question, we build on papers by Abowd et al. (1999) and Card et al. (2013) to run a decomposition of earnings into a firm component and a worker component, identified by examining the earnings changes as workers move across firms. In summary, we find that almost the entirety of the increase in between-firm inequality is due to greater segregation—that is, workers are increasingly moving into firms with workers who are similarly well or badly paid as they are.

This segregation of workers across firms is important for three reasons. First, a growing share of employee compensation is in the form of employee benefits (particularly health care and pension contributions), so that increased worker segregation will lead to rising health care and retirement inequality. Second, individuals typically increase their earnings with experience, and if this experience gradient is steeper in firms with higher-ability employees—if, for example, employees learn by copying other high-performing employees—then rising segregation will dynamically increase inequality. Finally, increased segregation in itself may be problematic if it reduces the ability of the political process to take appropriate action because the issue becomes less visible.

This paper is related to a large literature on inequality and, in particular, to a recent series of papers highlighting the importance of firms in accounting for inequality in a range of countries. In Germany, Card et al. (2013) also use matched employer-employee panel data and find that increasing inequality is approximately equally explained by increased heterogeneity between workers, increasing heterogeneity between establishments, and increasing assortative matches between the two. Likewise in Sweden, Håkanson et al. (2015) find that rising between-firm earnings differences account for the majority of the increase in overall inequality. In the United Kingdom, Mueller et al. (2015) relate rising inequality to firm size, finding that wages for high-skill jobs are diverging from wages for other jobs more at large firms than smaller firms, whereas the differential between wages for medium- and low-skill jobs is mostly unrelated to firm size. Faggio et al. (2007) also find a similar link between rising worker and firm inequality in a sample of U.K. firms, particularly in the service sector. Finally, Helpman et al. (2015) and Alvarez et al. (2015) collectively show how in Brazil the rise and then fall in inequality in from 1986 to 1996 and from 1996 to 2012, respectively, was accompanied by a rise and then fall of between-firm inequality.

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, building on a long literature documenting the existence of establishment wage differentials (see, for example, Groshen (1991)). However, Davis and Haltiwanger (1991) lacked data on wages within firms, which limited the scope of their analysis to between-firm data. Kremer and Maskin (1996) also highlighted the issue of rising inequality between firms and laid out an elegant model to explain this in terms of the offsetting effects of task asymmetry and task complementarity. Closest to our work, Barth et al. (2014) use the Longitudinal Employer-Household Dynamics data for nine states from 1992 to 2007 as a source of U.S. employer-employee matched data. They also find 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.[2] Our paper extends this analysis by doubling the sample period back to include the 1980s and post 2007 to the Great Recession. It also includes all U.S. states which is important for analyzing top-end pay since the top 1% are heavily concentrated in Northeast states such as Connecticut, New Jersey, and New York, which are not in their main dataset. We also focus on firms rather than establishments, which allows us to study pay inequality in larger multiestablishment firms and include their corporate headquarters, which is important given the striking differences in our data between smaller and larger firms.

The paper is organized as follows. Section 2 describes the data set and the construction of the matched employer-employee data set, presents summary statistics from the

[2] Preliminary work by Abowd et al. (2016) also uses the Longitudinal Employer-Household Dynamics data to analyze trends in inequality within and between firms, and finds similar results.

sample, and discusses the methodology. Section 3 presents the main results. Section 4 decomposes the change in earnings inequality in components related to changes in firm average earnings and worker segregation. Section 5 provides additional findings on the sources of increases in between-firm inequality, and Section 6 concludes.

2 Data

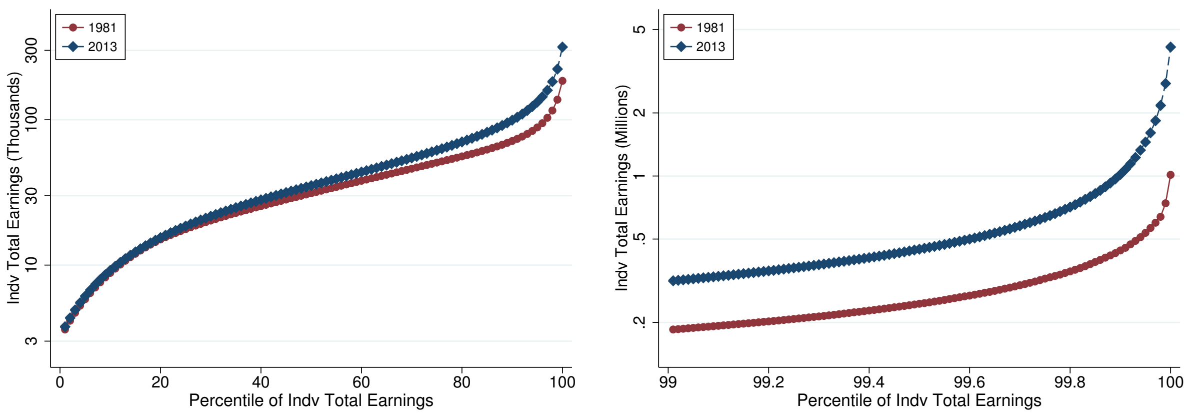
The main source of data used in this paper is the Master Earnings File (MEF), which is a confidential database compiled and maintained by the U.S. Social Security Administration (SSA). The MEF contains a separate line of record for every individual that has ever been issued a U.S. Social Security number. In addition to basic demographic information (sex, race, date of birth, etc.), the MEF contains labor earnings information for every year from 1978 to (as of this writing) 2013. Earnings data in the MEF are based on Box 1 of Form W-2, which is sent directly from employers to the SSA. Data from Box 1 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 U.S. Internal Revenue Service.[3] Because of potential measurement issues prior to 1981 (see Guvenen et al. (2014a)), we start our analysis from 1981. 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. 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. Since we do not have information on hours or weeks worked, we

[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 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 full-time individuals aged 20 to 60 are included in all statistics, where full-time 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.

measure individual annual earnings (or their total wage bill) rather than wage rates. As discussed in Subsection 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 income distribution in real terms in 1981 and 2013. Looking at 2013, we observe a strikingly 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. These figures are somewhat lower than data on earned income from, for example, Piketty and Saez (2003), primarily because they are based on individual (rather than household) values; see Figure A.14. 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.

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.[4] They are also often used in research on firms based on administrative data. This is often not the same, however, as the ultimate parent firm. 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.[5] Although it is unclear what level of aggregation is appropriate in order to define a "firm," we feel the EIN is a reasonable concept reflecting a unit of tax and financial accounting. An EIN is a distinct concept 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. (2014), 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 Abowd et al. (2016) show, 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 Master Earnings File against Other Data Sets

Aggregating wages and salaries from all W-2 records over all 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.

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 Current Population Survey (CPS). 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

[4] 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.

[5] Typically, this is because large firms file taxes at a slightly lower level than the ultimate parent firm. 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, and the main hospital and children's hospitals.

CPS excludes the institutionalized population, whereas the MEF includes them. Figure A.1b shows total employment in the MEF and CPS; these two series track each other well over time.

There are 6.1 million unique firms (EINs) in the MEF in 2013, each associated with at least one employee. This number is slightly higher than the 5.8 million firms (with employees) identified by the Census Bureau's Statistics of U.S. Businesses data set. In addition, as shown in 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

We restrict our baseline sample to individuals aged 20 to 60 who work full-time, where "full-time" 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. As we show in Appendix B, none of our results are sensitive to these assumptions—in particular, the results look similar using all ages, all firm sizes, all industries (Figure A.9), and minimum earnings thresholds up to full-time (2,080 hours) at minimum wage (Figure A.10). Some statistics describing the sample are shown in Table I. More details about the data procedures are discussed in Appendix B.

3 Inequality within and between Firms

3.1 Rising between-Firm Inequality

The key result in this paper—that rising inequality between workers is primarily a between—rather than within—firm phenomenon—can be shown graphically in a number of ways. We first examine a decomposition of variances over time. We then look at earnings percentiles, which is an approach similar to examining yearly changes in inequality

Table I – Percentiles of various statistics from the data

Year	Group	Statistic	25%ile	50%ile	75%ile
1981	Firm	Earnings (Unwgt)	16.6	23.8	32.5
1981	Firm	Earnings (Wgted)	21.5	30.6	43.2
1981	Firm	Employees	26	38	73
1981	Indiv.	Earnings	18.2	31.9	51.7
1981	Indiv.	Earnings/Firm Avg	0.72	1.05	1.45
1981	Indiv.	Employees	127	1153	12418
2013	Firm	Earnings (Unwgt)	19.3	30.5	43.8
2013	Firm	Earnings (Wgted)	21.4	35.8	52.1
2013	Firm	Employees	26	39	79
2013	Indiv.	Earnings	19.2	36	63.2
2013	Indiv.	Earnings/Firm Avg	0.68	1.03	1.50
2013	Indiv.	Employees	157	1381	14197

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 full-time individuals aged 20 to 60 are included in all statistics, where full-time 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.

over time, but focuses on particular key percentiles of the earnings distribution. Finally, we examine the long difference in earnings between 1981 and 2013, but do this for each percentile by worker and their firms, providing rich cross-sectional analysis but across one time period. As will become clear, all three approaches show a similar result: rising inequality is primarily a between-firm phenomenon.

3.1.1 Simple Variance Decomposition

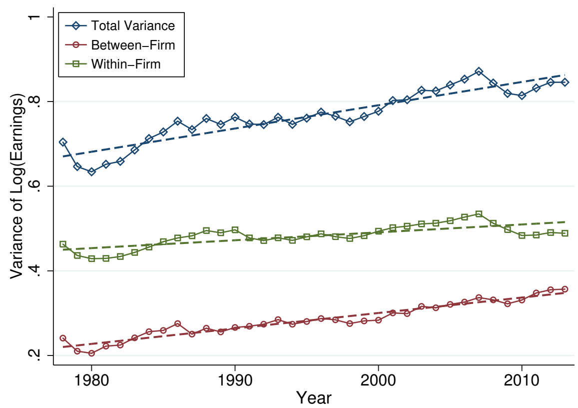
One simple analysis is to decompose the variance of earnings into a within- and between-firm component. In particular, let $y_t^{i,j}$ be the log earnings of worker i employed by firm j in period t.[6] This can be broken down into two components:

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

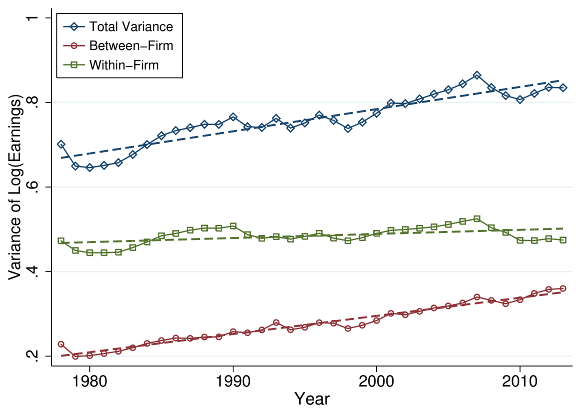
[6]For notational convenience, we suppress the dependence of the subscript j on worker i.

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

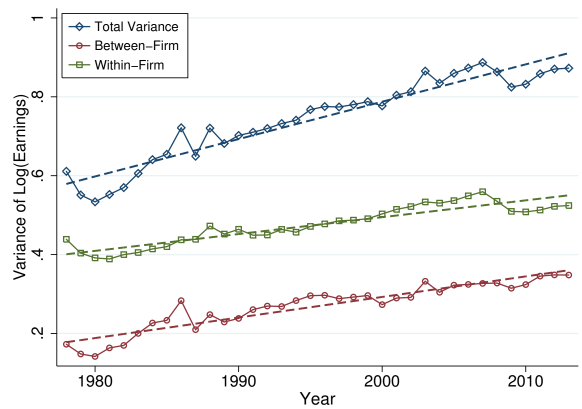
(A) Overall decomposition



(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 full-time individuals aged 20 to 60 are included in all statistics, where full-time 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.

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

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

This equation provides a straightforward way to decompose total earnings dispersion in the economy into (i) the between-firm dispersion in average earnings paid by each firm and (ii) the within-firm dispersion in pay weighted by the employment share of each firm. The components of equation (2) are plotted separately in Figure 2a. We find that the overall variance of log earnings has risen by 19 log points between 1981 and 2013, very similar to the results in Autor et al. (2008). Examining the within- and between-firm components of this increase, we see that 13 log points of this variance arise between firms and 6 log points within firms, so that 69% of the overall increase in inequality evaluated on this metric is a between-firm phenomenon.

3.1.2 Tracking Select Percentiles

Another way to examine income inequality over time is by tracking the evolution of select income percentiles. In Figure 3a we plot the change in average log earnings within the 99th, 90th, 50th, and 25th percentiles, revealing the well-known result that earnings inequality has increased since 1981, with higher percentiles enjoying substantially larger earnings growth. Since our sample covers around 70 million workers, each one of these percentiles contains around 0.7 million workers per year.

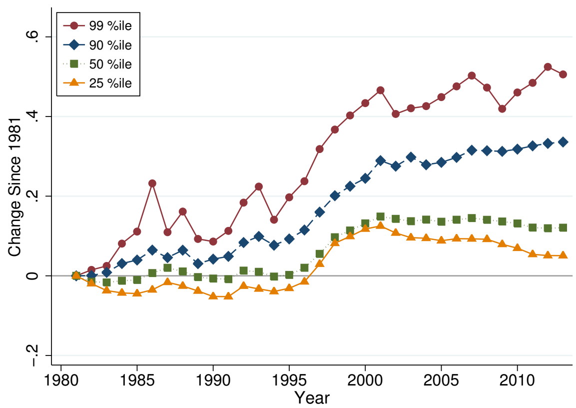
In Figure 3b we plot the change in average log earnings in the firms for each of these individual earnings percentiles. So, for example, the 99th percentile point for Figure 3b reports the increase in average earnings for the colleagues of the individuals in the 99th percentile line of Figure 3a.[7] Finally, in Figure 3c we report the relative change in the earnings of individuals compared with their colleagues, and reveal a set of flat percentiles. In short, while individuals have seen a large increase in pay inequality across their earnings percentiles since 1981, this increase has been tracked very closely by the earnings of their colleagues. So, for example, although the 99th percentile has seen real earnings increase by 51 log points between 1981 and 2013, the log earnings of their colleagues in the 99th percentile have increased by an average of 49 log points; thus, these individuals saw only a 2 log point increase in earnings relative to their colleagues.

We should also note that 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 will undertake a type of panel analysis pioneered by Abowd et al. (1999) and reveal that not only has inequality increased in

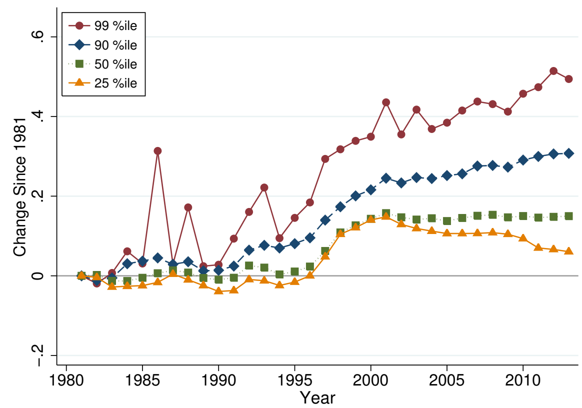
[7] That is, the line shows $\delta_q^{firm} \equiv E[\bar{y}^j_{2013} | i \in Q_{2013,q}] - E[\bar{y}^j_{1981} | i \in Q_{1981,q}]$, where $Q_{t,q}$ is the set of individuals in the qth percentile in year t, and j refers to the employer of worker i.

Figure 3 – Change in percentiles of annual earnings within and between firms relative to 1981

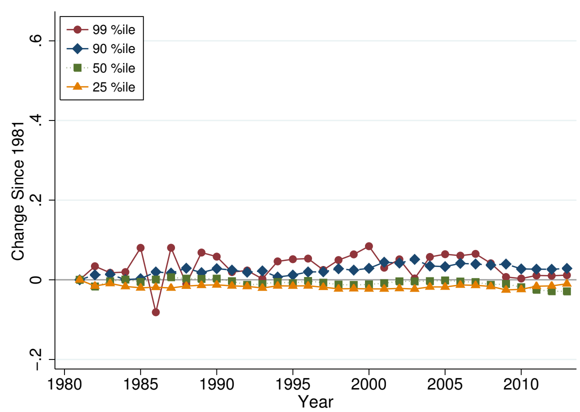
(a) Individuals



(b) Their Firms



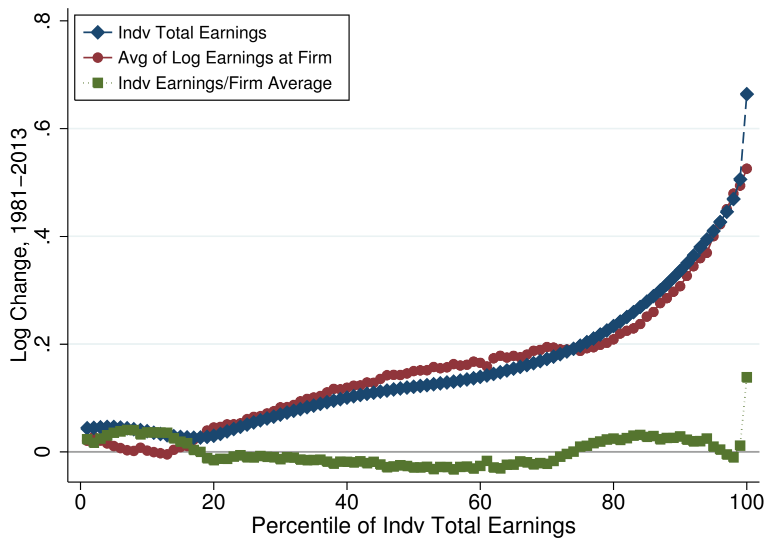
(c) Individuals/Their Firms



Notes: Only firms and individuals in firms with at least 20 employees are included. Only full-time individuals aged 20 to 60 are included in all statistics, where full-time 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.

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

FIGURE 4 – Change in inequality of annual earnings across percentiles from 1981 to 2013



Notes: See notes for Figure 3.

3.1.3 Inequality across Percentiles

Because inequality is a concept about the entire income distribution, the simple summary statistics (such as the variance and select percentiles) reported above can mask interesting and important variation hidden in various parts of the distribution. A more detailed look is provided by a graphical construct popularized by Juhn et al. (1993) and has been used extensively since then. We now use a variation of this graphical construct in three steps.

First, we start with individuals in the baseline sample in 1981 and group them into percentile bins on the basis of their income in 1981. Then we calculate the average of log real earnings (in 2013 dollars) for each percentile bin. Let $P_t x$ denote this average for percentile bin x in year t. We then repeat the same procedure for 2013 (now for individuals who satisfy the sample selection in that year). The blue line marked with diamonds (labeled "Indv Total Earnings") in Figure 4 plots $P_{2013}x - P_{1981}x$ for all percentile groups $x = 1, 2, ..., 99, 100$ against the percentile number y on the horizontal axis. So, for example, we see that between 1980 and 2013, the 50th percentile of earnings has increased by 12 log points (13%) from about \$32,000 to \$36,000. 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.

For the red line marked with circles (labeled "Avg of Log Earnings at Firm"), we put individuals into percentile bins based on their own wage earnings in 1981—just as we did for the "Individuals" line above—but for each percentile bin, we calculate the average of the mean log real earnings at each individual's *employer* (or *firm*). We repeat the same procedure for 2013. For example, in 1981, individuals in the 50th percentile of individual earnings were employed in firms with average log mean real earnings of 10.30 (corresponding to about $29,900); in 2013, individuals in the 50th percentile were employed in firms with average log mean real earnings of 10.45 (corresponding to about $34,700). The difference of 0.15 (i.e., 15 log points) is plotted on the graph at the 50th percentile.

Finally, the green line marked with squares (labeled "Indv Earnings/Firm Average") is based on the residual earning measure, $y_t^{i,j} - \overline{y}_t^j$. Specifically, we compute the average of $y_t^{i,j} - \overline{y}_t^j$ across all workers within a percentile in each year.[8] We then plot the change in this statistic between 1981 and 2013. For example, in 1981, individuals in the 50th percentile of individual earnings had average log earnings that were 0.05 higher than their firms' mean earnings (corresponding to about 106% of their firms' mean earnings). In 2013, individuals in the 50th percentile had average log earnings that were 0.03 lower than their firms' mean earnings (corresponding to about 103% of their firms' mean earnings). We plot the difference of –0.02 at the 50th percentile. Note that this "Individual/Firm" line will be mechanically equal to the difference between the "Individual" line and the "Firm" line.

For all these graphs, results should be interpreted similarly. A flat line indicates that inequality for that statistic has not changed over the time period, because the statistics for those at the top and the bottom have changed by the same amount. An upward-sloping line indicates that inequality has increased, because the statistic for those at the top has increased more than the statistic for those at the bottom; and by the same logic, a downward-sloping line indicates that inequality has decreased. This graphical construct thus allows us to detect changes in inequality that might be confined to one part of the earnings distribution and may not be very visible in broad inequality statistics.

Particular care should be given to the interpretation of the green (square-symbol) "Individual/Firm" line. The *level* of this line indicates the extent to which a particular

[8] Notice that in all likelihood, the workers we average over are employed in different firms, and each residual is computed with respect to a worker's own employer.

demographic group gains or loses relative to the firm average for all employees. When we examine the whole population or subsets of the population that, for each firm, include either everyone or no one at that firm, the green line's weighted average taken over all percentiles must be zero.[9] The key finding from this figure is that the green line is almost flat across all percentiles, indicating that within-firm inequality has remained nearly constant over the entire population of workers.

3.2 Robustness of Results

The results above show that, perhaps rather surprisingly, the majority of the increase in worker inequality can be accounted for by firms. To investigate the robustness of these results, we reran the analysis from Figure 4 within many subgroups and using many different definitions. The basic result—that between-firm inequality accounts for most of the inequality—remains true for each such analysis.

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 within each county and took the average (Figure A.2) and within each census region (Figure A.3), finding very similar results. In case these trends reflect changes in demographics, Figure A.4 reports the graphs by age breakdowns (20s, 30s, 40s, and 50s) and by gender, with again the results looking broadly similar for each subgroup.[10] 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 also similar within broad industry SIC one-digit categories as shown in Figure A.5, and also on average within narrow SIC four-digit categories as shown in Figure A.6.

We also experimented with different measures of the firm average earnings, using the log of average earnings (rather than the average of log earnings), firm median earnings, and the average log earnings among only those in the bottom 95%, and calculating

[9] However, the interpretation is different when we look at demographic subsets of the population, as in the next subsection, where we examine only a subset of each firm. For these analyses, there is no presumption that the level for any group must have an average of zero; instead, we interpret the average level as the extent to which the group has gained or lost relative to the firm average weighted by group-specific employment. More important, the slope of this line is a measure of change in inequality over time.

[10] For age and gender graphs, to improve comparability between them and with the firm statistics, sorting into percentile bins is based on the overall population.

firm average log earnings leaving out the individual themselves; once again we find very similar results (see Figure A.7). We examined a panel of continuing firms in case our results were being driven by the selection of firms, and once again, we see very similar results (see Figure A.8). We varied our definition of full-time earnings from 520 hours at the 2013 minimum wage to 260, 1040, and 2080 hours and again find broadly similar results (see Figure A.10). Finally, in Figure A.11 we compare changes in five-year (rather than one year) earnings in case the results were being driven by changes in temporary (rather than permanent) earnings, but we see very similar results.

We also considered other robustness issues around health care and self-employment 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. In fact, 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.[11] 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.

So overall, the basic result that the majority of increasing inequality is a between-firm phenomenon seems to be broadly robust. In the next two sections, we turn to subsplits by firm size and income percentile, which show some interesting and important variations in these results, although even here in all cases, the majority of the increase in inequality is between firms.

3.3 Firm Size

When we break firms down by size—defined by the number of employees according to our full-time and age definitions (earning above 520 hours times minimum wage during

[11]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, since this part of health case is independent of the employee-firm match, this does not influence our analysis.

the year and aged 20 to 60)—we see some differences between "smaller to large firms" (those with fewer than 10,000 employees) and the "mega-firms" (those with 10,000+ employees). Figures 2b and 2c plot the decomposition of variance for these two groups. We see in Figure 2b that in smaller to large firms—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 mega-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.

To examine why mega-firms see this much greater increase in inequality, in Figure 5 we plot the change in earnings for various positions in the firm, ranging from the top-paid employee down to the median-paid employee. We see two clear differences between larger and smaller firms. First, in larger firms, pay increases at the top end were far larger—the top employees in larger firms saw their average log pay increase by 86 log points (137%) in real terms since 1981, while the top employees in smaller firms saw an increase of 0.47 (45%). Second, large firms saw a fall in real median earnings of 0.07 (7%), while smaller firms saw an increase of 0.27 (31%). Hence, the gap in real pay increases between the median and top employees in the mega-firms between 1981 and 2013 was 156% (94 log points) compared with 22% (0.20 log points) in smaller firms, a strikingly large difference.

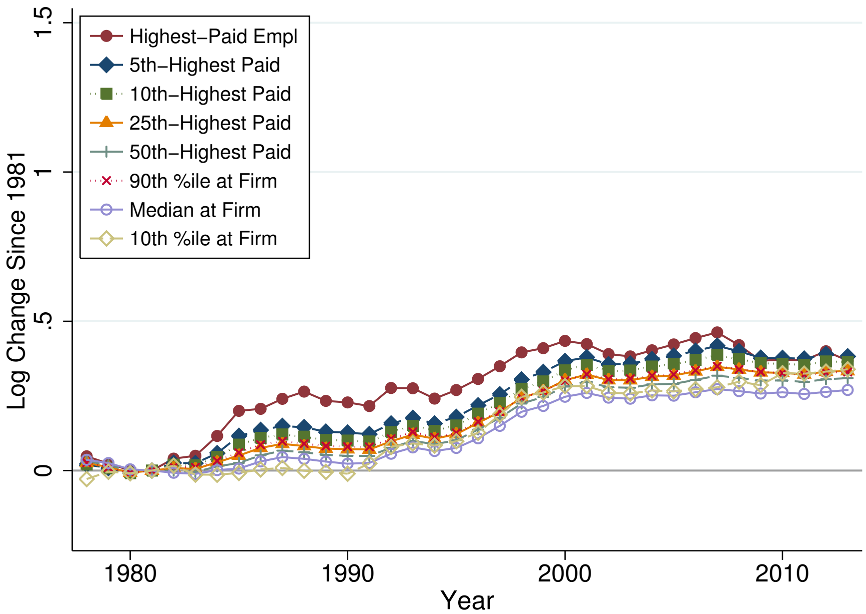
Why have large firms seen such striking gains in pay since 1981 in the higher pay ranks, particularly those who are among the 50 best-paid employees at each such firm? One potential reason is that larger firms are far more likely to be publicly traded companies with senior executives receiving compensation in the form of stock options and grants, something we discuss in Section 5. In Section 5, we also provide additional evidence on the decompression at the bottom of large firms' earnings distribution.

3.4 The Top 1%

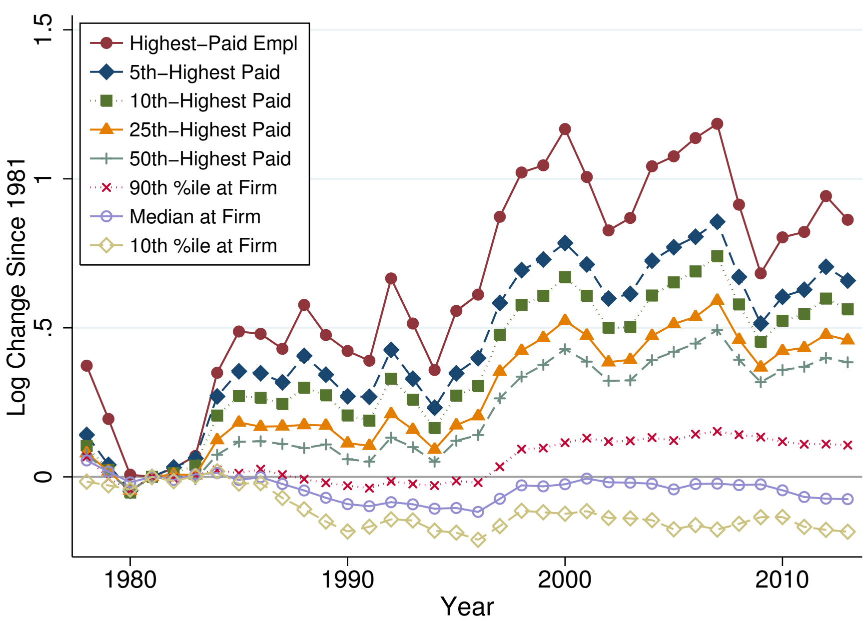
Much of the recent policy and media attention around inequality has focused on the top 1% of earners, following in particular the pioneering early work of Piketty and Saez (2003). Interestingly, it turns out that although the top 1% looks generally similar in terms of the role of firms accounting for the majority of the rise in inequality between workers, there are also some differences in the top 0.5%. To show this, Figure 6 plots the cross-sectional percentiles graph for just the top 1%, breaking this into 100 subdivisions of 0.01% each (since the entire population is about 70 million workers, each 0.01% thus

FIGURE 5 – Change in within-Firm Distribution of Annual Earnings: Smaller and Larger Firms

(A) Workers at Firms with 100 to 1000 employees

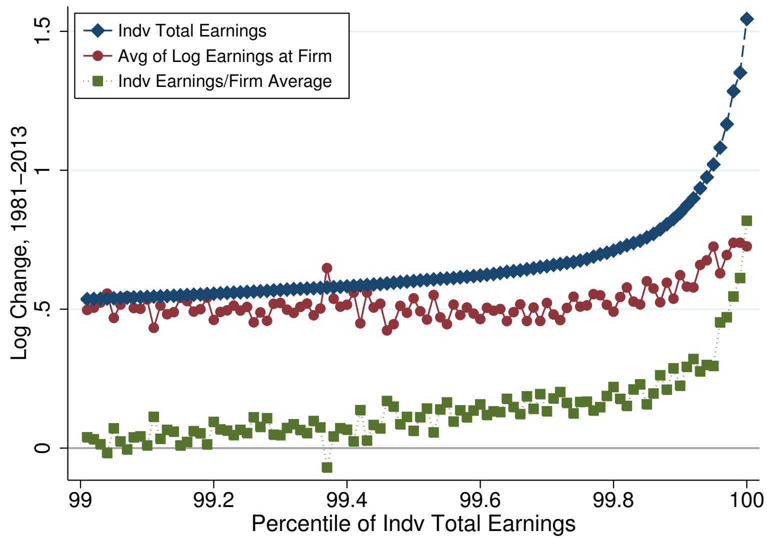


(B) Workers at Firms with more than 10,000 employees



Notes: Only firms and individuals in firms of the listed size are included. Only full-time individuals aged 20 to 60 are included in all statistics, where full-time 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 6 – Rise in Inequality of Annual Earnings between 1981 and 2013 among Top 1% of Earners



Notes: See notes for Figure 3.

represents about 7,000 people).

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 firms. 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 pay by only 73 log points (106%), generating a 29 log point gap.[12]

Thus, a group of about 70,000 people representing about the top 0.1% of earners has seen substantial pay increases over and above those of their colleagues. This group will likely include CEOs of Fortune 500 companies, but also a far wider group of individuals spanning the CEOs of a broader range of firms plus senior executives in most large firms.

[12]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.

4 The Role of Worker Sorting and Segregation

As we have seen, the increase in inequality observed over the last 35 years in the United States is primarily a between-firm phenomenon. But this 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.[13] Second, a "worker segregation" story: 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 worker segregation story appears to account for almost the entire increase in between-firm inequality.

4.1 Econometric Model of Worker and Firm Effects

To analyze the worker and firm movements in earnings we closely 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).[14] 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 restricted cohort 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 incor-

[13]This increasing spread in firm performance is suggested by the Furman and Orszag (2015) evidence showing an increased dispersion of profit rates in US publicly listed firms.

[14]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.

porating firm components into traditional earnings regressions. Clearly, this model is likely to be a simplification of firms' role in the setting of earnings, since in its basic form it does not allow for worker-firm interactions or for time-varying firm-specific components (something we discuss in Appendix C). Despite these reservations, we confirm that the model appears to summarize a range of key patterns in our data surprisingly well. Hence, 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 p), the firm-worker decomposition is

$$\text{var}(y_t^{i,j}) = \underbrace{\text{var}(\psi^j) + cov(\overline{\theta}^j, \psi^j) + var(\overline{\theta}^j)}_{\text{Between-firm component}} + \underbrace{var(\theta^i - \overline{\theta}^j) + var(\epsilon_t^{i,j}),}_{\text{Within-firm component}} \tag{4}$$

where the moments in the between-firm component are weighted by the number of workers.[15] Equation (4) shows how the between-firm component of the variance can be decomposed into three pieces: a part deriving from the variance of firm effects $var(\psi^j)$, a part from the variance of the average worker effect in each firm ($\overline{\theta}^j$), and a part deriving from the covariance of worker and firm effects. The first component is the "widening firm premium" part—perhaps because the variance of firm pay has increased. The second and third components are parts of the "worker segregation" story, with the third part a pure increase in average worker variance across firms and the second the component that is also correlated with firm earnings premia. Splitting the worker component in the rise of the variance, $var(\theta^i)$, into contributions to within- and between-firm components is new in the literature and allows us to better characterize the role of firms in accounting for earnings inequality.

[15]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 $var(\epsilon_t^{i,j})$).

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.[16] 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 the same restrictions on the data as in our descriptive analysis, with three exceptions. To maximize the number of observations in the connected set, we do not impose a restriction on firm size and do not exclude the education and public sector. Because of limitations in computing power, we estimate worker and firm effects separately for men and women (finding similar results for both gender groups). All other restrictions, including imposing a minimum earnings threshold, are the same as described in Section 2.

Although our implementation of AKM follows CHK, an important difference is that 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.[17] 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.[18] 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 effect of systematic labor supply differences in our findings. We have experimented by imposing increasingly stringent lower earnings

[16] The choice of intervals trades off limitations in computational power and the desire to analyze changes in the variance 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.

[17] In that sense, our implementation is comparable to Barth et al. (2014) and Abowd et al. (2016), who implement this model using quarterly earnings.

[18] 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.

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, for example, Figure A.10. 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. In addition, we have also tried to isolate full-year to full-year job transitions by only comparing earnings in years before and after job moves that were flanked by two years of positive earnings at the employer. Again, our results were robust to this more stringent specification. 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.[19]

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 and 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 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 the AKM model can be estimated without systematic bias (e.g., AKM, CHK, and Abowd et al. (2016)).

Following CHK, we summarize several pieces of evidence in favor of the CRM assumption and against an important role of match effects in explaining rising inequality. First, we find that the goodness of fit of the model 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 root mean squared error (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 complementarities (i.e., 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 C2).

Second, to check whether adding a match-specific component would substantially in-

[19] 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.

crease the fit of the model, we directly included a match effect (m_{ij}) in the model. Although, not surprisingly, allowing for a match effect reduces the RMSE and increases the adjusted R^2 by about the same amount each period, from 82% to 87%, the standard deviation of match effects declines somewhat over time. If the increasing covariance of worker and firm effects that we find reflected a rising importance of worker-firm complementarities omitted from the model, this would imply that the standard deviation of match effects should rise (see Appendix Table C2).[20]

Third, 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.16).

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. In Figure A.17, 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.[21] 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 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.

4.3 Decomposing the Change in the Variance of Earnings

Table 2 presents results for the variance decomposition of earnings (equation 4) for our five periods, as well as for the change from period 1 (1980-1986) to period 5 (2007-2013).

[20] Hence, as noted by CHK, this is consistent with an interpretation of the match effects as uncorrelated random effects rather than specification errors caused by incorrectly imposing additivity of the person and establishment effects.

[21] 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.

There are two key findings. First, in all periods, about half of the *level* of the variance of log annual earnings is explained by the variance of person effects, which at $48\% - 53\%$ is by far the biggest component. The two other within-firm components, the variance of time-varying worker characteristics ($7\%{-}10\%$) and the variance of residuals ($12\% - 16\%$) together explain roughly another 20% of the variance. Firm-related components together (the variance of fixed effects, and their correlation with worker effects and worker characteristics) explain about $20-$ 25% of the *level* variance.

Second, although person effects dominate in accounting for the level of the variance, when examining the change in the variance over time, the firm-based components dominate. As shown in the final column of Table 2, the firm component explains 69.1% of the rise in the overall variance.[22] This comes about equally from a rise in the variance of the average worker effect (35.6%) and the covariance of worker and firm effects (31.4%).

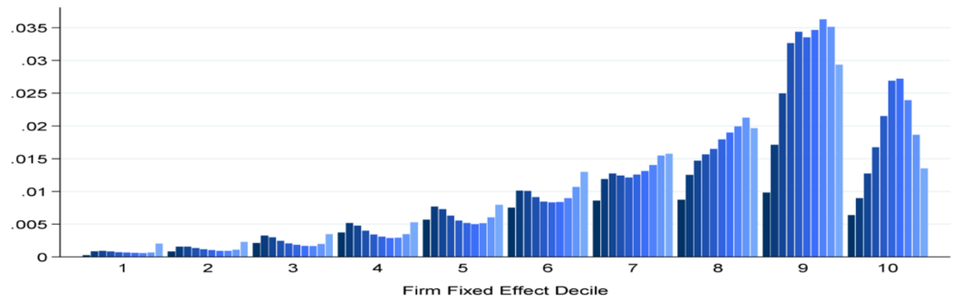
To reveal more about the rise in the covariance of worker and firm effects, the first two panels of Figure 7 display the joint distribution among deciles of worker and firm effects in 1980-1986 and 2007-2013, while the third panel shows the difference between them. The change in the pattern of sorting 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.

Table 3 contains additional key results. First, consistent with our descriptive work in Section 3, 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 87.4% (row labeled "Between-Firm Variance"). Breaking this down, we see that about half of this (42.6%) comes from the increased dispersion average individual effects, and the other half mostly comes from increased employee sorting across firms (33%), with some small additional contributions from the covariance of individual characteristics at the firm level ($6.3\% + 3.6\% = 10.2\%$ in total). If we drill down further into this group of firms in the right panel, keeping only firms with 1,000 employees or less (columns 7 to 12), we find the increase in inequality is entirely (102.1%) explained by a rise in the between-firm component. This comes about equally from two sources—the increased variance of the average worker effect (52.5%) and the increasing covariance of worker

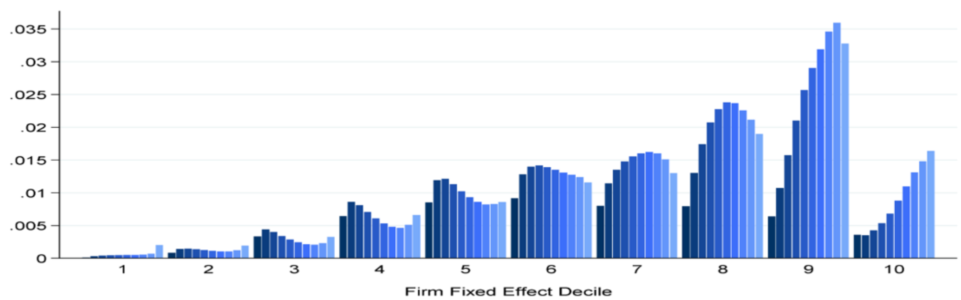
[22]This number is quite close to the corresponding statistic quoted in Subsection 3.1. However, statistics in this section may differ from those in Section 3.1 because of small differences in the sample selection and time periods analyzed.

Figure 7 – Distribution of Workers among Deciles of Worker and Firm Fixed Effects

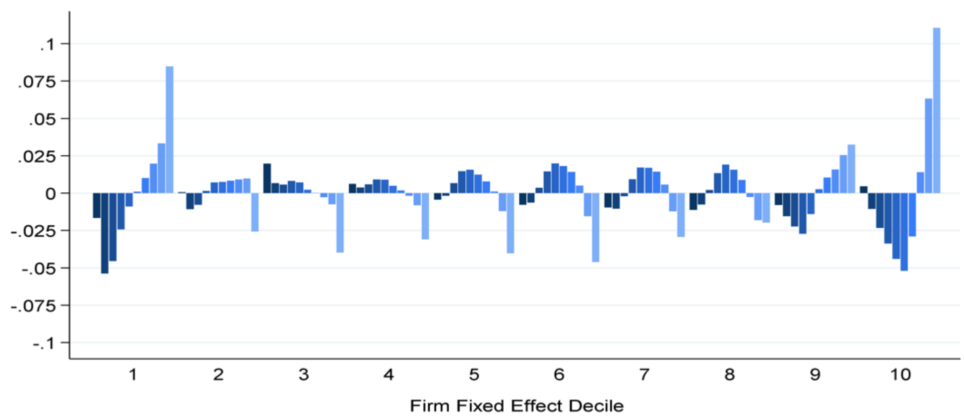
(a) 1980-1986



(b) 2007-2013



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



Notes: Firm and worker fixed effects from our AKM estimation sorted into deciles. Since higher fixed-effect firms are larger, there are more employees in the higher firm fixed-effect deciles.

and firm effects (31.9%), plus small additional contributions from the firm effects (4.9%) and employee characteristics $7.1\% + 5.2\% = 12.3\%$.

Finally, Table 3 also shows that larger firms experienced more substantial growth in inequality within firms. Given a similar absolute increase in between-firm inequality, this implies that larger firms experienced stronger increases in overall earnings inequality than smaller firms. Interestingly, initially large firms 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).[23]

5 Explaining Trends in within- and between-Firm Inequality

In this section, we try to account for changes in worker inequality. We first consider factors that are associated with between-firm inequality, since changes in this component account for the large majority of the overall change in inequality, and then turn to changes in within-firm inequality.

5.1 Accounting for between-Firm Inequality

To explain our results, we need to match several stylized facts, in particular that: (A) overall inequality is going up, (B) the majority of this increase in inequality is between firms, (C) this is happening within industries, regions, and demographic groups, (D) firm size has not changed over time (see Figure A.13—so this is not simply the atomization of firms), and (E) worker-firm match effects are not rising (as noted in Section 4).

One explanation that fits these findings is that rising overall inequality is driven by skill-biased technical change, whereas rising outsourcing is constraining the impact on within-firm inequality. This rise in outsourcing is potentially being driven by a combination of the falling costs of outsourcing (due to improving information-communications technology), by a desire to limit the extent of inequality within firms due to concerns over fairness (e.g., Akerloff and Yellen (1990) and Weil (2014)), and by the push by businesses to focus on "core competencies" (Prahalad and Hamel (1990)).[24] This would lead firms

[23] 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.

[24] While the concept of "core competencies" may not be well known in economics, this is an extremely popular idea in the business and consulting world; the Prahalad and Hamel (1990) article that coined the term has received over 80,000 citations as of May 2016.

to reorganize away from full-service production toward a focused occupation structure. So, for example, large engineering firms such as General Electric would outsource both lower-skill activities (e.g. catering, cleaning and security) as well as higher-skill activities (IT, legal services and human resources) to firms like Sodexo, ISS, Accenture, and Oracle. At the same time, firms like General Electric have increased employment in core activities by hiring more engineers and scientists (which is why firm size has not shrunk alongside outsourcing). Hence, occupations are increasingly concentrating within firms (Handwerker (2015)) and industries, as shown in Figure 8.

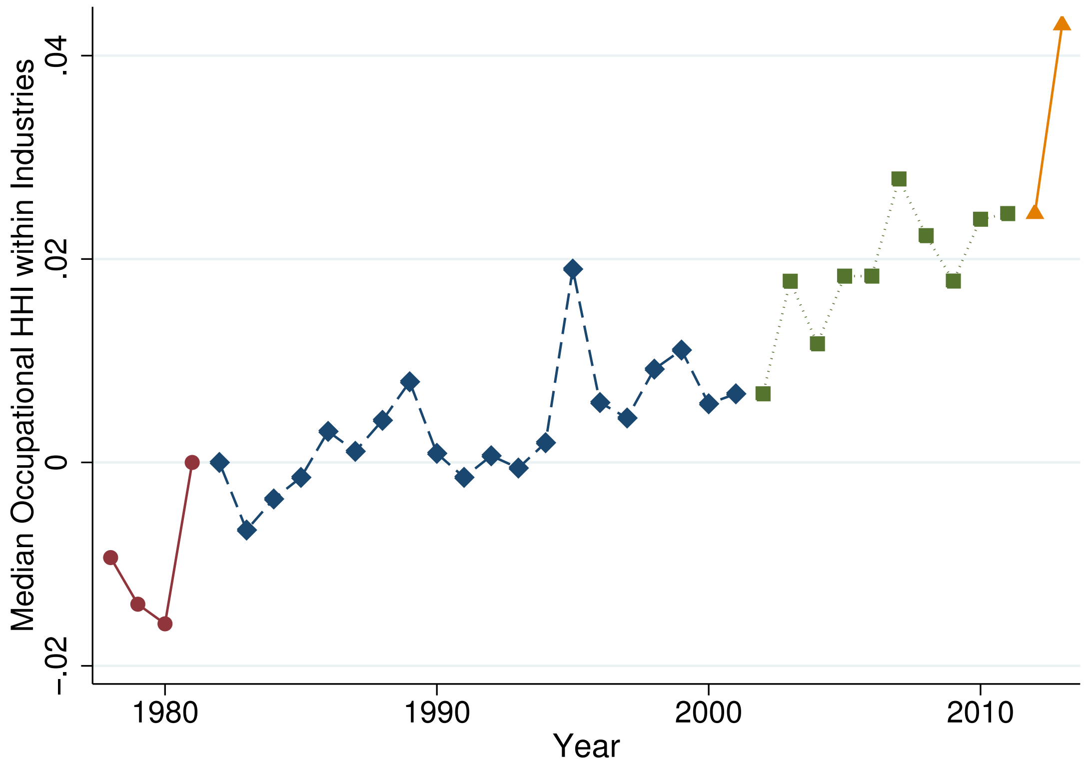
The rise in outsourcing is also consistent with the increased occupational, educational and ability segregation of employees found in Sweden by Håkanson et al. (2015) and in Germany by Card et al. (2013)). Goldschmidt and Schmieder (2015) also examine German data, finding clear evidence of a rising trend in outsourcing, interestingly alongside evidence of rising outsourcing being accompanied by a reduction in worker earnings that is partly driven by a decline in firm effects. An explanation based on outsourcing is also compatible with a stable distribution of firm fixed effects, especially in the United States, where existing low-wage firms could absorb outsourced workers.

There are, of course, other possible stories, and distinguishing between these stories is an important task for future research. We briefly discuss two others that seem plausible. One, proposed by Kremer and Maskin (1996), highlights via an assignment model that if firms operate a technology with complementarities between workers (or tasks), but some tasks are more critical than others, then increasing worker skill heterogeneity can lead to worker segregation. A second 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. Both of these models have appealing features and can generate increasing segregation and sorting. An exciting future research avenue is to test the implications of these models formally against the new empirical facts documented in this paper.

5.2 Accounting for within-Firm Inequality

We saw in Section 3 that within-firm inequality is also rising, but only within very large firms, due to both falling earnings in the bottom half of the earnings distribution and rapidly rising earnings in the top 1%. We now examine these two factors in turn.

Figure 8 – 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 (see Appendix B.2 for more details).

5.2.1 Stagnating Earnings for Lower-Paid Workers in Large Firms

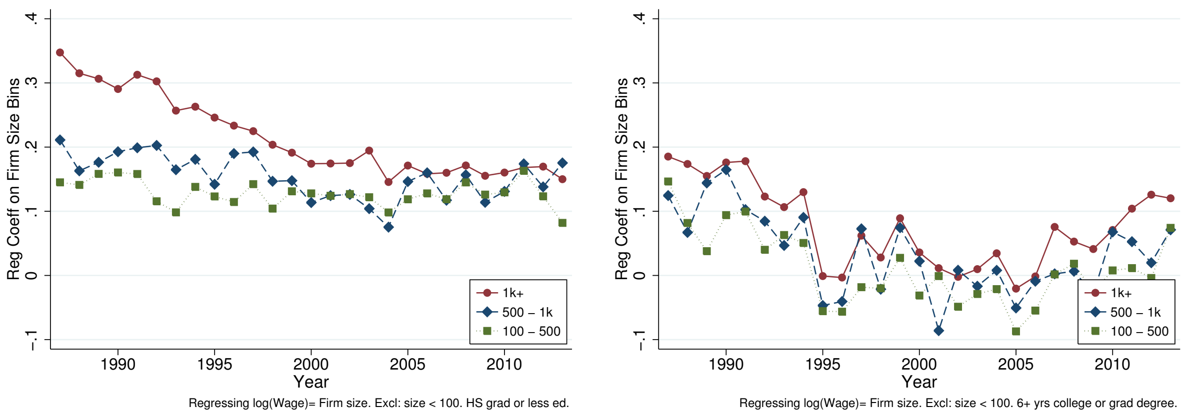
Figure 3 showed that in firms with 10,000+ workers, median pay has fallen by 7% in real terms between 1981 and 2013 (compared with a rise of 31% in firms with fewer than 10,000 employees). This collapse in earnings in the lower percentiles of large firms is the main factor driving rising within-firm inequality in these firms because of the large share (50%) of these employees in overall firm employment. The question is, why has pay fallen more in the lower percentiles of large firms compared with small firms?[25]

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

[25] This is related to the general debate over the collapsing large-firm wage premium (see, for example, the recent survey in Cobb et al. (2016)).

Figure 9 – The Pay Premium in Larger Firms, by Education

(a) High school or less (b) Grad school



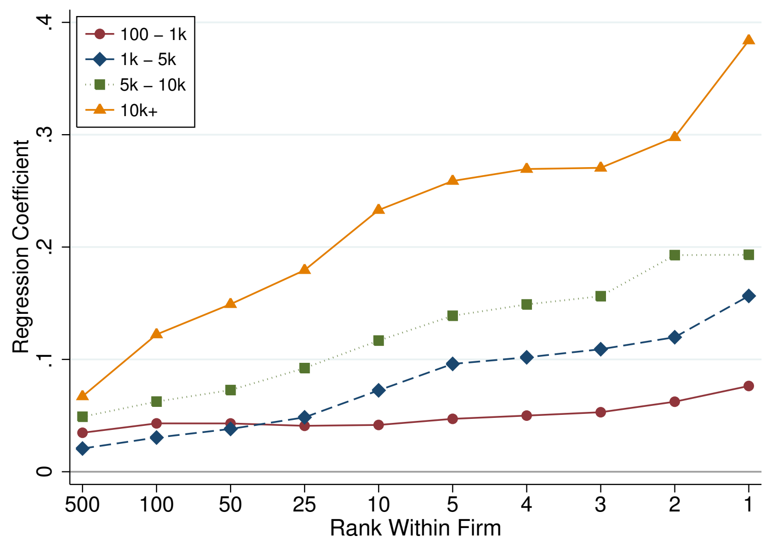
Notes: Data are from the Current Population Survey Annual Social and Economic Supplement. Only individuals aged 20-60, who earn a positive wage income in the given year, and who work at least 35 hours per week for 40 weeks are included. High school or less refers to those who have no more education than a high school diploma or equivalent; grad school includes those with 6+ years of college, or a master's degree, professional school degree, or doctorate degree. 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.

1981 the median-paid employee in 10,000+ employee firms was paid 40 log points more than the median paid employee in firms with fewer than 10,000 employees, but this gap has shrunk to 5 log points by 2013.[26]

To examine this convergence in pay for lower-earning employees in large firms, we used the CPS, which has had information on firm size since 1987. We found no evidence for a changing mix of employee types across firm sizes over time, so this fall in median pay in large firms is not due to a change in employee mix. However, as shown in Figure 9, we do find that 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 35% in 1987 to 15% in 2013. In comparison, the highest-skilled employees (those with 2 or more years of postgraduate education) have seen this earnings premium fall far less, from 19% in 1987 to 12% in 2013. Hence, the earnings premium for low-skilled employees in large firms has fallen by 20% in the last 27 years (1987-2013), potentially accounting for much of the 35%

[26]Consistent with this fact, the correlation between earnings and firm size has nearly disappeared since 1981; see Figure A.15.

FIGURE 10 – Earnings responsiveness to the S&P 500 returns



Notes: Only full-time individuals aged 20 to 60 are included in all statistics, where full-time 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.

difference in median earnings growth between the very largest firms and the rest over the last 33 years (1981-2013) seen in the SSA data.

5.2.2 Rising Earnings in the Top 1%

The other striking exception from the between-firm inequality result in Section 3 was the large gap between the earnings growth of the top 1% and the rest of the firm, particularly among the top 0.25% paid employees. This top 0.25% rising pay phenomenon was particularly striking in the largest (10,000+ employee) firms. To help explain this result, Figure 10 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 log earnings annual 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 10 shows how the earnings of the highest-paid employees at the 10,000+ employee firms have exceedingly 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 explanation for these results is that 10,000+ employee firms are more likely to be publicly listed, and publicly listed firms tend to reward their senior executives with stock options and stock grants. Moreover, this stock-based remuneration (which is included in the W-2 earnings figure as long as options are exercised) 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 5 shows, the senior executives at the largest firms received extremely generous pay 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. Simply applying the magnitudes of the 680% real increase in the S&P over the period 1981–1999 to the average 0.25 coefficient on the S&P returns in Figure 9 yields a real cumulative pay increase of 170%, which is similar to the earnings gains of up to 200% that this group made over the same period (see Figure 5). One outstanding question this analysis raises, however, is why these stock-driven pay 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 pay levels.

6 Conclusions

Using a massive, new, matched employer-employee database that we construct for the United States, we report three stylized facts.

First, the rise in earnings inequality between workers over the last three decades has primarily been a between-firm phenomenon. Over two-thirds of the increase in earnings inequality from 1981 to 2013 can be accounted for by the rising variance of earnings between firms and only one-third by the rising variance within firms. This rise in between-firm inequality is particularly strong in smaller and medium sized firms (explaining 84% for firms with fewer than 10,000 employees). In contrast, in the very largest firms with 10,000+ employees, almost half of the increase in inequality is within firms, driven by both declines in earnings for employees below the median and sharp rises for the top 50 or so best-paid employees.

Second, this dominance of rising between firm inequality in accounting for the increase in overall inequality is an extremely robust stylized fact. It holds within narrowly defined industries, within counties, by employee demographic (age and gender), by firm type (continuing or entering/exiting firm), by subperiod, and by definition of earnings (one-year or five-year). This phenomenon also seems international, with similar patterns seen in every other country for which detailed worker-firm earnings data are available (i.e., Brazil, Germany, Sweden, and the United Kingdom).

Third, examining the sources of this increase in between-firm inequality, we find that it has been driven mainly by increased employee segregation. That is, highly paid employees are increasingly clustering in high-wage firms with other high-paid workers, while low-paid employees are clustering in other firms. Similarly, we also see segregation of employees by occupation and skills in the United States and other countries whenever we can measure this.

These results raise the question as to what is driving this dramatic increase in worker segregation 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, and HR. Since firm size is slowly growing over this period, firms are not atomizing; instead they appear to be reorganizing around a more concentrated set of occupations, leading to greater cross-firm segregation by earnings and education. Our evidence supporting this explanation is tentative, however, and this is an area that would benefit from further research.

Finally, this increase in between-firm inequality raises a question over its impact on individual welfare. We believe increased firm segregation is worrisome for three reasons. One concern is that firms play an important role in providing employee health care and pensions, so rising earnings segregation will flow through into rising health care and retirement inequality. Second, given the importance of work experience to long-run earnings growth, if employees gain experience more rapidly by working alongside higher-ability colleagues, then rising segregation will dynamically increase inequality. Finally, increased segregation itself may obscure the underlying inequality, making it harder to appropriately address this issue with future policy.

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Table 2: 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
		Var. Component (1)	Share of Total (2)	Share of Total (4)	Share of Total (4)	Share of Total (6)	Share of Total (6)	Share of Total (8)	Share of Total (8)	Var. Component (9)	Share of Total (10)	Var. Component (11)
	Var(log(y))	**0.748**	**100**	**0.855**	**100**	**0.861**	**100**	**0.921**	**100**	**0.915**	**100**	**0.167**
Between-Firm	Var(m_we_f)	0.083	11.1	0.106	12.4	0.121	14.0	0.131	14.2	0.143	15.6	0.060
Components	Var(firm effect)	0.120	16.0	0.115	13.5	0.099	11.5	0.110	12.0	0.108	11.9	-0.011
of Variance	Var(m_xb_f)	0.009	1.2	0.013	1.5	0.012	1.4	0.009	1.0	0.010	1.1	0.001
	2cov(m_we_f,firm)	0.012	1.6	0.035	4.1	0.049	5.7	0.060	6.5	0.065	7.1	0.052
	2cov(m_we_f,m_xb_f)	0.015	2.0	0.022	2.5	0.021	2.4	0.021	2.3	0.025	2.8	0.010
	2cov(firm,m_xb_f)	0.020	2.7	0.025	2.9	0.021	2.5	0.022	2.4	0.024	2.6	0.004
	Between Firm Variance	**0.260**	**34.7**	**0.315**	**36.8**	**0.323**	**37.5**	**0.354**	**38.4**	**0.375**	**41.0**	**0.115**
Within-Firm	Var(diff_we_f)	0.272	36.4	0.309	36.2	0.325	37.7	0.348	37.8	0.341	37.2	0.068
Components	Var(diff_xb_f)	0.048	6.4	0.065	7.6	0.076	8.8	0.055	6.0	0.056	6.1	0.008
of Variance	Var(diff_r_f)	0.151	20.3	0.158	18.5	0.149	17.2	0.156	16.9	0.136	14.9	-0.015
	2cov(diff_we_f,diff_xb_f)	0.017	2.2	0.009	1.0	-0.011	-1.2	0.008	0.9	0.007	0.8	-0.009
	Within Firm Var	**0.488**	**65.3**	**0.540**	**63.2**	**0.538**	**62.5**	**0.567**	**61.6**	**0.540**	**59.0**	**0.052**
Raw Decomposition	Between Firm Var	0.260	34.7	0.315	36.8	#DIV/0!	#DIV/0!	0.354	38.4	0.375	41.0	0.115
	Within Firm Var	0.488	65.3	0.540	63.2	0.538	62.5	0.567	61.6	0.540	59.0	0.052
Segregation Index	Var(m_we_f)/Var(we)	0.235		0.255		0.271		0.273		0.296		0.061

Notes.
log(y) - natural log of annual earnings
m_we_f - mean worker effect across firms
m_xb_f - mean Xb across firms
m_r_f - mean residual across firms
diff_we_f - difference of worker effect from mean worker effect across firms
diff_xb_f - difference of Xb from mean xb across firms
diff_r_f - difference of the residual from the mean residual across firms
Estimates are from the baseline 100% sample - 520 hrs at minimum wage, male, age 20-60, with normalization: age'=(age-40)/40.
Raw decomposition refers to the between and within firm variance composition simply on log wages, rather than using the CHK components.

Table 3: Decomposition of the Rise in Earnings Inequality Between- and Within-Firms by Firm Size

		Sample Excluding Firms with Greater than 10,000 Employees						Sample Excluding Firms with Greater than 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	
		Var. Component (1)	Share of Total (2)	Var. Component (3)	Share of Total (4)	Var. Component (5)	Share of Total (6)	Var. Component (7)	Share of Total (8)	Var. Component (9)	Share of Total (10)	Var. Component (11)	Share of Total (12)
	Var(log(y))	**0.774**	**100**	**0.912**	**100**	**0.138**	**100**	**0.791**	**100**	**0.900**	**100**	**0.109**	**100**
Between-Firm	Var(m_we_f)	0.100	12.9	0.159	17.4	0.059	**42.6**	0.119	15.0	0.176	19.6	0.057	**52.5**
Components	Var(firm effect)	0.114	14.7	0.116	12.7	0.002	**1.2**	0.118	14.9	0.123	13.7	0.005	**4.9**
of Variance	Var(m_xb_f)	0.009	1.1	0.009	1.0	0.000	**0.3**	0.010	1.2	0.010	1.1	0.000	**0.4**
	2cov(m_we_f,firm)	0.007	0.9	0.053	5.8	0.046	**33.0**	-0.006	-0.8	0.029	3.2	0.035	**31.9**
	2cov(m_we_f,m_xb_f)	0.013	1.7	0.022	2.4	0.009	**6.6**	0.013	1.6	0.020	2.3	0.008	**7.1**
	2cov(firm,m_xb_f)	0.017	2.2	0.022	2.4	0.005	**3.6**	0.014	1.8	0.020	2.2	0.006	**5.2**
	Between Firm Variance	**0.260**	**33.6**	**0.381**	**41.7**	**0.121**	**87.4**	**0.267**	**33.8**	**0.379**	**42.1**	**0.112**	**102.0**
Within-Firm	Var(diff_we_f)	0.291	37.6	0.339	37.2	0.048	**34.9**	0.298	37.7	0.331	36.8	0.033	**29.9**
Components	Var(diff_xb_f)	0.049	6.3	0.053	5.8	0.004	**3.0**	0.050	6.3	0.053	5.9	0.003	**2.5**
of Variance	Var(diff_r_f)	0.161	20.8	0.139	15.2	-0.022	**-16.1**	0.167	21.1	0.142	15.8	-0.024	**-22.3**
	2cov(diff_we_f,diff_xb_f)	0.013	1.7	0.002	0.2	-0.012	**-8.5**	0.010	1.2	-0.002	-0.2	-0.012	**-10.9**
	Within Firm Variance	**0.514**	**66.4**	**0.532**	**58.4**	**0.018**	**13.3**	**0.525**	**66.4**	**0.524**	**58.2**	**-0.001**	**-0.9**
Raw Decomposition	Between Firm Var	0.259	33.5	0.381	41.7	0.121	**87.6**	0.267	33.7	0.378	42.0	0.112	**102.1**
	Within Firm Var	0.514	66.5	0.531	58.3	0.017	**12.4**	0.524	66.3	0.522	58.0	-0.002	**-2.1**
Segregation Index	Var(m_we_f)/Var(we)	0.255		0.319		0.064		0.285		0.347		0.063	

Notes.
log(y) - natural log of annual earnings
m_we_f - mean worker effect across firms
m_xb_f - mean Xb across firms
m_r_f - mean residual across firms
diff_we_f - difference of worker effect from mean worker effect across firms
diff_xb_f - difference of Xb from mean xb across firms
diff_r_f - difference of the residual from the mean residual across firms
Estimates are from the baseline 100% sample - 520 hrs at minimum wage, male, age 20-60, with normalization: age'=(age-40)/40.
Raw decomposition refers to the between and within firm variance composition simply on log wages, rather than using the CHK components.

Table C1: Summary Statistics for Overall Sample and Individuals in Largest Connected Set

	All full-time men, age 20-60					Individuals in largest connected set				
			Log real annual earnings					Log real annual earnings		
	(1)	(2)	(4)	(5)	(6)	(7)	(8)	(10)	(11)	(12)
7 Year Interval	Number worker/yr. obs.	Number workers	Mean	Median	Std. dev.	Number worker/yr. obs.	Number workers	Mean	Median	Std. dev.
1980-1986	336,095,166	66,253,680	10.381	10.505	0.868	332,624,208	65,311,438	10.379	10.506	0.865
Ratio: largest connected/all						99.0	98.6	100.0	100.0	99.6
1987-1993	378,061,870	71,852,732	10.355	10.473	0.929	373,806,862	70,802,234	10.354	10.474	0.925
Ratio: largest connected/all						98.9	98.5	100.0	100.0	99.6
Between Firm Variance										
1994-2000	408,883,618	76,590,263	10.421	10.514	0.931	403,724,055	75,365,461	10.421	10.515	0.928
Ratio: largest connected/all						98.7	98.4	100.0	100.0	99.7
2001-2006	431,749,460	81,950,386	10.484	10.578	0.961	425,006,770	80,409,315	10.485	10.581	0.960
Ratio: largest connected/all						98.4	98.1	100.0	100.0	99.8
2007-2013	422,334,068	82,761,555	10.487	10.566	0.958	414,466,857	80,920,372	10.489	10.570	0.956
Ratio: largest connected/all						98.1	97.8	100.0	100.0	99.9
Change from first to last interval			0.106	0.061	0.089	-0.83	-0.80	0.109	0.063	0.092

Notes:

Table C2: 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 Var. Component (4)	Interval 5 Share of Total (4) (5)
Sample	**# Worker Effects**	65,311,438	70,802,234	75,365,461	80,409,315	80,920,372
Summary	**# Firm Effects**	5,206,888	5,733,422	5,884,023	5,889,906	5,258,436
Statistics	**Sample size**	332,624,208	373,806,862	403,724,055	425,006,770	414,466,857
	SD(log(y))	0.865	0.925	0.928	0.960	0.956
Summary of	**SD(WE)**	0.596	0.644	0.667	0.692	0.695
AKM Parameter	**SD(FE)**	0.346	0.339	0.314	0.332	0.329
Estimates	**SD(Xb)**	0.238	0.278	0.297	0.254	0.256
	Between Firm Variance	0.030	0.080	0.116	0.131	0.141
	Corr(WE,XB)	0.113	0.084	0.027	0.084	0.091
	Corr(FE,Xb)	0.124	0.133	0.115	0.129	0.143
	RMSE(residual)	0.438	0.445	0.431	0.442	0.415
	Adj R^2	0.743	0.768	0.784	0.788	0.812
Comparison	**RMSE(match residual)**	0.369	0.374	0.360	0.369	0.347
Match Model	**Adj R^2**	0.817	0.836	0.850	0.852	0.868
	SD(match effect)	0.260	0.266	0.264	0.267	0.244

Notes:
• A 100% sample of the SSA Master Earnings File. Male only, ages 20-60, over 520 hours worked at minmum wage.
• Age is normalized as age=(age-40)/40 as in CHK.
• We include an unrestricted set of year dummies and quadratic and cubic terms in age.
We do not interact 5 education dummies with other covariates as in CHK.
• The dependent variable is log annual earnings at main job.
• Annual earnings are adjusted for inflation with the PCE deflator at base year 2013.

Table C3: Basic Decomposition of the Rise in Inequality of Annual Earnings

		Interval 1		Interval 2		Interval 3		Interval 4		Interval 5		Change from	
		1980-1986		1987-1993		(4)		(5)		2007-2013	h	1 to 5	
		Variance Component	Share of Total	Variance Component	Share of Total	Variance Component	Share of Total	Variance Component	Share of Total	Variance Component	Share of Total	Variance Component	Share of Total
		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Total Variance	Var(log(y))	0.748	100	0.855	100	0.861	100	0.921	100	0.915	100	0.167	100
Components of Variance	Var(WE)	0.355	47.5	0.415	48.5	0.445	51.7	0.479	52.0	0.483	52.8	0.128	76.7
	Var(FE)	0.120	16.0	0.115	13.5	0.099	11.5	0.110	12.0	0.108	11.9	-0.011	-6.6
	Var(Xb)	0.057	7.6	0.077	9.0	0.088	10.2	0.065	7.0	0.065	7.2	0.009	5.3
	Var(residual)	0.151	20.3	0.158	18.5	0.149	17.2	0.156	16.9	0.136	14.9	-0.015	-9.2
	Between Firm Variance	0.012	1.6	0.035	4.1	0.049	5.7	0.060	6.5	0.065	7.1	0.052	31.4
	2*Cov(WE,Xb)	0.032	4.3	0.030	3.5	0.011	1.2	0.029	3.2	0.033	3.6	0.001	0.3
	2*Cov(FE,Xb)	0.020	2.7	0.025	2.9	0.021	2.5	0.022	2.4	0.024	2.6	0.004	2.2
											21.6		
Counterfactuals	1. No rise in Corr(WE,FE)	0.748		0.833		0.825		0.874		0.864		0.116	69.5
	2. No fall in Var(FE)	0.748		0.861		0.889		0.933		0.930		0.182	109.3
	3. Both 1 and 2	0.748		0.838		0.849		0.885		0.877		0.129	

Notes:

• Var(log(y)) - variance of annual earnings, Var(WE) - variance of worker fixed effects, Var(FE) - variance of firm fixed effects, Var(Xb) - variance #VALUE!

• See notes to Table III.

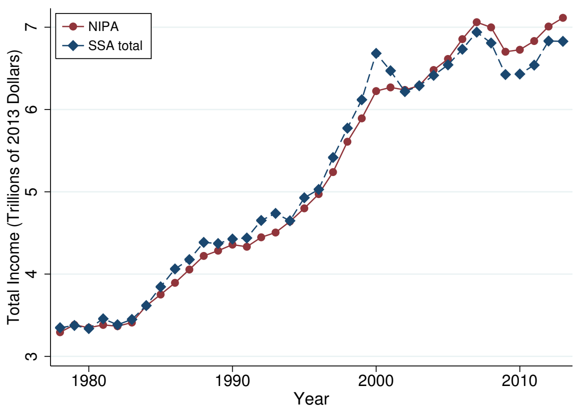
Supplemental Online Appendix

A Appendix: Additional Figures

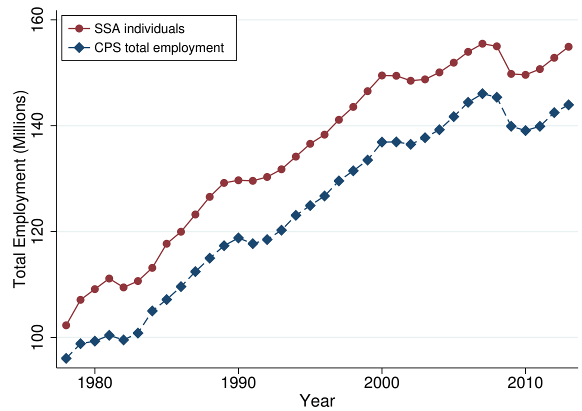
A.1 Sensitivity and Robustness

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

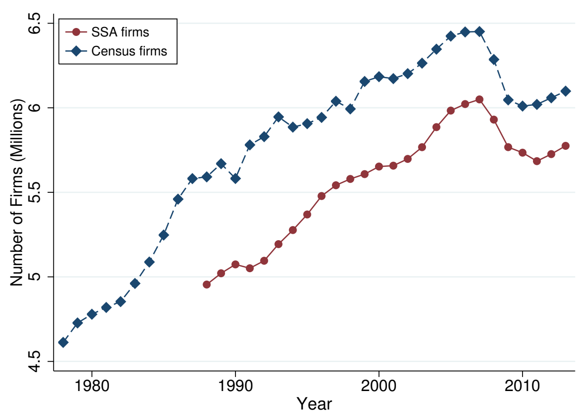
(a) Total earnings



(b) Total employment

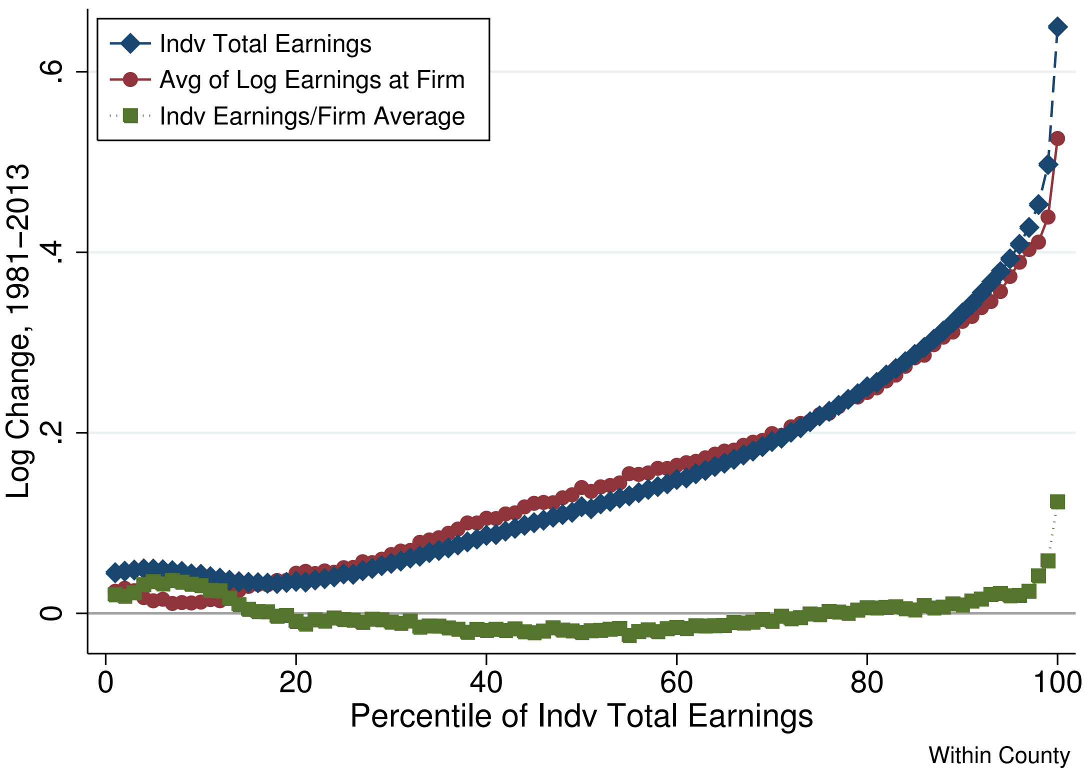


(c) Total firms



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.

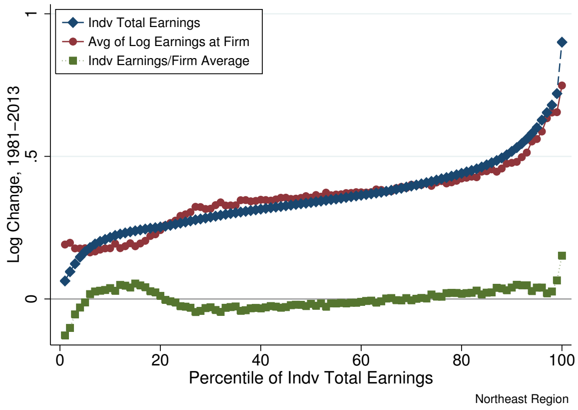
Figure A.2 – Robustness: Controlling for Geography at County Level



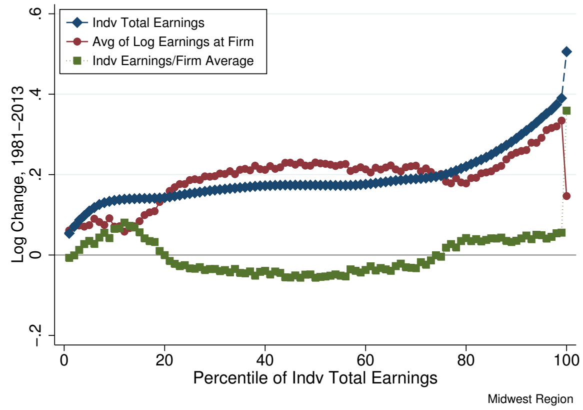
Notes: See notes for Figure 3. Data for a graph similar to 3 is calculated for each county (of the firm) in each year, then averaged together by year, weighting counties by employment.

Figure A.3 – Robustness by region

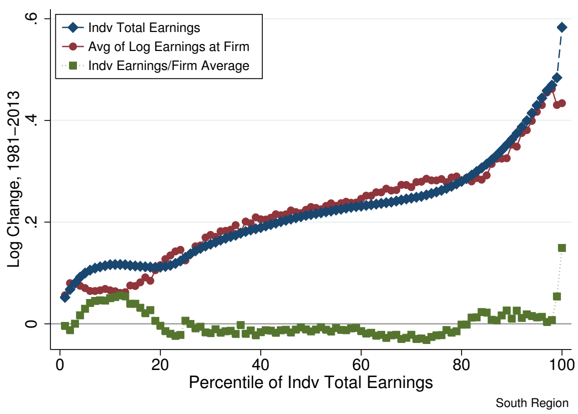
(A) Northeast



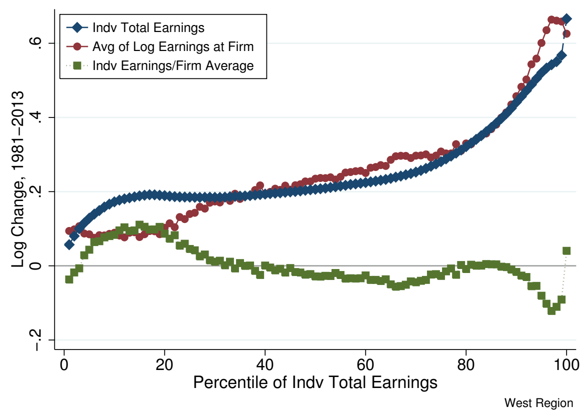
(B) Midwest



(C) South



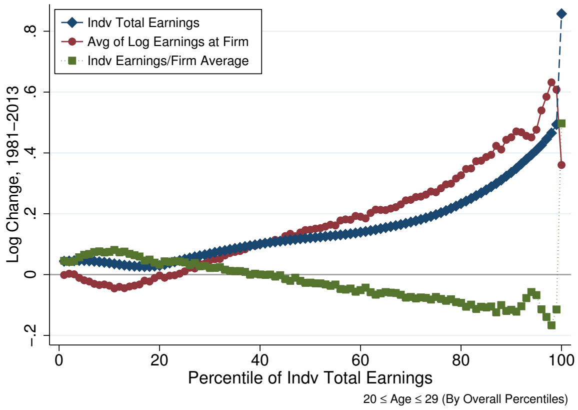
(D) West



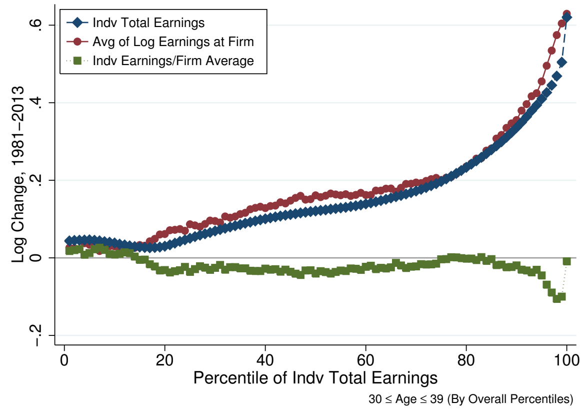
Notes: See notes for Figure 3. Regions are based on Census region definitions. Percentiles are based on only those individuals in the given region.

Figure A.4 – Robustness by demographic (age group and gender)

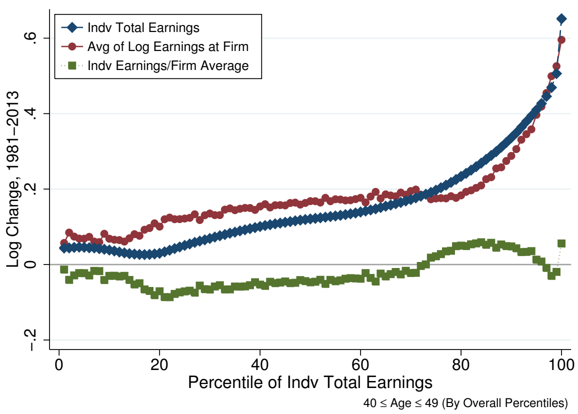
(a) Age: 20 to 29



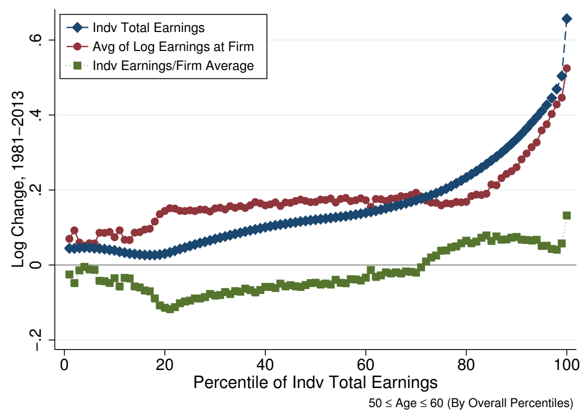
(b) Age: 30 to 39



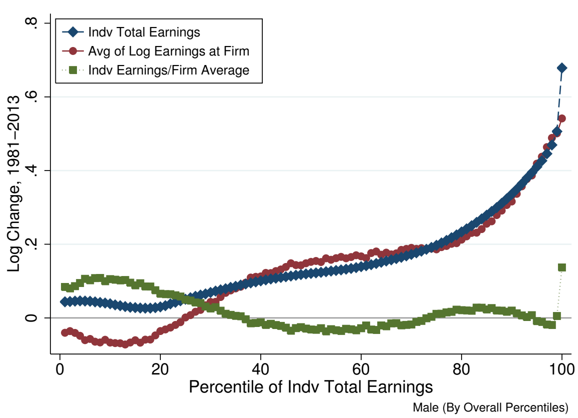
(c) Age: 40 to 49



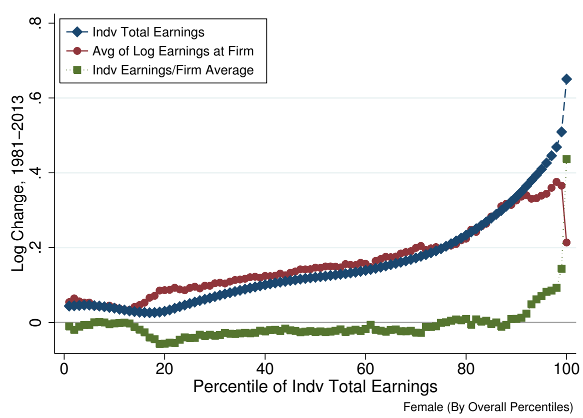
(d) Age: 50 to 60



(e) Men



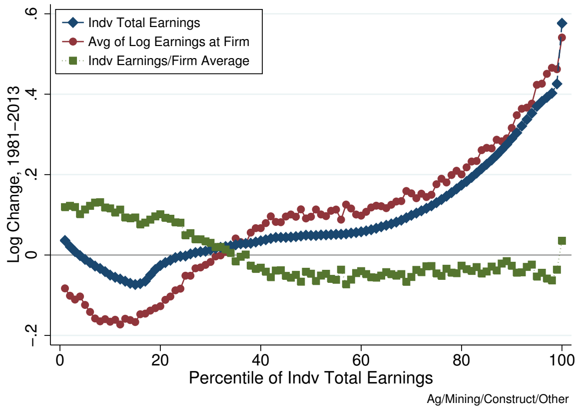
(f) Women



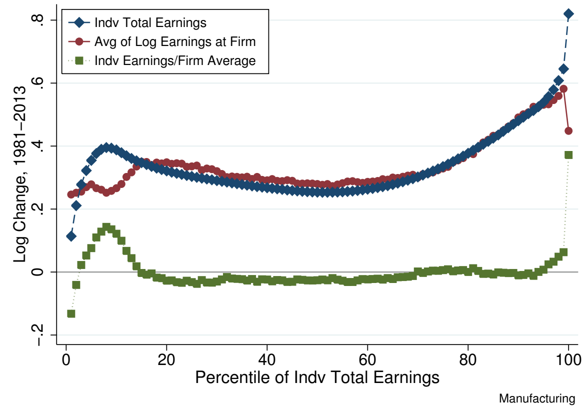
Notes: See notes for Figure 3. Percentiles are based on all individuals, regardless of age or gender.

FIGURE A.5 – Robustness by industry: results by SIC 1-digit industry

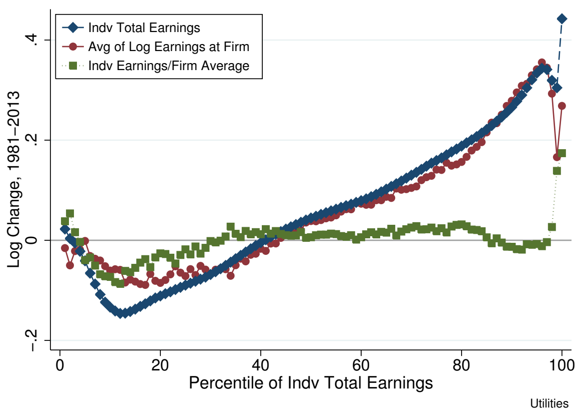
(A) Agriculture, Mining, Construction & Other



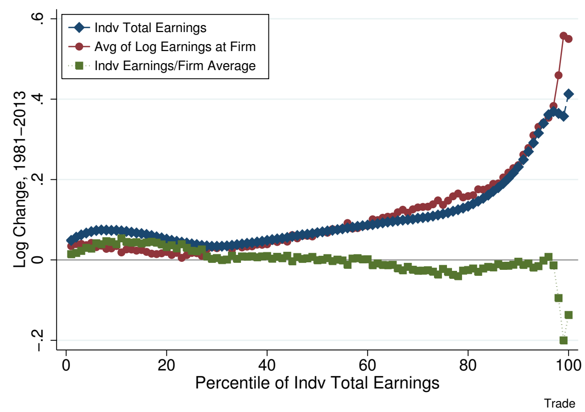
(B) Manufacturing



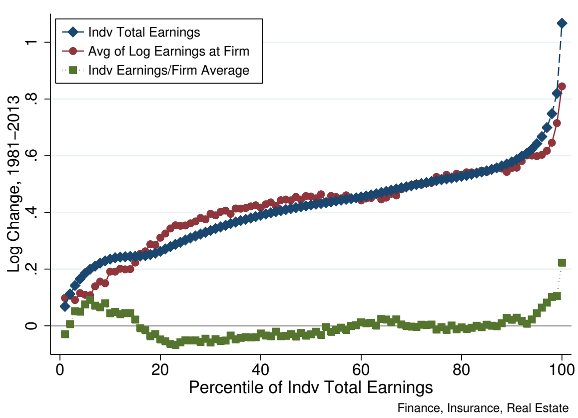
(C) Utilities



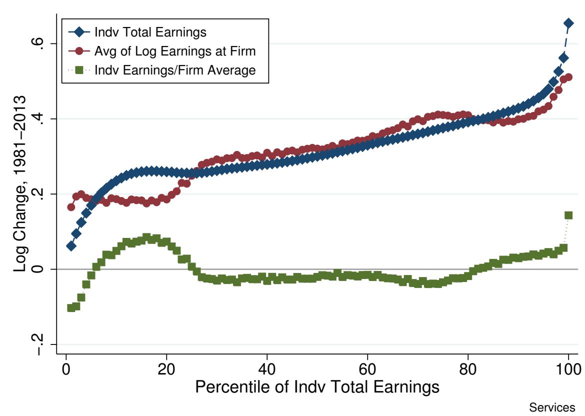
(D) Trade



(E) Finance, insurance and real estate

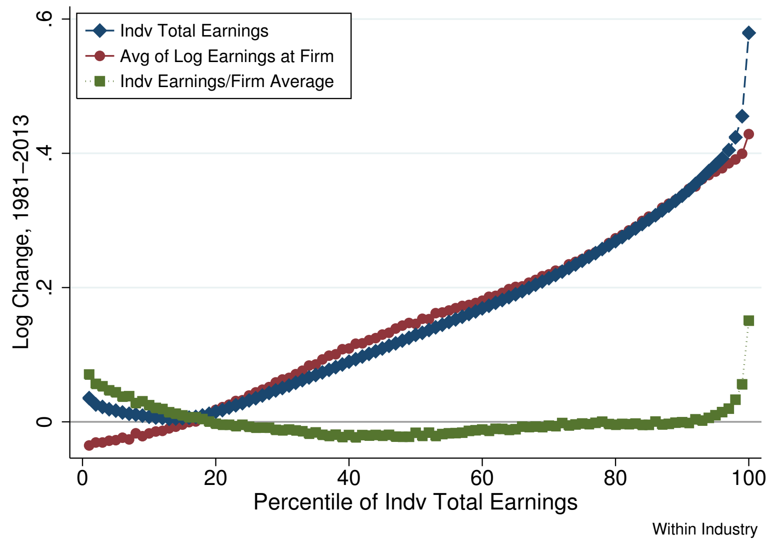


(F) Services



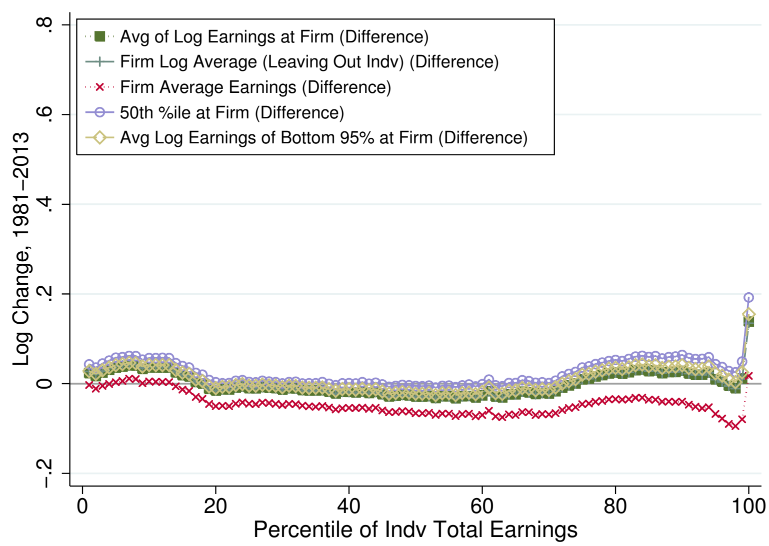
Notes: See notes for Figure 3. Industries are based on definitions from https://www.osha.gov/pls/imis/sic_manual.html. Percentiles are based on only those individuals employed in the given industry.

Figure A.6 – Robustness by industry: averaged across analysis within SIC 4-digit industry



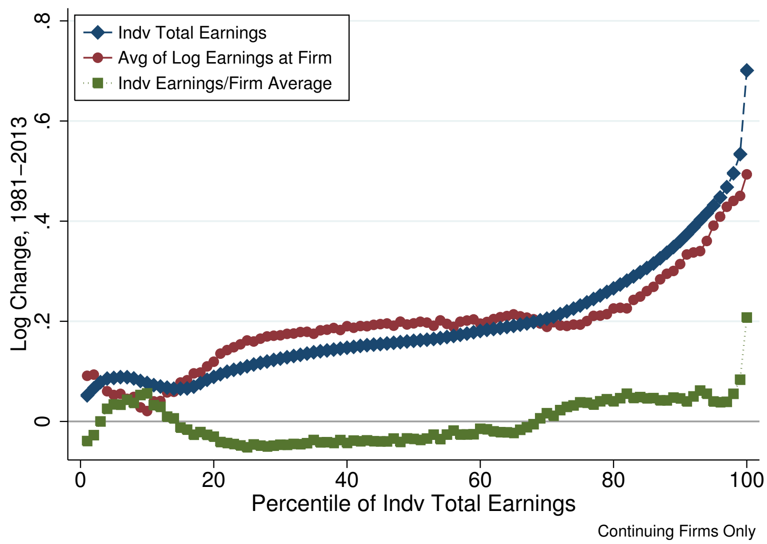
Notes: See notes for Figure 3. Data for a graph similar to 3 is calculated for each 4-digit industry in each year, then averaged together by year, weighting industries by employment.

Figure A.7 – Robustness by measure of firm average earnings



Notes: See notes for Figure 3. Individual statistics are the same for all lines; firm statistics are calculated differently, as indicated.

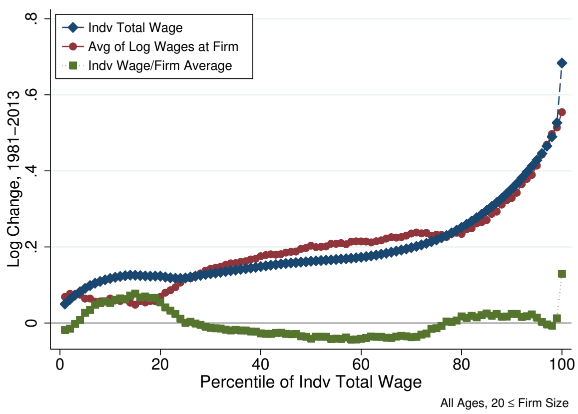
Figure A.8 – Continuing firms only



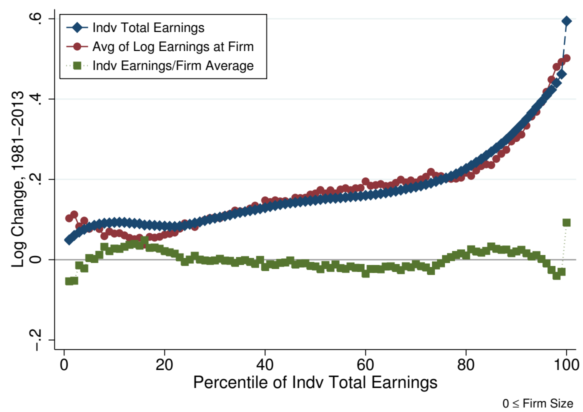
Notes: See notes for Figure 3. Only firms (and individuals in those firms) that are in the sample in both 1981 and 2013 are included in the analysis.

Figure A.9 – Less-restrictive sample selection

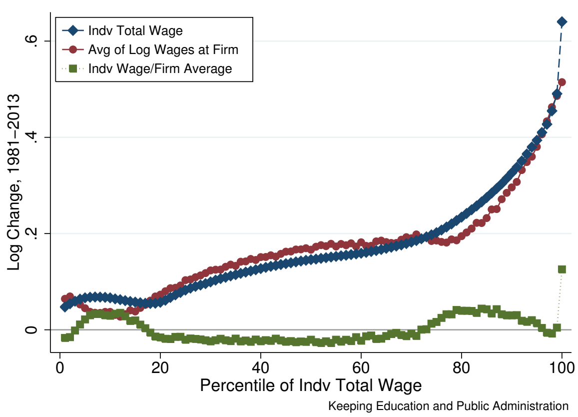
(a) All ages



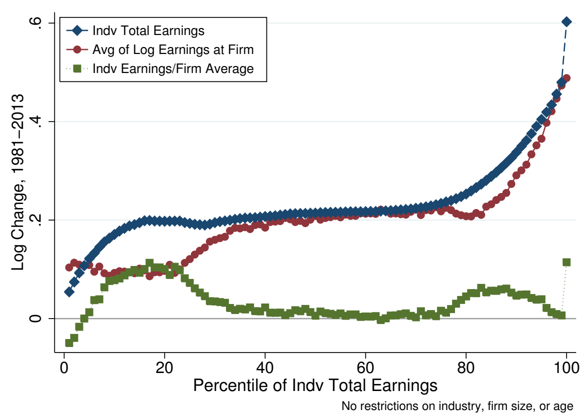
(b) All firm sizes



(c) All industries



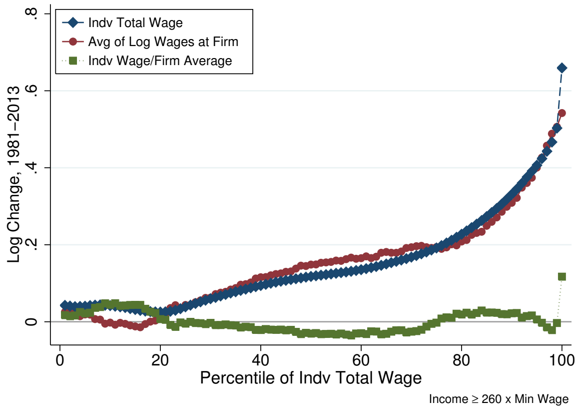
(d) All ages, firm sizes, and industries



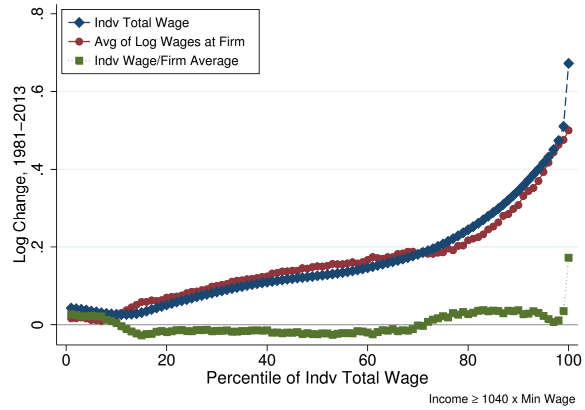
Notes: See notes for Figure 3. Sample selection criteria are relaxed as indicated.

Figure A.10 – Different definitions of full-time workers

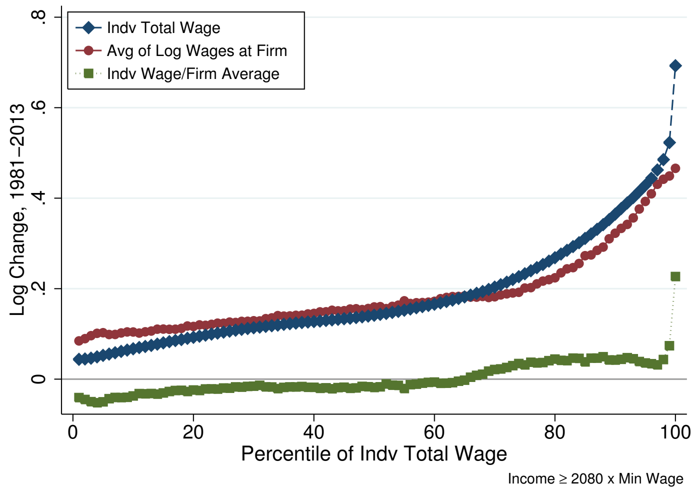
(a) 6.5 weeks



(b) 26 weeks

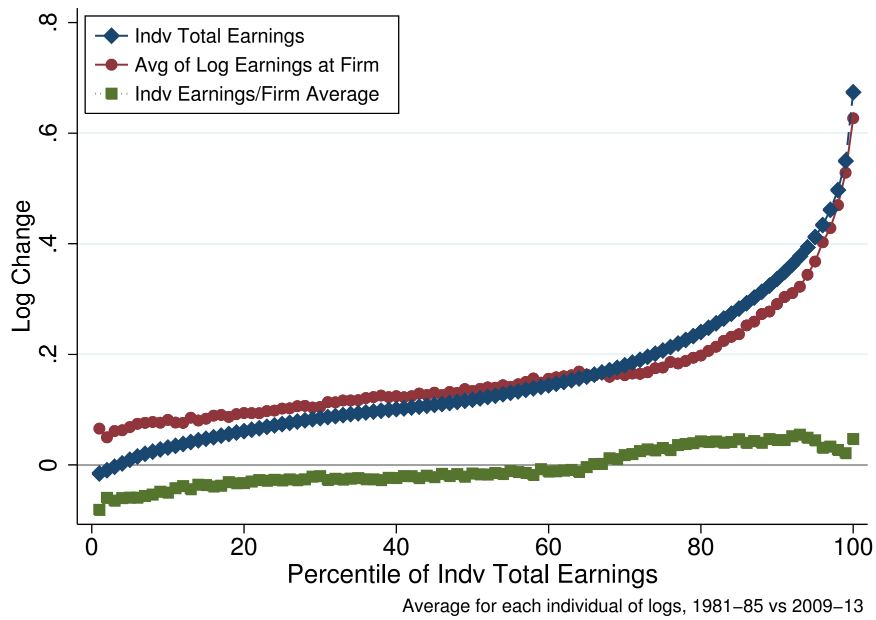


(c) 52 weeks



Notes: See notes for Figure 3. Minimum earnings thresholds are adjusted to the equivalent of 40 hours per week at minimum wage for the given number of weeks.

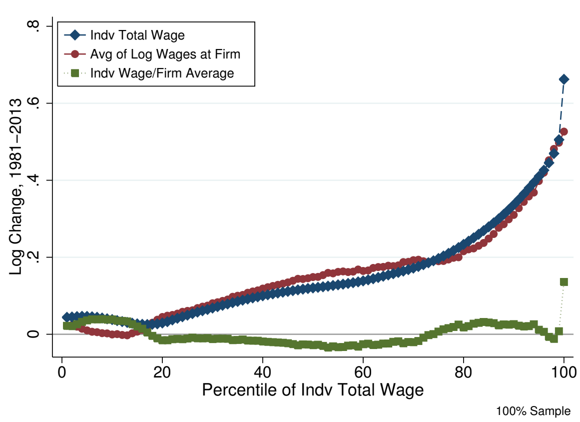
Figure A.11 – Five year average earnings: comparing 1981-1985 vs 2009-2013



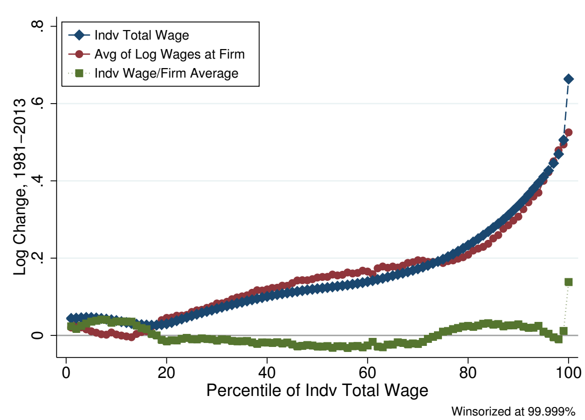
Notes: See notes for Figure 3. Only individuals who are in the sample for all five years are included. Individual income is calculated as the average of log earnings over the five years. Firm statistics are based on the average of mean log earnings at the firm that the individual was in, in each of the five years (even if that includes different firms).

Figure A.12 – Other restrictions

(a) 100% sample



(b) Winsorizing at Execucomp maximum



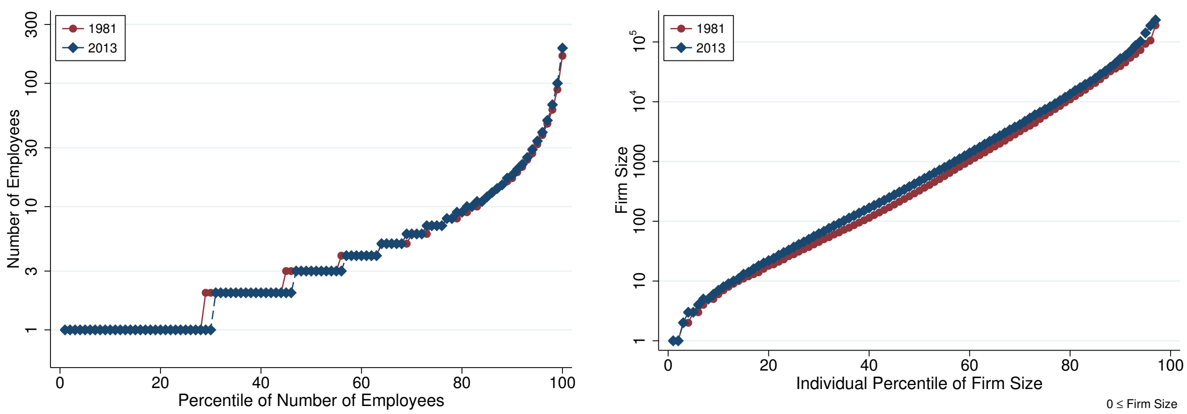
Notes: See notes for Figure 3.

A.2 Other figures

FIGURE A.13 – Cumulative firm size distribution

(A) Unweighted

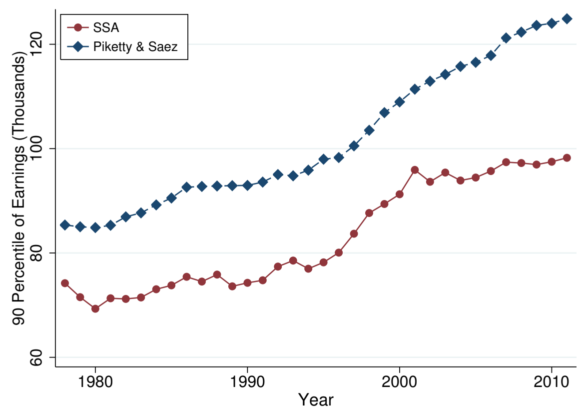
(B) Weighted by employment



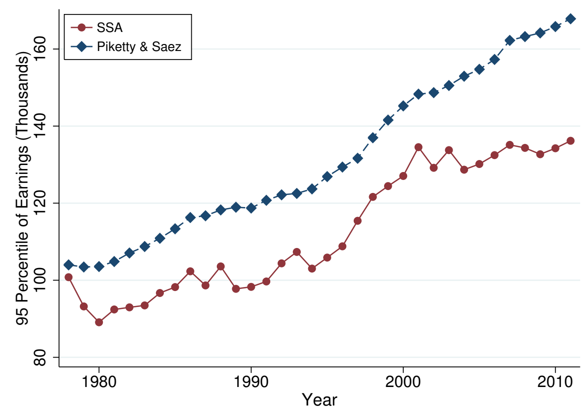
Notes: Only full-time individuals aged 20 to 60 are included in all statistics, where full-time is defined as earning the equivalent of minimum wage for 40 hours per week in 13 weeks. Individuals and firms in public administration or educational services are not included. Both graphs are inverse cumulative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

Figure A.14 – Comparison to Piketty and Saez (IRS data)

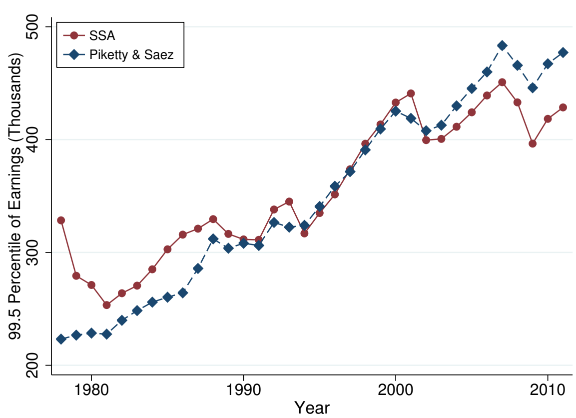
(a) 90th Percentile



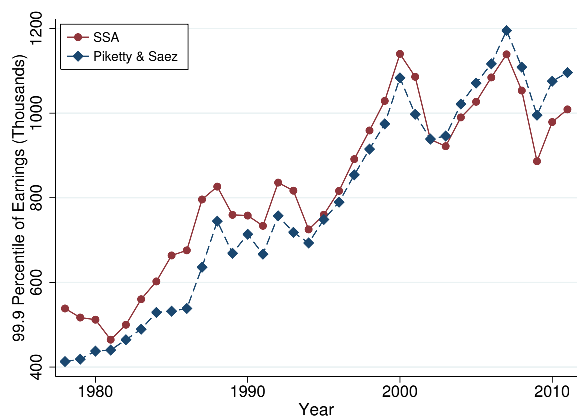
(b) 95th Percentile



(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 full-time individuals aged 20 to 60 are included in all SSA statistics, where full-time 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.

Figure A.15 – Earnings and firm size

(a) Individual earnings and average firm size (b) Correlation between firm size and wage

Notes: Only firms and individuals in firms with at least 20 employees are included. Only full-time individuals aged 20 to 60 are included in all statistics, where full-time 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. For each percentile in Figure A.15a, statistics are based on individuals in that percentile of earnings in each year. Correlation in Figure A.15b is calculated at the firm level in each year, and is weighted by firm size.

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, we consider an individual to be full-time 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 the minimum wage (so $3,770 in 2013). (As discussed above, we also conducted robustness checks with other threshold levels, which show similar results; see Figure A.10.) 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. (1993) 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 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 in the firm and worker fixed effects analysis, in which we use a 100% sample). Results are robust to using a 100% sample; see Figure A.12a. 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 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.

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 5 and 10, 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: see Figure A.12b for results top-coding at the maximum value in Execucomp. Finally, we adjust all dollar values in the data set to be equivalent to 2013 dollars with the Personal Consumption Expenditure (PCE) price index.[27]

B.2 Current Population Survey Data

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 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, Barth et al. (2014), Abowd et al. (2016)). Nevertheless, we are well aware of the limitations of the model, and incorporate it 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

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

are unbiased.[28] 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.[29] 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 C1).

C.2 Model Fit

Table C1 shows basic characteristics for the full sample as well as for observations 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 an appendix. Table C1 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.

Table C2 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.[30] 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 74.1% in 1980-1986 to 81.2% in 2007-2013.

[28] 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 is not affected by the normalization. The covariance of worker and firm effects may be affected insofar as workers are sorted into firms by age.

[29] 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.

[30] 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.

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 each period, to $82-87\%$. 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.16b 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. 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.[31] Figure A.16c shows the change in mean residuals within cells over time. The changes are of opposite signs of the deviations in A.16b, 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.

Our last 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 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

[31]Not surprisingly given the presence of labor supply effects, the mean residuals in Figure A.16 are on average larger than those shown CHK (Figure VI).

earnings for flexible time trends. Overall, we conclude that despite the fact we are modeling information on annual earnings rather than daily or hourly wages, our model delivers a good approximation of the underlying earnings process.

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

Tables 2 and 3 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 7 displays 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 7a. 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 7b show these pattern have changed substantially over time. Figure 7c shows the net change of density of the two distributions at corresponding deciles.[32] 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.

To better display the relative patterns of change within firm categories, Figure **??** shows the conditional distribution of workers within firm effect deciles for our first and last time period and the change over time. Figure **??** displays the change in the pattern of sorting most clearly—middle-wage workers move to the middle-and high-wage workers move to the top. The only exception to this pattern is the lowest decile of firm effects. Yet, Figure 7 shows this group contains few workers to begin with (Figure 7a), and exhibits very little net change (Figure 7c).

Figures 7 and **??** 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

[32] 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.

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.18 and A.19 for three firm size groups (firms with number of workers in range $1-100$, $101-9999$, and $10,000+$).

From Figure A.18 it is clear that on average, high-wage firms tend to be larger. However, over time, Figure A.18c shows that large employers have experienced a substantial shift out of high-wage firms to middle and lower-wage firms. Figure A.19 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 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.

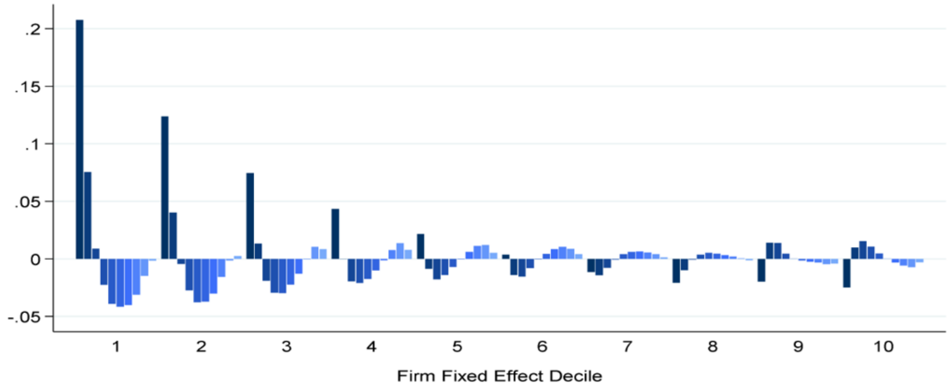
To examine potential differences in sorting patterns, we have also examined the joint distribution of firm and worker fixed effects within each size class. These figures are displayed in our appendix. The results show that the pattern of sorting is quite similar among our two larger firm size classes, and reflects the pattern shown in Figure 7 – 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 2 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 are again contained in our appendix. 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. As explained in our data section, these are likely to be disproportionately new employers, which might be likely to have low firm fixed effects.

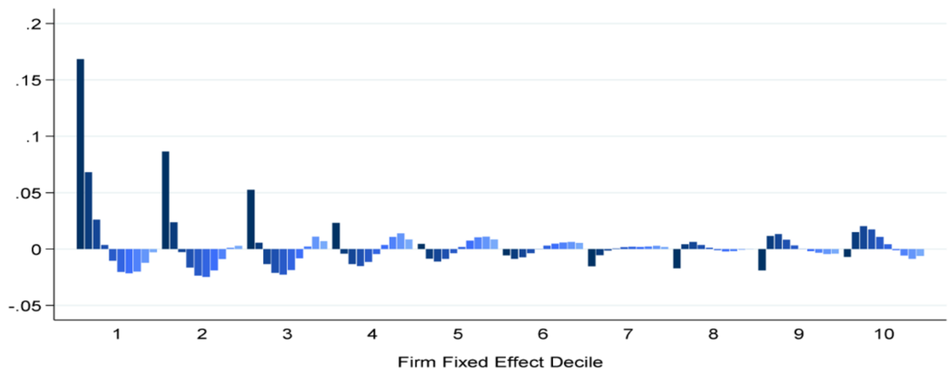
Overall, the findings from the figures corroborate and strengthen our core results from the detailed variance composition in Table 3. There is a clear pattern of increasing sorting of higher-wage workers into higher-wage firms over time. In particular, from the early 1980s to today, high-wage firms appear 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 is similar as for 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.

Figure A.16 – Regression residuals by firm fixed effect decile

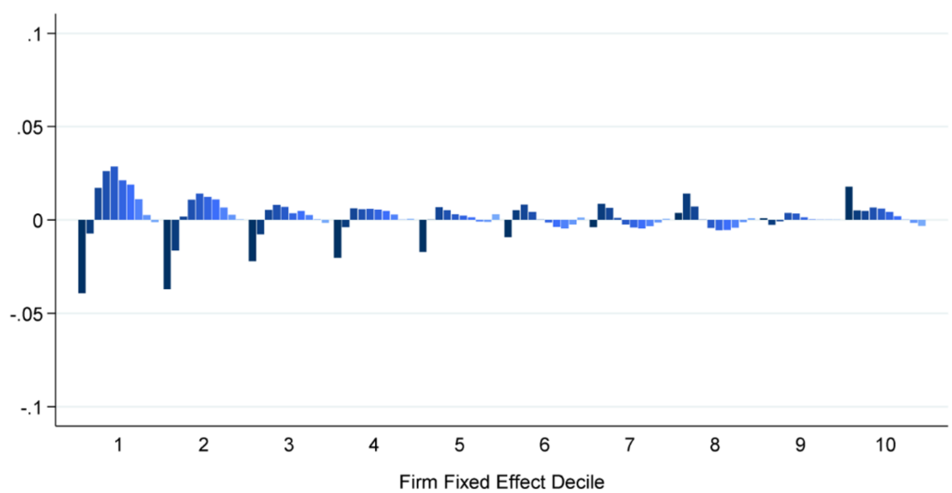
(a) 1980-1986



(b) 2007-2013



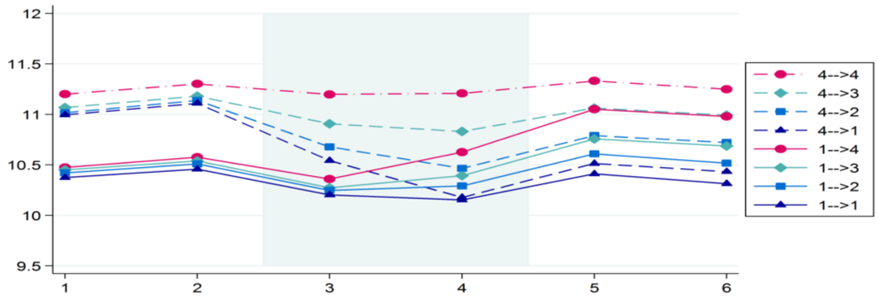
(c) Change from 1980-1986 to 2007-2013



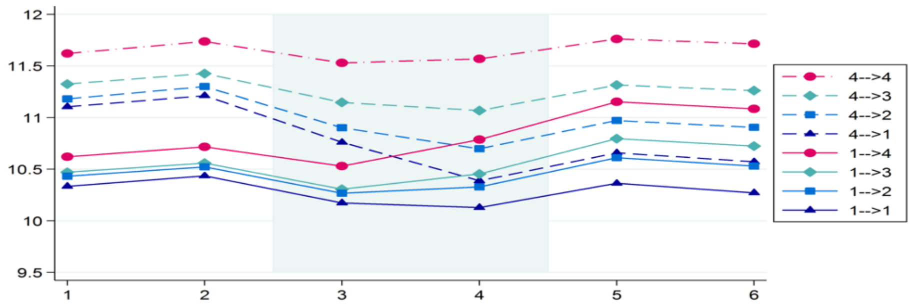
Notes:

Figure A.17 – Event study of change in mean earnings for job changers

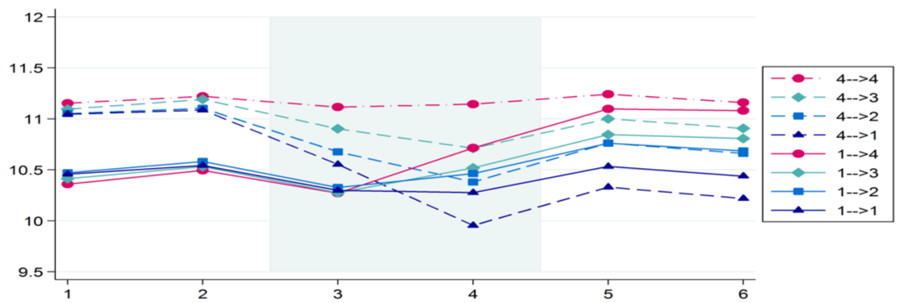
(a) Firms ranked by earnings: 1980-1986



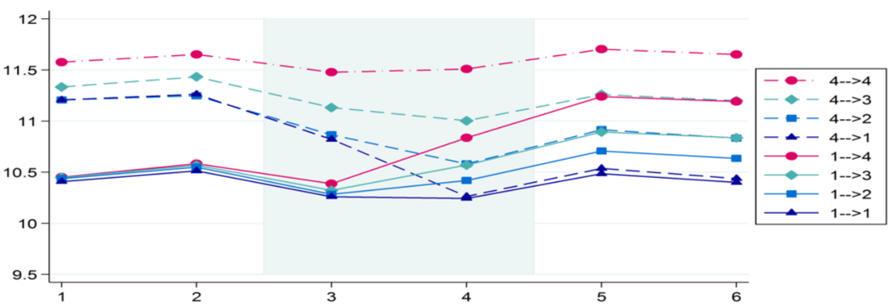
(b) Firms ranked by earnings: 2007-2013



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



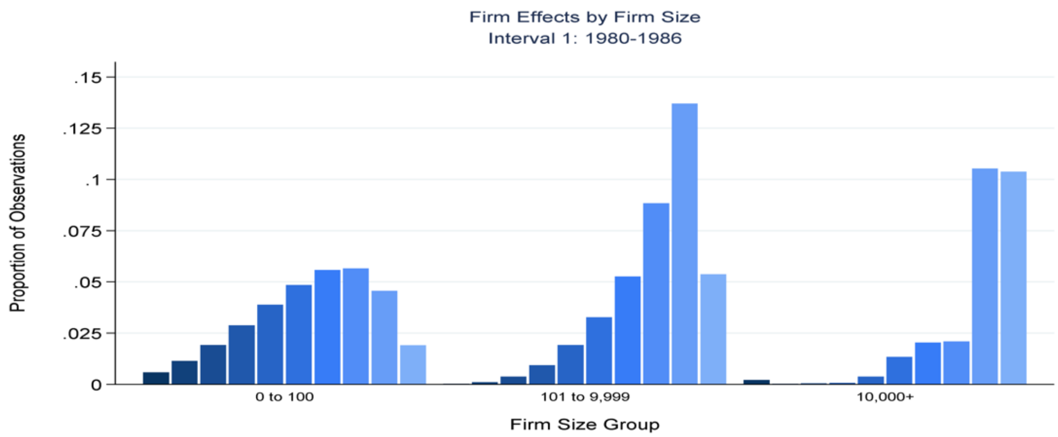
(d) Firms ranked by earnings: 2007-2013



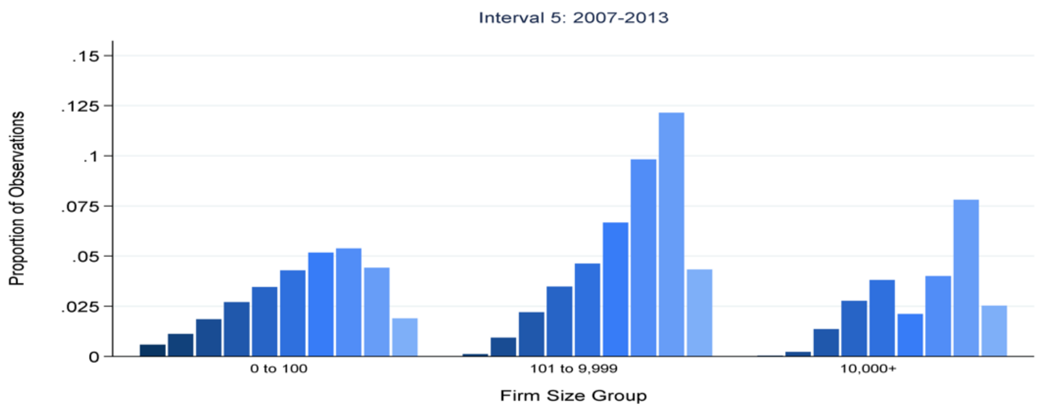
Notes:

Figure A.18 – Distribution of workers and firm, by firm size

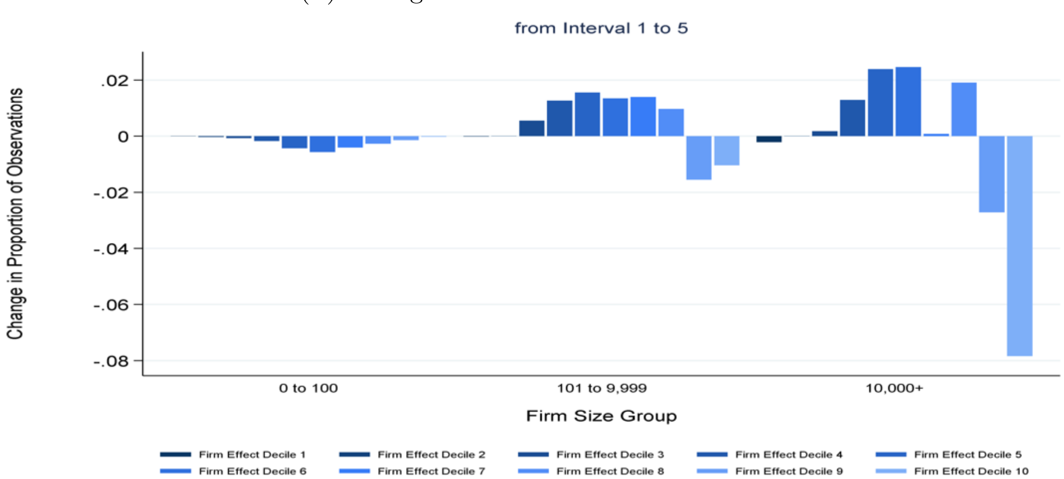
(a) 1980-1986



(b) 2007-2013



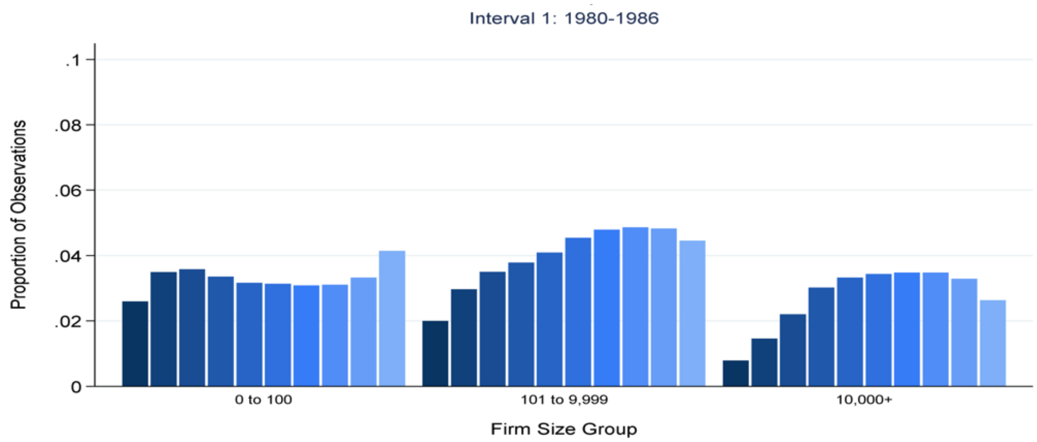
(c) Change from 1980-1986 to 2007-2013



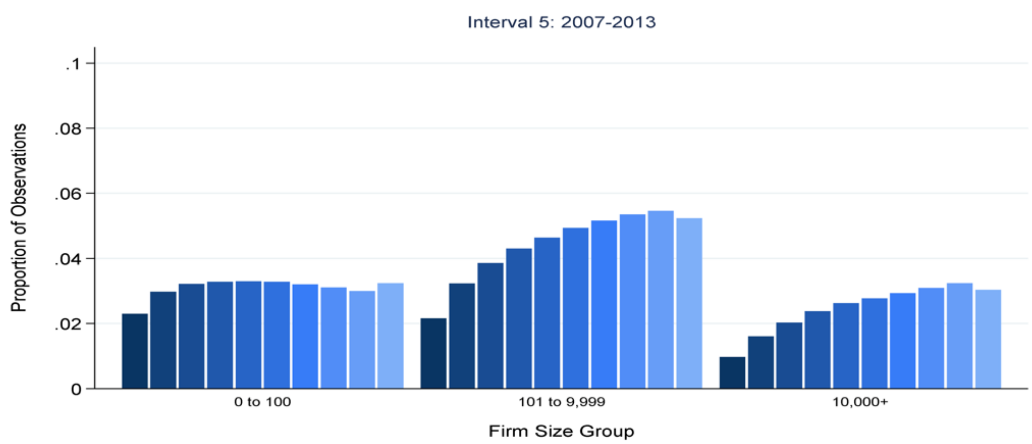
Notes:

Figure A.19 – Distribution of workers among worker FE deciles, by firm size

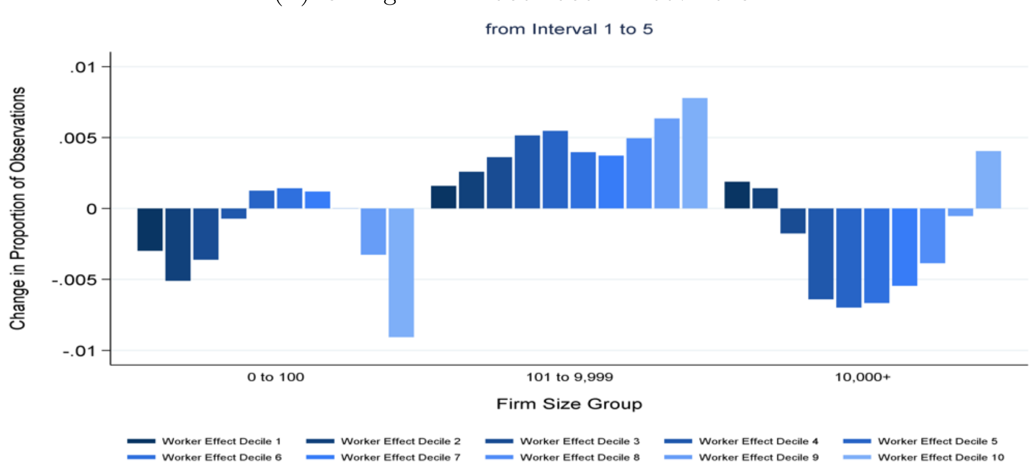
(a) 1980-1986



(b) 2007-2013



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



Notes: