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## FIRMING UP INEQUALITY\*

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We use a massive, matched employer-employee database for the United States to analyze the contribution of firms to the rise in earnings inequality from 1978 to 2013. We find that one-third of the rise in the variance of (log) earnings occurred within firms, whereas two-thirds of the rise occurred due to a rise in the dispersion of average earnings between firms. However, this rising between-firm variance is not accounted for by the firms themselves but by a widening gap between firms in the composition of their workers. This compositional change can be split into two roughly equal parts: high-wage workers became increasingly likely to work in high-wage firms (i.e., sorting increased), and high-wage workers became increasingly likely to work with each other (i.e., segregation rose). In contrast, we do not find a rise in the variance of firm-specific pay once we control for the worker composition in firms. Finally, we find that two-thirds of the rise in the within-firm variance of earnings occurred within mega (10,000+ employee) firms, which saw a particularly large increase in the variance of earnings compared with smaller firms. *JEL* Codes: E23, J21, J31.

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## I. INTRODUCTION

The dramatic rise in U.S. earnings inequality from the 1970s to today has been well documented (see [Acemoglu and Autor 2011](#) for a detailed review). An enormous body of theoretical and empirical research has been conducted over the past two decades in an attempt to understand the causes of these trends. Until recently, the analysis of the role of employers has been largely absent from this literature, chiefly because of the lack of a comprehensive, matched employer-employee data set in the United States covering the period of rising inequality.

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

Important questions are to what extent the differences in firm pay premiums have widened and to what extent this widening can explain the observed rise in earnings inequality. In a recent paper, [Card, Heining, and Kline \(2013\)](#) show that a rise in the dispersion of firm pay premiums has contributed substantially to recent increases in wage inequality in Germany. They also show that inequality rose in equal measure because of large changes in worker composition—high-wage workers became increasingly

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1. For the clarity of the discussion in this article, it is important to distinguish this notion of “firm pay premium”—how much a firm pays a hypothetical worker with average observable and unobservable characteristics—from what we call “firm average earnings”—which is simply the average of the labor earnings of all employees in a given firm. We write “between-firm inequality” to refer to the dispersion in firm average earnings (across firms) and “within-firm inequality” to refer to the within-firm dispersion of worker earnings around firm average earnings. Although firm average earnings are easily measured in the data, its value depends on both the hard-to-measure firm pay premium (net of worker characteristics), as well as the actual composition of workers who are employed at the firm. This distinction will be important throughout the article.

likely to work in high-wage firms (i.e., sorting increased), and high-wage workers became increasingly likely to work with each other (i.e., segregation rose).

Similar phenomena of changes in firm pay premiums and worker composition could explain some of the shifts in inequality in the United States, which has experienced a stronger and more persistent increase in inequality than have Germany and many other continental European countries. Indeed, as we will discuss, many of the mechanisms considered in the U.S. literature on inequality have potential implications for the contribution of firms and worker sorting to inequality, but so far these have not been evaluated. The firm dimension is also particularly interesting because it may help us better understand the rise in earnings at the very top, which many attribute to an increase in executive compensation, a phenomenon contributing to rising inequality within firms.

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

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

of firm average earnings explain almost all of the rise in inequality below the 80th percentile, while changes in the within-firm distribution of earnings explain some of the increase in inequality above that point.

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

To distinguish among these factors, we follow the modeling approach of [Abowd, Kramarz, and Margolis \(1999\)](#) (AKM) and [Card, Heining, and Kline \(2013\)](#) (CHK) to estimate unobserved permanent worker and firm components of each worker’s annual earnings. With this approach, we can decompose rising overall inequality into the portion due to the changing dispersion of worker effects, the changing dispersion of firm effects, and the changing covariance between the two.<sup>2</sup> Based on this approach, our second main finding is that the rising variance of worker effects—potentially due to rising returns to skill—explains 68% of rising inequality, while the rising covariance between worker and firm effects explains 35%. In contrast, the third component, the variance of firm effects, declined slightly during this time, making a small, negative contribution to rising inequality.

Although this last finding may appear surprising in light of our first result—that the rising dispersion of firm-wide average earnings explains more than two-thirds of the rise in the variance

2. We estimate this set of results separately for men and women because it would be computationally infeasible to estimate the results for both groups together. Results reported here are for men only, with similar results for women only. All other results—those that do not follow AKM and CHK—include data on both men and women.

of total earnings—these results are perfectly consistent, which is our third main finding. Using the estimated worker and firm fixed effects, we show that the rise in between-firm inequality can be completely explained by changes in the composition of workers between firms. Increases in sorting (a rise in the covariance between worker and firm effects) and segregation (a rise in the variance of average worker fixed effects at a firm) explain the entire increase in between-firm inequality in our data. The increased variance in individual fixed effects can itself lead to increases in such sorting and segregation; we show that rising returns to skill, absent any firm-level changes, could account for about a third of rising segregation but almost none of the increase in sorting.

Our fourth result is that of the 31% of the increase in the total variance of annual earnings that occurs within firms, most comes from large firms. The increase in the total variance of log earnings in firms with 10,000+ employees—which we call “mega firms,” a group comprising about 750 firms employing about 23% of U.S. workers in 2013—is 58% between firms and 42% within firms. In contrast, the change in the variance of log earnings in firms with 20 to 1,000 workers is 92% between and 8% within firms. This rise in within-firm inequality in mega firms comes from substantial changes at both the bottom and the top of the within-firm earnings distribution. For example, between 1981 and 2013, median workers at mega firms saw their earnings fall by an average of 7%, those at the 10th percentile saw an average drop of 17%, and those at the 90th percentile saw an average rise of 11%. Overall, we calculate that the bottom half of the distribution is responsible for 35% of the rise in within-firm dispersion from 1981 to 2013 in mega firms. Changes in the 90th percentile and above explain 46% of the rise in dispersion.

We also find that in these mega firms, the top 50 managers have seen robust earnings increases. For example, the 50th highest-paid manager in mega firms—who would typically be a senior executive—has, on average, seen a 47% rise in earnings between 1981 and 2013. The top-paid employee (presumably the chief executive officer) has seen earnings rise by 137% over the same period. However, because there are few of these top-50 employees relative to the size of total employment at these mega firms (about 35,000 of them versus about 20 million total employees in these firms), we find that rising top executive earnings explain little of the increase in the variance in overall earnings.

For example, the top 50 employees account for about 3% of the total increase in the within-firm dispersion of earnings from 1981 to 2013 at mega firms, whereas the top five employees account for less than 1% of the increase. Turning to smaller firms, we find that top paid employees have seen their earnings rise more in line with the rise in the average earnings at their firm. Consequently, the numerical contribution of taxable earnings of top executives to the rise in overall inequality in earnings during this period appears limited.

To summarize, our findings imply that the large rise in earnings inequality in the United States can be formally decomposed into three equally important components—a rise in the sorting of higher-paid workers into higher-paying firms, a rise in segregation of higher-paid workers to the same firms, and a rise in earnings inequality within firms. The rise in within-firm inequality was largely driven by mega firms, which saw a four times larger rise in within-firm inequality relative to all other firms, while accounting for only a quarter of total employment in the economy.

These findings highlight several potential mechanisms underlying rising earnings inequality. For example, it has long been hypothesized that persistent differences in firm pay premiums reflect rent-sharing (e.g., [Dickens and Katz 1987](#); [Katz and Summers 1989](#); [AKM](#)). Our finding of increasing sorting suggests that the distribution of rents may have become increasingly skewed, with an increasing share going to high-wage workers. A complementary explanation is the rise in domestic outsourcing and temporary work (e.g., [Abraham and Taylor 1996](#); [Segal and Sullivan 1997](#); [Weil 2014](#)). Indeed, [Katz and Krueger \(forthcoming\)](#) find that contingent workers, such as independent contractors and freelancers, make up an increasing part of the workforce. Similarly, [Goldschmidt and Schmieder \(2017\)](#) show that domestic outsourcing in Germany can explain a rise in sorting and a rise in inequality. These alternative work arrangements could help explain rising segregation and sorting, as a previously diverse workforce splits into a homogeneous well-paying lead firm and a range of homogeneous lower-paying suppliers and service providers.

Our results are consistent with a substantial literature documenting that technological changes have increased inequality by shifting the demand for different skill groups (e.g., [Acemoglu and Autor 2011](#) for a survey). Rising returns to skill, even with a stable distribution of skill across firms, could mechanically lead to increased sorting and segregation if more skilled employees tend to

be clustered together in typically higher-paying firms. Then rising returns to skill would cause top workers to have even higher-paid coworkers (which we would see as part of higher segregation) and top firms to have even higher-paid employees (which we would see as part of sorting). Although this point is relatively straightforward, it is an important one in light of the empirical evidence on rising returns to skill during this period, so we discuss it further in [Section V.A](#). Finally, the reduction in earnings for low-wage workers within large firms that we document corroborates the view that low-wage workers may have experienced a decline in access to high-paying jobs for institutional reasons, such as a decline in unionization or changes in company culture.

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

Our finding that the variance of firm pay premiums has been approximately stable in the U.S. contrasts with findings in [CHK](#) that rising dispersion in firm pay was an important driver of inequality in Germany. Yet [CHK](#) provide evidence that the decline in sectoral bargaining in Germany led to a change of pay-setting norms among firms and growth in the lower tail of firm effects, especially among new establishments. The U.S. has no sectoral



bargaining system, and even in the early 1980s, union coverage was nowhere near what it still is in Germany. Instead, the premium that large firms have traditionally paid in the United States has steadily declined (e.g., [Cobb and Lin 2017](#)). In related work ([Bloom et al. 2018](#)), we show that a reduction in firm fixed effects can explain much of that decline, tending to reduce the dispersion of firm pay premiums.

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

Finally, our results speak to studies analyzing the sources of earnings inequality at the very top of the earnings distribution. Absent data on the full distribution of wages within firms, a popular hypothesis has been that inequality at the very top of firms' pay (which can be seen for top executives in public firms in Execucomp) is a driving force leading to an increase in overall inequality (e.g., [Piketty 2013](#); [Mishel and Sabadish 2014](#)). Other research by [Smith et al. \(2017\)](#) has looked at the role of business owners' business income but does not connect it to the earnings of other employees at that firm. (As discussed below, our data do



not include this business income, but the trends found by [Smith et al. 2017](#) may amplify the between-firm results we find.)

The article is organized as follows. [Section II](#) describes the data set and the construction of the matched employer-employee data set and presents summary statistics from the sample. [Section III](#) presents the main results. [Section IV](#) decomposes the change in earnings inequality into components related to changes in firm average earnings, worker sorting, and worker segregation. [Section V](#) provides additional discussion on the sources of increases in within- and between-firm inequality, and [Section VI](#) concludes. All appendix material is available as an [Online Appendix](#).

## II. DATA

### *II.A. The Master Earnings File*

The main source of data used in this article is the Master Earnings File (MEF), which is a confidential database compiled and maintained by the U.S. Social Security Administration (SSA). The MEF contains earnings records for every individual who has ever been issued a U.S. Social Security number. In addition to basic demographic information (sex, race, date of birth, etc.), the MEF contains annual labor earnings information from 1978 to (as of this writing) 2013. Earnings records are derived from Box 1 of Form W-2, which is sent directly by employers to the SSA. These earnings data are uncapped and include wages and salaries, bonuses, tips, exercised stock options, the dollar value of vested restricted stock units, and other sources of income deemed as remuneration for labor services by the Internal Revenue Service.<sup>3</sup> Because of potential measurement issues prior to 1981 (see [Guvenen, Kaplan, and Song \(2014\)](#), [Kopczuk, Saez, and Song \(2010\)](#)), we start most of our analysis in 1981, although results back to 1978 look similar. All earnings are converted to 2013 real values using the personal consumption expenditures (PCE) deflator.

Because earnings data are based on the W-2 form, the data set includes one record for each individual, for each firm they

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

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

Although the MEF contains much data that are essential for answering questions posed in this article, these data have several limitations. First, our data only include labor earnings, not capital or self-employment income. Because those other types of income are not generally connected to a particular firm, it is beyond the scope of this study on firms and inequality.<sup>4</sup> Second, there are several worker- and firm-level variables that could be useful but are not available to us—for example, individuals' education and occupation, or firm profits. Third, we observe only total earnings in a year without data on hours or weeks worked, so we cannot measure wage rates. As discussed in [Section II.D](#), we only include worker earnings above a minimum threshold to minimize the effect of variation in hours worked.

In [Figure I](#), Panel A we plot the earnings distribution in 1981 and 2013. Looking at 2013, we observe a wide distribution of individual labor income—ranging from about \$9,800 a year at the 10th percentile, to \$36,000 at the median, \$104,000 at the 90th percentile, and \$316,000 at the 99th percentile.<sup>5</sup> By 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

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

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

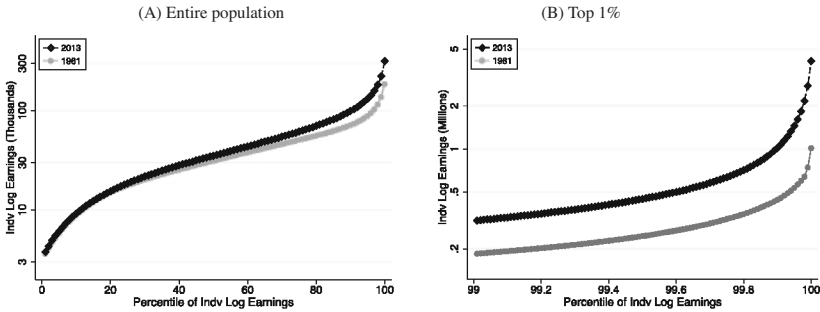


FIGURE I

## Cumulative Distributions of Annual Earnings in the SSA Data

For each percentile, statistics are based on the minimum earnings among individuals in that percentile of earnings in each year. All values are adjusted for inflation to 2013 dollars using the PCE price index. Only individuals in firms with at least 20 employees are included. Only employed individuals aged 20 to 60 are included in all statistics, where “employed” is defined as earning the equivalent of minimum wage for 40 hours per week in 13 weeks. Individuals and firms in public administration or educational services are not included.

notably for the top 1% in Figure I, Panel B. These patterns have been studied extensively in the literature on earnings inequality, and in particular in Kopczuk, Saez, and Song (2010) using the MEF. Here we focus on the role of employers in accounting for these changes.

*II.B. What Is a Firm?*

Throughout the article, we use 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.<sup>6</sup> They are often used in research on firms based on administrative data.

An EIN is not always the same, however, as the ultimate parent firm. Typically, this is because large firms file taxes at a slightly lower level than the ultimate parent firm.<sup>7</sup> Although it is

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

7. The 4,233 New York Stock Exchange publicly listed firms in the Dun & Bradstreet database reported operating 13,377 EINs in 2015, or an average of

unclear what level of aggregation is appropriate to define a “firm,” we follow much of the existing literature and view the EIN as a sensible concept reflecting a unit of tax and financial accounting. An EIN is a concept distinct from an “establishment,” which typically represents a single geographic production location and is another commonly used unit of analysis to study the behavior of “firms” (this is the definition used by [Barth et al. 2016](#), who study inequality using U.S. Census data). Around 30 million U.S. establishments in the Longitudinal Business Database in 2012 are owned by around 6 million EIN firms, so an establishment is a more disaggregated concept. As [Online Appendix Figure A.4](#) shows, 84% of the increase in cross-establishment inequality can be accounted for by firms, so firms are an appropriate unit of analysis.

### *II.C. Benchmarking the MEF against Other Data Sets*

Key statistics from our sample align quite well with their counterparts from aggregate data and from nationally representative data sets. In particular, when compared to the Current Population Survey (CPS), the SSA data match the changes in the variance of log annual earnings quite closely; see [Online Appendix Figure A.2](#).<sup>8</sup> We also checked a range of other statistics. For example, 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 [Online Appendix Figure A.1a](#) for the two series over time. Although the level of employment is higher in the MEF than in the CPS, the trend in the total number of individuals in the MEF who received W-2 income in a given year (our measure of total employment) closely tracks total employment in the

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3.2 EINs each. For example, according to Dun & 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 online divisions. As another example, Stanford University has four EINs: the university, the bookstore, the main hospital, and the children’s hospitals.

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

CPS (see [Online Appendix Figure A.1b](#)).<sup>9</sup> There are 6.1 million unique firms (EINs) in the MEF in 2013, each associated with at least one employee. This number is similar to the 5.8 million firms (with employees) identified by the Census Bureau's Statistics of U.S. Businesses data set in 2015. In addition, as shown in [Online Appendix Figure A.1c](#), the trends in each of these data sets are similar over time (at least since 1988, when the census data begin).

#### *II.D. Baseline Sample*

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

### III. INEQUALITY WITHIN AND BETWEEN FIRMS

In this section, we present our first main result—that a substantial part of the overall rise in earnings inequality in the

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

TABLE I  
PERCENTILES OF VARIOUS STATISTICS FROM THE DATA

Year	Group	Statistic	10%ile	25%ile	50%ile	75%ile	90%tile
1981	Firm	Earnings (unwgt)	12.6	16.6	23.8	32.5	41.9
1981	Firm	Earnings (wgted)	15.2	21.5	30.6	43.2	52.1
1981	Firm	Employees	22	26	38	73	169
1981	Individual	Earnings	9.46	18.2	31.9	51.7	73.8
1981	Individual	Earnings/firm avg	0.43	0.724	1.05	1.45	2.06
1981	Individual	Employees	42	127	1,153	12,418	62,718
2013	Firm	Earnings (unwgt)	13.8	19.3	30.5	43.8	61.4
2013	Firm	Earnings (wgted)	15.3	21.4	35.8	52.1	73.6
2013	Firm	Employees	22	26	39	79	189
2013	Individual	Earnings	9.82	19.2	36	63.2	104
2013	Individual	Earnings/firm avg	0.421	0.681	1.03	1.5	2.22
2013	Individual	Employees	45	157	1,381	14,197	78,757

*Notes.* Values indicate various percentiles for the data for individuals or firms. All dollar values are in thousands of 2013 dollars, adjusted for inflation using the PCE deflator. Only firms and individuals in firms with at least 20 employees are included. Firm statistics are based on mean earnings at firms and are either unweighted or weighted by number of employees, as indicated. Only employed individuals aged 20 to 60 are included in all statistics, where “employed” is defined as earning the equivalent of minimum wage for 40 hours per week in 13 weeks. Individuals and firms in public administration or educational services are not included.

United States happened between firms rather than within firms. Throughout this section we refer to a rise in the dispersion of average firm earnings as a rise in inequality occurring “between” firms. This result can be seen graphically in three ways. First, we start with a classic variance decomposition. Second, we compare changes in the earnings of a worker over time with those of his or her colleagues at selected percentiles of the earnings distribution. Finally, we perform a nonparametric density decomposition (à la [Machado and Mata 2005](#)), which allows us to ask how earnings inequality (at every point in the earnings distribution) would have changed if within-firm inequality—or, alternatively, between-firm inequality—had remained fixed at its initial level.

All three approaches confirm the central role played by the rise in between-firm inequality in rising overall earning inequality. That said, these results are not informative about the role played by the dispersion in firm pay premiums (net of worker composition) versus changes in worker compositions between firms in driving the rise in between-firm inequality, a question we tackle rigorously in [Section IV](#).

### III.A. A Simple Variance Decomposition

We decompose the overall (cross-sectional) variance of log earnings into within- and between-firm components. In particular, let  $y_t^{i,j}$  be the log earnings of worker  $i$  employed by firm  $j$  in period  $t$ .<sup>10</sup> This can be broken down into two components:

$$(1) \quad y_t^{i,j} \equiv \bar{y}_t^j + [y_t^{i,j} - \bar{y}_t^j],$$

where  $\bar{y}_t^j$  is the firm average earnings for firm  $j$ . Some simple algebra shows that the overall variance can be decomposed into two terms:

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

The first term is the between-firm variance of firm average earnings, and the second term is the employment-weighted mean of within-firm dispersion in employee earnings, where  $\omega_j$  denotes the employment share of firm  $j$  in the sample.

Figure II, Panel A plots the three terms in equation (2) separately for each year between 1978 and 2013. Of the 19 log point rise in the overall variance of log earnings during this period, about 13 log points was due to the between-firm component and 6 log points from the within-firm component. Thus, by this basic metric, 69% of the rise in earnings inequality happened because of a rise in the variance of average firm earnings.

In Section III.D we examine the robustness of this result within different subpopulations. A recurring theme that emerges is that firm size matters when it comes to the relative importance of within- versus between-firm inequality. In its simplest form, this can be seen in Figure II, Panels B and C, where we plot the same variance decomposition as before but do so separately for employees in small and medium-sized firms (20 to 10,000 employees) and for employees in mega firms (with 10,000+ employees). Between-firm inequality accounts for a higher share—about 84%—of the rise in inequality for smaller to medium firms, compared with 58% for mega firms. Indeed, although mega firms

10. For notational convenience, we suppress the dependence of subscript  $j$  on worker  $i$ , such that  $j \equiv j(i)$ .



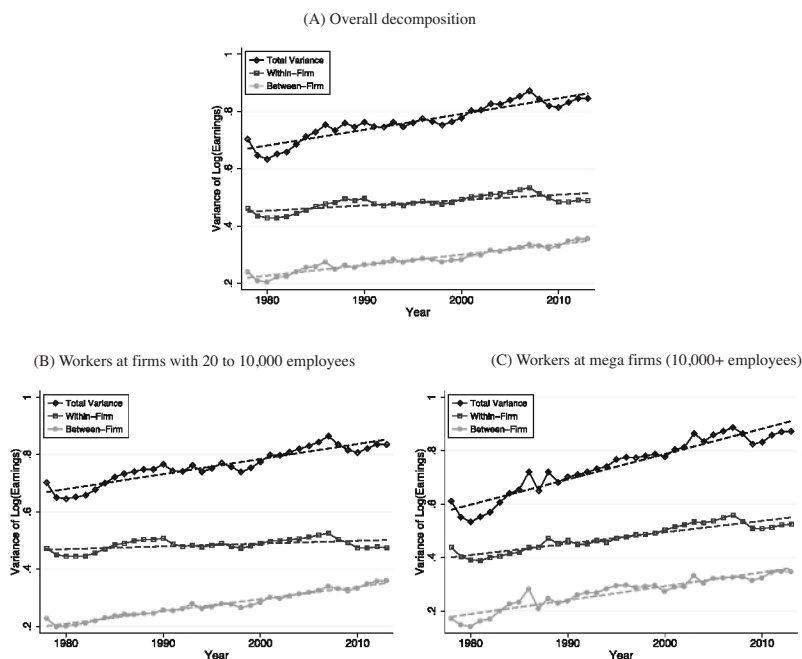


FIGURE II

Decomposition of the Variance of Log Annual Earnings within and between Firms: All, Smaller, and Mega Firms

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

employ only about a quarter of workers in our sample, they account for two-thirds of the rise in within-firm inequality.<sup>11</sup>

11. We calculate this by decomposing total within-firm variance at time  $t$  into  $V_t = f_{st}V_{st} + f_{lt}V_{lt}$ , where  $f$  is the fraction of the sample in each size of firms in a given year;  $V$  is within-firm variance;  $s$  denotes smaller and medium firms; and  $l$  denotes larger (mega) firms. We can decompose  $V_2 - V_1 = f_{s2}(V_{s2} - V_{s1}) + f_{l2}(V_{l2} - V_{l1}) + R$ , where  $R$  includes terms related to how the  $f$  terms change over time. The first term, relating to the rise in variance for smaller and medium firms, accounts for 36% of the rise in total within-firm variance; the second term accounts for 65%; and  $R$  accounts for the remainder.

TABLE II  
ROBUSTNESS CHECKS ON VARIANCE DECOMPOSITION

	Total var, 1981	Between- firm var, 1981	Total var, 2013	Between- firm var, 2013	Total var increase	Frac increase between
Baseline sample	0.652	0.222	0.846	0.357	0.194	0.694
Demean: county	0.611	0.181	0.800	0.311	0.189	0.687
Demean: 4-digit SIC	0.517	0.088	0.705	0.216	0.187	0.684
Demean: gender	0.564	0.166	0.819	0.337	0.256	0.668
Demean: year of birth	0.568	0.186	0.695	0.260	0.127	0.578
Workers in 20-10k firms	0.651	0.206	0.835	0.360	0.184	0.837
Workers in 10k+ firms	0.552	0.164	0.873	0.348	0.320	0.577

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

Restricting the sample to firms with 20 to 1,000 employees raises the share of the between-firm component even further to 92%, from 69% in the baseline sample. (Additional breakdowns and statistics are reported in [Table II](#) and discussed in [Section III.D.](#))

### III.B. Comparing Workers’ and Coworkers’ Earnings Changes

Although the variance decomposition is a useful and widely employed tool, it can mask differential trends in inequality across the earnings distribution. Additional insights on the relative importance of between- versus within-firm components can be gained by examining the percentiles of the earnings distribution. To this end, [Figure III](#), Panel A begins by plotting selected percentiles—99th, 90th, 50th, and 25th—of the overall (log) earnings distribution in each year, expressed as log deviations from their respective 1981 values. These percentiles spread out over time, confirming the rise in inequality revealed by the variance analysis and showing that it reflected a pervasive phenomenon across the income distribution.

Next [Figure III](#), Panel B plots the percentiles of the firm average earnings distribution that correspond to the percentiles of

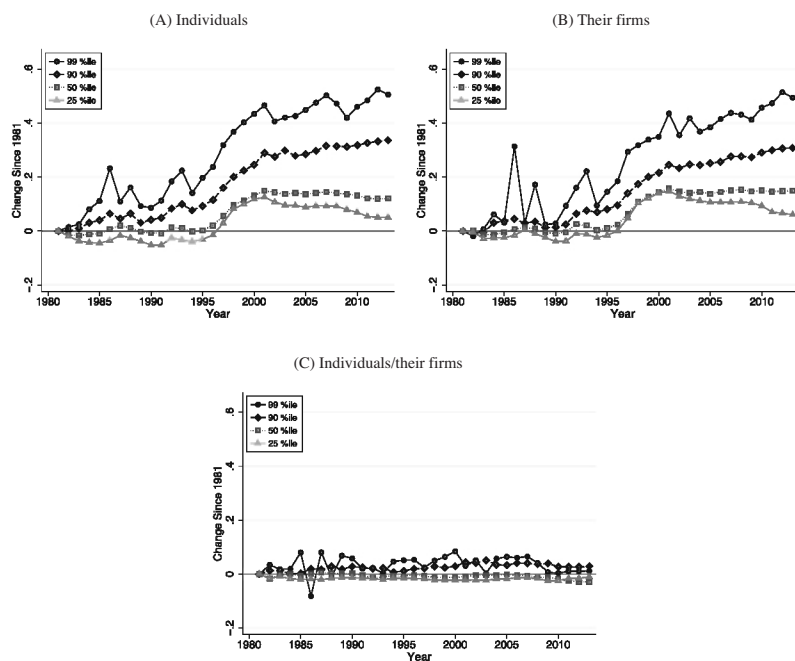


FIGURE III

Change in Percentiles of Earnings within and between Firms Relative to 1981

Only firms and individuals in firms with at least 20 employees are included. Only employed individuals aged 20 to 60 are included in all statistics, where “employed” is defined as earning the equivalent of the 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 to 2013 dollars using the PCE price index.

the worker earnings in Panel A. Specifically, for each worker we take the firm average earnings of his or her employer and average it across all the workers in the same earnings percentile.<sup>12</sup> So, for example, the line with circle markers in Figure III, Panel B shows how much the average earnings of the colleagues of workers who

12. The firm average earnings will appear as many times across various percentiles as its number of employees.

are in the 99th percentile of the earnings distribution (of Panel A) changed relative to their 1981 value.<sup>13</sup>

Comparing the two figures, notice how closely the corresponding percentiles in Figure III, Panels A and B align with each other over time. The implication is that workers' earnings broadly tracked those of their coworkers, a pattern that holds for workers across the earnings distribution. For example, the 99th percentile of the earnings distribution increased by 51 log points over this period, and the colleagues of these workers saw a similar average rise of 49 log points; thus, the gap between these workers and their colleagues increased by only 2 log points. To see this point more clearly, the final panel of Figure III, Panel C plots the difference between the corresponding percentile lines shown in Panels A and B: the differences stay close to zero over time, showing that workers' earnings in almost all percentiles have evolved in line with those of their coworkers during this 30+ year period.

In Online Appendix C.2, we provide further details showing that these trends hold true across the entire earnings distribution up to the 99.5th percentile (Figure A.11). The gap starts to widen above this point and especially inside the top 0.1% of the distribution (Figure A.12). The worker-coworker gap accounts for less than 10% of the rise in earnings at the 99.5th percentile, about 30% at the 99.8th percentile, and almost 50% at the 99.99th percentile.

This last finding is consistent with the general perception that the very top earners experienced faster earnings growth than their colleagues, leading to an expansion of inequality within firms. That said, it does not necessarily imply that rising top earnings was an important contributor to rising overall inequality. To examine this point, we recomputed the rise in the variance of log earnings from 1981 to 2013 by excluding several groups of top earners from the sample. As we report in Table A.3 in Online Appendix C.2, dropping the highest-paid, the top five highest-paid, or the top 1% highest-paid workers in each firm makes very little difference to the calculated rise in inequality, resulting in 19.5, 18.8, and 18.5 log point rises, respectively, compared with a 19.4 log point rise for the baseline sample.

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

### III.C. A Nonparametric Density Decomposition

The analysis in the previous section takes the workers as the primary focus and compares how their earnings evolved relative to their coworkers. Although this comparison is informative, another perspective is to take the firms as the primary focus and ask: how much would overall earnings inequality have risen had between-firm inequality remained unchanged? To answer this question, we employ a [Machado and Mata \(2005\)](#)–style density decomposition of the overall earnings distribution, slightly adapted (and more nonparametric) for our purposes. The method is described in detail in [Online Appendix E](#), but we briefly explain it here.

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

First, the line marked with diamonds (Full 2013) shows the actual change in firm average log earnings from 1981 to 2013 for a given percentile. Second, the Between-Firm Changes Only line (marked with circles) calculates the counterfactual individual earnings distribution if the firm percentiles had changed to 2013 values but the 50,000 quantiles of deviation within each firm-based percentile (500 quantiles within each of 100 firm-based percentiles) had remained at 1981 levels. Third, the Within-Firm Changes Only line (marked with squares) displays the counterfactual individual earnings distribution with 1981 values for firm-based percentiles but 2013 values for the distribution of earnings within quantiles.

The results of this counterfactual calculation in [Figure IV](#) are striking. First, the rise in between-firm dispersion of firm average earnings alone (the Between-Firm Changes Only line) can explain almost all of the rise in inequality for all percentiles below the 80th or so. This confirms our first main finding from our variance decomposition ([Figure II](#)) that a rise in the dispersion of firm average earnings can explain a substantial part of the rise in earnings inequality. However, also consistent with those previous findings, increases in the dispersion of earnings within firms do explain some rising inequality above the 80th percentile,

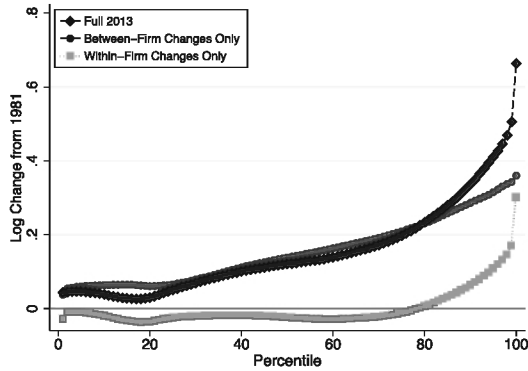


FIGURE IV

Counterfactual Rise in Inequality with Between- or Within-Firm Changes Only

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

with more explained at higher percentiles. In fact, about half of the rise in earnings inequality among the top 1% is accounted for by changes in within-firm variance using this method.

### III.D. Robustness of Results

The foregoing results show that perhaps rather surprisingly, the majority of the increase in earnings inequality among workers is associated with a rise in between-firm inequality. To investigate the robustness of these results, we reran the analysis in [Section III.A](#) in several different ways. The main finding—that the rise in the variance of firm average earnings accounts for most of the rise in earnings inequality—remains true for each such analysis. Results for some breakdowns are presented in [Table II](#). Results for a much larger set of breakdowns are presented in [Online Appendix Tables A.3 and A.4](#).

First, as [Moretti \(2013\)](#), [Diamond \(2016\)](#), and others have shown, housing costs and amenities have displayed different trends across U.S. regions, raising a natural question: could the rise in between-firm inequality simply reflect compensation for widening gaps in costs of living across U.S. regions? The answer turns out to be no: as seen in [Table II](#), most of the increase in the variance of earnings within counties occurred between firms. Another possible driver could be variations across industries: perhaps differential trends arising from trade, technology, or other industry factors are driving the rise in between-firm inequality (e.g., [Autor, Dorn, and Hanson 2013](#)). However, the results are similar within narrow four-digit SIC categories. Next, to see if these trends could be due to changes in demographics, we de-mean the data by gender or by year of birth and find that the between-firm component explains 67% and 58%, respectively, of the overall rise in variance.

Another possible complication would be if the increase in earnings inequality within firms is driven by differences within firms but across establishments. To address this possibility, in [Online Appendix](#) Figures A.4 and A.5 we use the Census Longitudinal Business Database (LBD) to show that inequality is primarily a between-firm phenomenon, rather than a within-firm but between-establishment phenomenon. This holds true even among the largest firms. We consider other robustness issues around health care, self-employment income, and business income in [Online Appendix](#) C.3. Overall, the main result that the majority of increasing inequality is associated with increasing dispersion in firm average earnings between firms seems to be broadly robust.

#### IV. THE ROLE OF WORKER AND FIRM EFFECTS

The rise in the dispersion in average earnings between employers that we document in [Section III](#) could come from two different sources. First, the distribution of firm pay premiums could have risen over time—that is, firms may have become increasingly unequal in the earnings they pay their workers above common market wages (which we refer to as the firm “pay premium”) because some firms had become economic “winners” and are sharing the increased profits with their workers, whereas other “loser” firms are not. Second, rising variance in firm average earnings could be driven by changes in worker composition: high-wage workers may be increasingly sorted into high-wage



firms, or workers may be increasingly segregating among firms (so that high-ability workers are clustering in some firms and low-ability workers in others). As we show below, changes in worker composition—including worker sorting and segregation—appear to jointly account for almost the entire increase in between-firm inequality in average earnings documented in [Section III](#).

#### IV.A. *Econometric Model of Worker and Firm Effects*

To analyze the worker and firm movements in earnings, we follow the [CHK](#) implementation of the model introduced by [AKM](#) and solved by [Abowd, Creedy, and Kramarz \(2002\)](#).<sup>14</sup> We 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

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

where  $\theta^{i,p}$  captures earnings related to fixed worker characteristics (such as returns to formal schooling or to innate ability),  $\beta^p$  captures the effect of time-varying worker characteristics (in our case, a polynomial in age and year fixed 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 denote by  $m^{i,j}$ .

The AKM model has proven to be an empirically successful extension of the standard human capital earnings function and has developed into the workhorse model for incorporating firm components into traditional earnings regressions. We confirm that the model appears to summarize a range of key patterns in our data surprisingly well. Hence, despite well-known limitations (which we discuss below and in [Online Appendix D](#)), we believe there is sufficient support for the model to treat it as a useful diagnostic device to better understand the patterns underlying the

14. To simplify notation, in what follows we again leave the dependence of the identity of the firm on the worker implicit, such that  $j \equiv j(i)$ . Note that although 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.

stark changes in the between-firm component of the variance in earnings over time that we documented in [Section III](#).

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

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

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

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

$$(5) \quad \begin{aligned} \text{var}(y_t^{i,j}) = & \underbrace{\text{var}(\theta^i - \bar{\theta}^j) + \text{var}(\epsilon_t^{i,j})}_{\text{Within-firm component}} \\ & + \underbrace{\text{var}(\psi^j) + 2\text{cov}(\bar{\theta}^j, \psi^j) + \text{var}(\bar{\theta}^j)}_{\text{Between-firm component}}, \end{aligned}$$

where the moments in the between-firm component are again weighted by the number of worker-years.<sup>15</sup>

[Equation \(5\)](#) shows how the between-firm component of the variance of earnings discussed in [Section III.A](#) can be decomposed into three pieces: a part deriving from the variance of firm effects,  $\text{var}(\psi^j)$ ; a part deriving from the covariance of worker and firm

15. As before, the within-firm component is  $\text{var}(\theta^i - \bar{\theta}^j) = E_j\{\text{var}(\theta^i | i \in j)\}$ , that is, the worker-weighted mean of the firm-specific variances of the worker effect (and similarly for  $\text{var}(\epsilon_t^{i,j})$ ).

effects,  $\text{cov}(\bar{\theta}^j, \psi^j)$ ; and a part deriving from the variance of the average worker effect in each firm,  $\text{var}(\bar{\theta}^j)$ .

The first component is the “widening firm premium” part, measuring whether the variance of firm pay premiums has increased. The second covariance component reflects worker sorting—high-paid workers are increasingly sorting into high-paying firms. Note that increased dispersion of individual fixed effects (e.g., due to rising skill prices) could lead to an increase in the sorting component even without a change in who works at which firm because that component measures a covariance rather than a correlation (see the discussion in [Section V.A](#)). The third part reflects worker segregation—lower- and higher-paid workers are increasingly likely to work in different firms. Similar to the sorting term, increased dispersion of individual fixed effects could increase the segregation term even without differences in who works with whom (also discussed in [Section V.A](#)). Splitting the worker component into the sorting covariance and segregation variance terms allows us to better characterize the role of firms in accounting for earnings inequality, since sorting increases aggregate inequality, whereas segregation does not.

#### IV.B. 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.<sup>16</sup> As is well known, firm fixed effects are identified by workers moving between firms and hence can only be performed for firms connected by worker flows and estimated relative to an omitted firm. Estimation of [equation \(3\)](#) is done on the largest set of firms connected by worker flows. We impose similar restrictions on the data as in our descriptive analysis, with one major exception: because of limitations in computing power and the computational intensity of the AKM estimation, we present worker and firm effects only for men in the main text; results for women only, which are substantively similar, are presented in [Online Appendix D](#). All other restrictions, including restricting the sample to firms with

16. The choice of intervals trades off limitations in computational power and the desire to analyze changes in the variance over time with the sampling error in estimates of the worker and firm effects and the resulting bias in the variance and covariance terms, which depend on the number of movers between firms. We experimented with intervals up to 10 years and found that our results did not change substantially.

20+ total (male and female) employees, dropping workers in education and public administration, and imposing a minimum earnings threshold, are the same as described in [Section II](#).<sup>17</sup>

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.<sup>18</sup> Given the nature of our data, such differences can arise because of variation at 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.<sup>19</sup>

It is worth noting that under the plausible assumption that job moves occur randomly within a year, there is no mechanical reason labor supply effects should introduce a bias into our

17. To maximize the number of observations in the connected set, when we estimate the model we do not impose a restriction on firm size and do not exclude the education and public sectors; those observations are excluded after firm and worker effects have been estimated. (The only exceptions are [Online Appendix Tables A.5 and A.6](#), which report summary statistics based on all observations used to calculate fixed effects.) One more minor difference between results in this section and other results is that these results impose a minimum earnings threshold of 520 (equal to 40 hours for 13 weeks) times the 2013 hourly minimum wage, adjusted for inflation to the given year with the PCE. Other results impose a threshold of 520 times the contemporaneous minimum wage. Results are similar with both definitions, but due to limits on the number of results disclosures, we have had to keep this different definition. There are also two figures in the current version with slightly different samples, also due to limits on the number of results disclosures: [Figure V](#) and [Online Appendix Figure A.17](#) include men who earn more than 520 times the contemporaneous minimum wage, regardless of industry or firm size. For clarity, all tables and figures include sample definitions.

18. In that sense, our implementation is comparable to [Abowd, McKinney, and Zhao \(2018\)](#), who implement this model using quarterly earnings. [Lachowska, Mas, and Woodbury \(2018\)](#) implement the AKM model with data on hours worked from the state of Washington and find only moderate systematic differences in firm effects due to hours variation.

19. For example, systematic worker differences in the propensity to take part-time jobs or to be unemployed for part of the year 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.

estimates of firm effects. To further investigate this possibility, we analyzed a sample where earnings are unlikely to be affected by job change: a “sandwich sample” where we drop an observation for an individual in year  $t$  if that individual’s primary EIN in year  $t$  is different from their EIN in years  $t - 1$  or  $t + 1$ . Those results are in the third column of [Online Appendix Table A.7](#); results are qualitatively similar to the baseline even though the sample is only about half the size, and is likely weighted toward a different set of individuals.

We tried various additional ways to address the potential effects of systematic labor supply differences in our findings. We have experimented by imposing increasingly stringent lower earnings restrictions. Using retrospective data from the CPS, one can show that this approach tends to eliminate part-time or part-year workers. Our results are robust to variation in this restriction; see the “full-time” sample in the last column of [Online Appendix Table A.7](#). Because 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. Importantly, CPS data do not reveal any trend in the aggregate variance of weekly hours worked or weeks a 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.<sup>20</sup>

Estimating the model requires a set of identification assumptions, which given the prior literature on this, we do not discuss in detail in the article but relegate to [Online Appendix D](#). Because 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 CRM assumption). After reviewing the evidence, we join an increasing number of papers whose results indicate that the AKM

20. 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.

model can be estimated without too much systematic bias (e.g., AKM, CHK, and Abowd, McKinney, and Zhao 2018).

In particular, we do not find that an increasing dispersion in worker-firm match effects plays a role in explaining rising inequality. To check whether adding a match-specific component would substantially increase the fit of the model, we followed CHK and indirectly included a match effect ( $m_{ij}$ ) in the model. Although, not surprisingly, allowing for a match effect reduces the root mean squared error (RMSE) and raises the adjusted  $R^2$ , the standard deviation of match effects declines somewhat over time. Similarly, we find that the goodness of fit of the model without a match component has increased over time from an  $R^2$  of 74% (1980–1986) to an  $R^2$  of 81% (2007–2013), driven by a reduction in the RMSE and an increase in the variance of earnings. If the rise in the sorting of workers to firms that we find had resulted from an increasing role of match effects, we would have expected the RMSE to rise and the goodness of fit of the model without match effects to decline over time (see [Online Appendix Table A.6](#)).<sup>21</sup>

Finally, if the model is correctly specified, on average workers changing from one firm to another should experience earnings changes corresponding to the estimated firm effects. To implement this comparison, we used our data to perform event study analyses of the effect of job mobility on earnings akin to those shown in CHK (see their figure VII). In [Figure V](#), 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.<sup>22</sup> On average, the patterns of earnings changes are approximately symmetric for

21. 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 [Online Appendix Figure A.14](#)).

22. 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. Because we are following workers for six years, we adjust earnings for flexible time trends. In [Online Appendix C, Figure A.17](#), we show a version of the figure in which the four firm classes are generated based on average earnings within the firm.

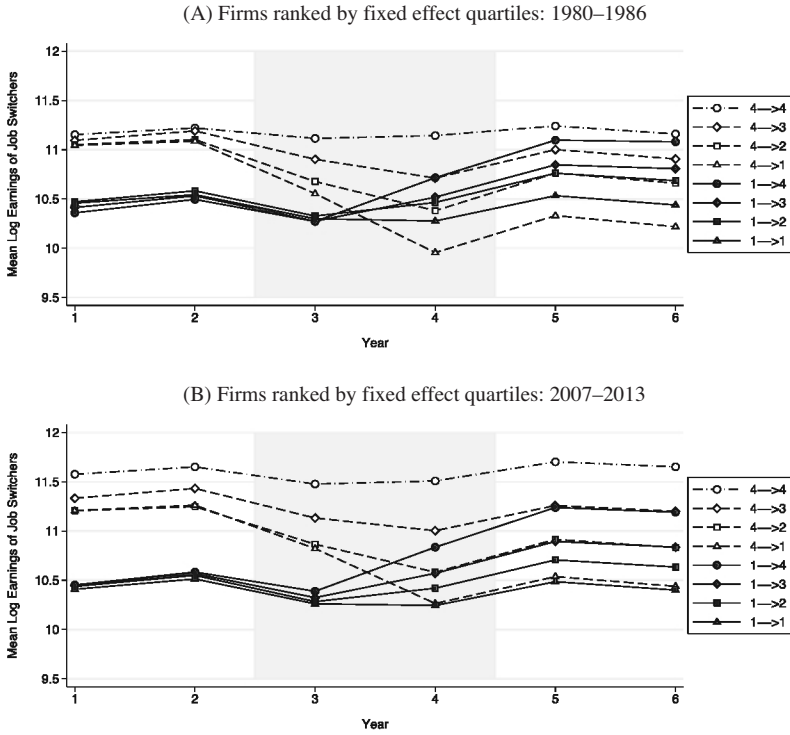


FIGURE V

## Event Study of Change in Mean Firm Fixed Effects for Job Changers

Calculations based on SSA data. Only men are included in these statistics. Men are included regardless of industry or firm size. Only employed individuals aged 20 to 60 are included in all statistics, where “employed” is defined as earning the equivalent of the contemporaneous minimum wage for 40 hours per week in 13 weeks. For an explanation of the methodology, see [Section IV.B](#) and [Online Appendix D.2](#). For all observations, the main job is the same in years 1, 2, and 3 and then switches to a new main job for years 4, 5, and 6. The shaded region marks the possible years of the job switch. Firm fixed effect quartiles are weighted by worker-years and calculated in years 2 and 5. Log earnings are detrended by subtracting the time-varying observable AKM component from each observation.

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.<sup>23</sup>

Although the CRM assumption is sufficient for the AKM model to give unbiased estimates of fixed effects, it is well known that estimates of the variances and covariance of the fixed effects are biased. This bias arises because of variance and correlation of the sampling errors of worker and firm effects, respectively. As a result, the bias declines with the number of firm moves that determine the precision of the estimates. This so-called limited mobility bias, first noted by [Abowd et al. \(2003\)](#), has gained attention recently, with bias-corrected estimates proposed by [Borovičková and Shimer \(2017\)](#) and [Kline, Saggio, and Sølvsten \(2018\)](#). However, we are primarily interested in the change in the variances and covariance; that change should be approximately correctly estimated to the extent that mobility patterns have not changed substantially. Indeed, we follow [Andrews et al. \(2012\)](#) and estimate the model with only 10% of the sample, and as expected we find somewhat higher variances and a lower covariance, but the changes over time are approximately the same as in the 100% sample. We have examined the incidence and characteristics of mobility in our sample, and find stable patterns across intervals (see [Online Appendix Table A.12](#)). Ideally, we would estimate changes in bias-corrected estimates of the variances and covariances; however, this goes beyond the scope of this article, given the additional assumptions imposed by [Borovičková and Shimer \(2017\)](#) and the high computational cost of the [Kline, Saggio, and Sølvsten \(2018\)](#) estimator.

#### *IV.C. Decomposing the Change in the Variance of Earnings*

The main implications of our statistical analysis for understanding the role of firms in explaining the evolution of earnings inequality are shown in [Tables III and IV](#). [Table III](#) shows the components of the standard decomposition of variance in [equation \(4\)](#) for our five periods, as well as for the change from period 1 (1980–1986) to period 5 (2007–2013). The basic

23. In [Online Appendix D](#) we provide further discussion of our implementation and sensitivity analysis; among other objectives, to assess the potential role of labor supply differences, we show that our results are not affected by excluding the year of the move or by strengthening our restriction on earnings to isolate full-time workers ([Table A.7](#)). We show that the estimated firm effects are correlated over time ([Table A.13](#)) and that there is unlikely to be differential selection between movers and stayers in terms of observable characteristics once we condition on age and firm effects ([Table A.12](#)).

TABLE III  
BASIC DECOMPOSITION OF THE RISE IN INEQUALITY OF ANNUAL EARNINGS

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

Notes: Var(y): variance of annual earnings, Var(WFE): variance of worker fixed effects, Var(FFE): variance of firm fixed effects, Var(Xb): variance of covariates, Var(ε): variance of residual.  
Sum of firm-related components is equal to var(FFE) + Cov(WFE, FFE) + Cov(WFE, Xb) + Cov(FFE, Xb). Only men are included in these statistics. Only firms and individuals in firms with at least 20 employees are included. Only employed individuals aged 20 to 60 are included in all statistics, where “employed” is defined as earning the equivalent of 2013 minimum wage, adjusted for inflation with the PCE, for 40 hours per week in 13 weeks. Individuals and firms in public administration or educational services are not included.

TABLE IV  
DETAILED DECOMPOSITION OF THE RISE IN EARNINGS INEQUALITY BETWEEN AND WITHIN FIRMS

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

TABLE IV  
(Continued)

	Interval 1 (1980–1986)		Interval 2 (1987–1993)		Interval 3 (1994–2000)		Interval 4 (2001–2007)		Interval 5 (2007–2013)		Change from 1 to 5	
	Comp. (1)	Share (2)	Comp. (3)	Share (4)	Comp. (5)	Share (6)	Comp. (7)	Share (8)	Comp. (9)	Share (10)	Comp. (11)	Share (12)
<b>Segregation Index</b>	$\frac{\text{Var}(m\_WFE)}{\text{Var}(WFE)}$	0.161	0.186		0.216		0.223		0.252		0.091	
	$N$ (millions)	221.62	256.22		285.57		304.45		302.77		81.15	

Notes:  $y$ : natural log of annual earnings,  $m\_y$ : firm average log earnings,  $m\_WFE$ : firm average of worker fixed effect,  $PFE$ : firm fixed effect,  $m\_Xb$ : firm average of its employees'  $Xb$  component,  $\text{diff\_}y$ : difference of a worker's log earnings from  $m\_y$  for its employer,  $\text{diff\_}WFE$ : difference of a worker's  $WFE$  from  $m\_WFE$  for its employer,  $\text{diff\_}Xb$ : difference of  $Xb$  from  $m\_Xb$  for its employer,  $\epsilon$ : AKM residual. Only men are included in these statistics. Only firms and individuals in firms with at least 20 employees are included. Only employed individuals aged 20 to 60 are included in all statistics, where "employed" is defined as earning the equivalent of 2013 minimum wage, adjusted for inflation with the PCE, for 40 hours per week in 13 weeks. Individuals and firms in public administration or educational services are not included.

variance decomposition from [equation \(4\)](#) yields two key findings. First, as found by others, in all periods, about half of the level of the variance of men's log annual earnings is explained by the variance of worker effects, which at 46% to 52% is by far the biggest component. On the other hand, firm fixed effects and the covariance between firm and worker fixed effects together explain about 20% of the total variance in each period.

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

These changes contrast with CHK's results from a similar exercise in Germany. CHK found that approximately equal shares of the rise in variance were explained by worker fixed effects (39%), establishment fixed effects (25%), and their covariance (34%). The larger role for a rising dispersion of worker fixed effects in the United States could have many causes, but one potential explanation is the role of rising returns to skill, discussed in more detail in [Section V.A](#). On the other hand, the larger role for rising dispersion in firm fixed effects in Germany could be due to the decline in sectoral contracting, as discussed by CHK; no such change happened in the United States. In any case, it is interesting that the covariance explains a similar proportion of the rise in inequality in both countries. Indeed, the rise in correlation between worker effects and firm/establishment effects is similar in the United States (0.10 to 0.38) and Germany (0.03 to 0.25).

To better understand these patterns and connect them to our descriptive analysis in [Section III](#), [Table IV](#) presents results for the more detailed variance decomposition of earnings shown in [equation \(5\)](#). Again, the table shows results separately for our five periods, as well as for the change from period 1 (1980–1986) to period 5 (2007–2013). As shown in the final column of [Table IV](#), consistent with our results in [Section III](#), the sum of the firm components—chiefly consisting of a rise in the covariance term and a rise in our measure of segregation (i.e.,  $\text{var}(\bar{\theta}^j)$ ) explains 74% of the rise in the overall variance.<sup>24</sup>

24. This number is quite close to the corresponding statistic reported in [Section III.A](#). However, statistics in this section may differ from those in

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

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

[Table V](#) also shows that larger firms experienced more substantial growth in inequality inside the firm (an increase of 5.6 log points with all firm sizes but a reduction of 0.7 log points in firms with fewer than 1,000 employees). Given a similar absolute increase in between-firm inequality, this implies that larger firms experienced stronger increases in overall earnings inequality than smaller firms. (The same fact could also be seen by comparing the panels of [Figure II](#), which plot the entire time series during this period.) Interestingly, large firms initially appear to have had lower within-firm inequality than smaller firms. This is consistent with

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[Section III.A](#) because of differences in the sample selection (including the fact that these statistics involve men only) and time periods analyzed.

TABLE V  
DECOMPOSITION OF THE RISE IN EARNINGS INEQUALITY BETWEEN AND WITHIN FIRMS BY FIRM SIZE

	Excluding mega firms (10,000+ employees)					Excluding firms with over 1,000 employees				
	Interval 1 (1980–1986)		Interval 5 (2007–2013)		Change from 1 to 5	Interval 1 (1980–1986)		Interval 5 (2007–2013)		Change from 1 to 5
	Comp.	Share	Comp.	Share		Comp.	Share	Comp.	Share	
<b>Total variance</b>	0.736	—	0.920	—	0.184	0.762	—	0.903	—	0.141
<b>Between-firm variance</b>	0.204	27.7	0.370	40.2	0.166	0.205	26.9	0.353	39.1	0.148
	Var(m_WFE)	8.1	0.128	13.9	0.068	0.069	9.1	0.133	14.7	0.063
	Var(m_FFE)	0.073	9.9	0.078	8.5	0.068	8.9	0.074	8.2	0.006
	Var(m_Xb)	0.006	0.8	0.007	0.7	0.006	0.8	0.007	0.7	0.000
	2Cov(m_WFE, m_FFE)	0.037	5.0	0.108	11.8	0.036	4.8	0.095	10.5	0.058
<b>Within-firm variance</b>	2Cov(m_WFE, m_Xb)	0.012	1.6	0.026	2.8	0.012	1.5	0.024	2.6	0.012
	2Cov(m_FFE, m_Xb)	0.017	2.3	0.024	2.6	0.014	1.8	0.022	2.4	0.008
	Var(diff_y)	0.532	72.3	0.550	59.8	0.557	73.1	0.550	60.9	−0.007
	Var(diff_WFE)	0.300	40.8	0.356	38.7	0.317	41.7	0.355	39.4	0.038
	Var(diff_Xb)	0.052	7.0	0.050	5.4	0.054	7.1	0.050	5.6	−0.004
<b>Segregation Index</b>	Var(ε)	0.163	22.2	0.141	15.3	0.171	22.5	0.145	16.0	−0.027
	2Cov(diff_WFE, diff_Xb)	0.014	1.9	0.003	0.3	0.011	1.5	0.000	0.0	−0.011
	2Cov(diff_WFE, ε)	0.003	0.4	0.000	0.0	0.003	0.4	−0.001	−0.1	−0.004
	2Cov(diff_Xb, ε)	0.000	0.0	0.000	0.0	0.000	0.0	0.000	0.0	0.000
	$\frac{\text{Var(m\_WFE)}}{\text{Var(WFE)}}$	0.166		0.264		0.179		0.272		0.093
	N (millions)	159.19	220.79		61.60	108.07		146.55		38.48

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



the 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 (first row).<sup>25</sup>

We also examined to what extent our main findings in Table IV can be explained by differential patterns occurring across industries. The results are shown in Online Appendix Figure A.19 and Table A.15. Although there are some interesting differences in the time trends in the variance components across industries, our three main patterns of a rise in sorting, a rise in the variance of worker effects, and a stagnation (or small reduction) in the variance of firm effects occur within major sectors. Hence, most of our findings are driven by changes within sectors, and changes in sector composition have only a moderate effect.

## V. EXPLAINING THE EMPIRICAL TRENDS

Here we establish that increasing returns to skills could mechanically explain part of the rise in sorting and segregation we find, but this mechanical effect cannot explain all of it. We discuss factors that could underlie the rise in sorting and segregation we document and then turn to changes in within-firm inequality, especially within larger firms.

### V.A. *Rising Returns to Skill, Segregation, and Sorting*

We found in Section IV.C that worker fixed effects diverged substantially over the past three decades. A substantial literature provides evidence of a rising skill premium as a key driver of rising income inequality.<sup>26</sup> The same rise in skill premium could mechanically explain part of the observed rise in segregation and sorting. Here we discuss how such an effect could arise and present some simple calculations to estimate its potential importance.

Define  $s^i$  as individual  $i$ 's skill level and  $r^p$  as the returns to skill in period  $p$ , so that the worker fixed effect can be written as  $\theta^{i,p} = r^p s^i$ . Suppose that the distribution of worker skills is fixed over time, whereas the returns to skill are allowed to vary. In that

25. 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.

26. For detailed reviews of the evidence on the rising skill premium, see, for example, Acemoglu and Autor (2011).

case, the change in returns to skill between periods 1 and 5 can be calculated as

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

where the values for the variances are taken from columns (1) and (9) of Table III.

To evaluate how much of the rise in sorting we estimate can be driven by changing skill prices, suppose counterfactually that the distribution of worker skills across firms had not changed. In that case, average worker effects within each firm would change by a factor of  $\frac{r^5}{r^1}$ .<sup>27</sup> Thus, if only skill prices had changed, we would expect

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

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

Next we turn to the rise in segregation, which can be affected more strongly by changing skill prices. To see this, note that the change in segregation,  $\text{var}(\bar{\theta}^{j,p})$ , between periods 1 and 5 is

$$(8) \quad \frac{\text{var}(\bar{\theta}^{j,5})}{\text{var}(\bar{\theta}^{j,1})} = \left(\frac{r^5}{r^1}\right)^2 = (1.2)^2,$$

implying a 44% rise in segregation if the only change was the rising returns to skill. In the data, we found a 126% increase in  $\text{var}(\bar{\theta}^{j,p})$  during this time (i.e.,  $\text{Var}(\text{m\_WFE})$  rising from 0.053 to 0.12 in Table IV), implying that the mechanical effect of returns to skill can account for about 35% ( $= \frac{0.44}{1.26}$ ) of the observed increase of the rise in segregation we find.

Of course, these calculations rely on assumptions about the unchanging distribution of skills in the economy as a whole and within firms. Additionally, our estimates would vary if worker fixed effects do not have the simple form assumed here. In any case, the estimates in this section suggest that a nonnegligible

27. This is because  $\bar{\theta}^{j,p} = \frac{1}{N_j} \sum_{i|j(i)=j} \theta^{i,p} = r^p \times \frac{1}{N_j} \sum_{i|j(i)=j} s^i$ .

fraction of the rise in segregation might be driven by changing returns to skills rather than changes in sorting among coworkers, but less so for the rise in sorting we find.

### *V.B. Accounting for the Rise in Between-Firm Inequality*

An important question for understanding the strong rise in inequality in the United States is which mechanisms underlie a rise in sorting of high-wage workers to high-wage firms. Any hypothesis should also be compatible with other key findings, including a stable distribution of firm pay premiums ( $\psi^j$ , i.e., firm differences in composition-adjusted pay), a rise in worker segregation, a relatively stable distribution of firm size (see [Online Appendix](#) Figure A.6—so this is not simply the atomization of firms), and the fact that a rise in sorting and segregation is occurring within industries, regions, and demographic groups. Our finding in [Section IV](#) that the variance of the worker-firm (“match”) component in earnings is stable over time provides additional discipline on possible models. There are several candidate explanations, including outsourcing, changes in rent-sharing, changes in search costs, or technological or organizational innovations that arise in worker-firm or worker-worker complementarities, but it is difficult to fit all of the facts within any basic model.

One explanation is that rising overall inequality is driven by skill-biased technical change, whereas rising outsourcing is constraining the impact on within-firm inequality. Likely drivers of the rise in outsourcing include falling costs of outsourcing (due to improving information-communications technology), a desire to limit the extent of inequality within firms due to concerns over fairness (e.g., [Akerlof and Yellen 1990](#); [Dube, Giuliano, and Leonard 2015](#); [Breza, Kaur, and Shamdasani 2018](#)), and a push by businesses to focus on “core competencies” ([Prahalad and Hamel 1990](#)).<sup>28</sup> ([Weil 2014](#) discusses these and other causes of the increasingly fissured workplace.)

The rise in outsourcing is also consistent with the increased occupational, educational, and ability segregation of employees found in Sweden by [Håkanson, Lindqvist, and Vlachos \(2015\)](#), in Germany by [CHK](#), and in the United States by [Barth et al.](#)

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

(2016) and Handwerker (2015). Furthermore, Goldschmidt and Schmieder (2017) examine German data, finding clear evidence that a rise in outsourcing contributed to increasing inequality. An explanation based on outsourcing could also be compatible with a stable distribution of firm fixed effects and firm size, especially in the United States, where existing low-wage firms could absorb outsourced workers.

Another class of explanations rely on complementarities in production between (heterogeneous) workers. Kremer and Maskin (1996) consider a Cobb-Douglas production function with tasks as inputs that differ in their contribution to output (i.e., the exponent). When the skill gap across workers is not too large, optimal assignment of workers across firms (i.e., production functions) calls for distributing high-skill workers across firms and assigning them to the more critical (high exponent) tasks (as managers) and assigning lower-skill workers to less critical tasks. When the skill gap is larger, the input of high-skill managers is undermined by the low-skill workers, so it becomes optimal to have each firm employ workers with similar skills, using some as managers and others as workers at less critical tasks, leading to greater sorting.

Another set of explanations include models with complementarities between workers and firms. A frequent hypothesis in the literature on inequality is that high-skilled workers and technology or complex tasks are complements in production. If high-wage firms are technological leaders and increasingly attract high-wage workers, this would naturally lead to sorting. Although this would imply an increasing variance of the worker-firm match component, which is at odds with our findings, firms may be able to attract such workers in other ways. Finally, there is a long tradition in labor economics suggesting that firms pay different wages to workers with the same skills, possibly due to monopsony power in the labor market, or the presence of efficiency wages. If high-wage workers are more mobile or have a higher elasticity of labor supply, perhaps because they are more geographically mobile, they will be more likely to work at high-wage employers (e.g., Card et al. 2018). A reduction in search costs, perhaps due to a decline in the cost of acquiring information or a rise in labor market intermediation, could then raise the degree of sorting without increasing the relative pay of high-wage workers at high-wage firm (i.e., the match effect).

### V.C. Accounting for the Rise in Within-Firm Inequality

As we documented in Sections III.A and IV.C, the rise in within-firm inequality has primarily occurred in mega firms. In this section, we delve deeper into these mega firms to better understand which part(s) of the within-firm earnings distribution contributed to rising within-firm inequality.

Figure VI plots the average change in earnings for employees in various positions (ranks) in the firm, ranging from the top-paid employee down to the employee in the 10th percentile. Three key differences emerge between smaller firms (here, firms with 100 to 1,000 employees) and mega firms. First, over this 30+ year period, the real earnings of the median-paid employee actually fell—by 7 log points (7%)—in mega firms while rising robustly—by 27 log points (31%)—in smaller firms. Second, in mega firms, earnings increases at the top end were far larger: since 1981, the highest-paid employees in mega firms saw their average log earnings increase by 86 log points (137%) compared with a 37 log points (45%) increase in smaller firms. As a result, the top-to-median employee earnings gap widened by 94 log points (155%) in mega firms and only 10 log points (11%) in smaller firms—a strikingly large difference. Finally, albeit smaller than the changes at the top, mega firms experienced a widening in the bottom half of the earnings distribution as well, a phenomenon absent in smaller to medium-sized firms. We turn to examining these two changes in large firms.

*1. Stagnating Earnings for Lower-Paid Workers in Mega Firms.* The 7% decline in the median employee's earnings in mega firms is only part of the story: earnings percentiles below the median fell even more in these firms, explaining about one-third of the rise in within-firm variance for these firms.<sup>29</sup> The question

29. We calculate this by noting that within-firm variance is defined as  $\text{var}(y_t^{i,j} - \bar{y}_t^j) = \frac{1}{N} \sum_i (y_t^{i,j} - \bar{y}_t^j)^2$ . We then define the fraction  $F_S$  of variance accounted for by a subset of the population  $s$  as  $F_S = \frac{\sum_{i \in S} (y_t^{i,j} - \bar{y}_t^j)^2}{\sum_i (y_t^{i,j} - \bar{y}_t^j)^2}$ . This large contribution to inequality of below-median inequality may seem surprising judging from Figure VI, which shows a much larger expansion at the top. Clearly, this is because there are more than 5,000 employees below the median for these firms compared to the 50 highest-paid employees that show large rises in that figure.

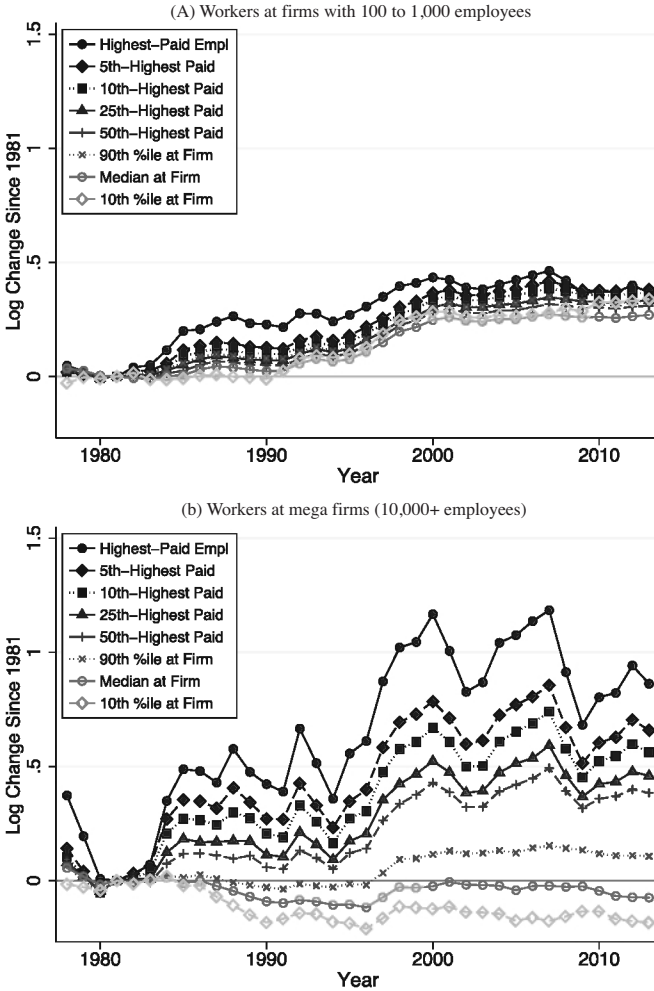


FIGURE VI

### Change in Within-Firm Distribution of Earnings: Small versus Mega Firms

Only firms and individuals in firms of the listed size are included. Only employed individuals aged 20 to 60 are included in all statistics, where “employed” is defined as earning the equivalent of the 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 to 2013 dollars using the PCE price index.

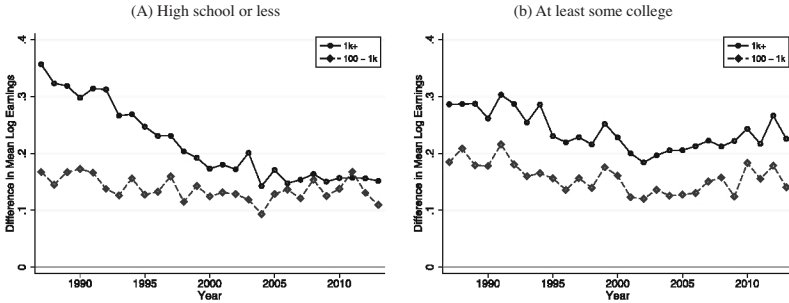


FIGURE VII

The Earnings Premium between Larger Firms (100+ Employees) and Smaller Firms (Less than 100 Employees), by Education

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

is, why have earnings fallen more in the lower percentiles of mega firms but not in smaller firms?

One fact that helps explain this inequality is that the lower percentile earnings in large firms have converged from above with those in smaller firms. For example, in 1981 the median-paid employee in mega firms was paid 40 log points more than his or her counterpart in smaller firms, but this gap shrank to only 5 log points by 2013.

To further examine this convergence and its potential link to education, we used the CPS, which reports information on employer size since 1987. As shown in Figure VII, for individuals with a high-school degree or less, the earnings premium between large firms (1,000+ employees using the CPS definition) and small firms (fewer than 100 employees) has fallen by over half, from 36% in 1987 to 15% in 2013. In contrast, the premium has fallen far less for individuals with at least some college education, from 29% in 1987 to 23% in 2013. This 21% decline in the premium for low-skilled workers can potentially account for an important part of the decline in earnings in the bottom half of the distribution at mega firms that we found in SSA data. This

collapse and its connection to inequality are further explored by Cobb and Lin (2017) and Bloom et al. (2018).<sup>30</sup>

2. *Rising Earnings in the Top 1%.* We saw in Figure VI that the earnings of the highest-ranked employees behave differently in mega firms and smaller firms during this period. One possible reason is suggested by the widespread use by large firms of stock options and stock grants to reward their senior executives. This can potentially drive some of the rise seen in the data because this practice has increased during this period and because even without a change, the large run-up in stock prices in the 1980s and 1990s could lead to very fast earnings growth for these executives.

To shed light on this question, we regressed the yearly change in log earnings for top earners at different positions in firms of different sizes that we obtained from the SSA data on the year-to-year change in the S&P 500, controlling for annual GDP growth and the unemployment rate. Figure VIII plots the coefficients on the change in the S&P 500. For example, the top right point with a triangle marker on the “10k+” line shows a coefficient of 0.38 for the top-paid employee (presumably the CEO) in mega firms. In other words, for every 10% rise in the S&P 500, the earnings of the top-paid employee rose by 3.8%. The coefficients decline with rank: 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, the top-paid employee in firms with 100 to 1,000 employees has a coefficient of only 0.08, in line with what we would expect if larger firms use stock-based compensation more extensively than smaller ones.

Simply applying the magnitudes of the 680% real increase in the S&P 500 over the period 1981–1999 to the average 0.25 coefficient on the S&P 500 returns for top employees in mega firms in Figure VIII yields a real cumulative earnings increase of 170%, which is similar to the earnings gains of up to 200% that this group made over the same period (see Figure VI). Given the dramatic increases in the earnings at the top, it is perhaps

30. Note that the fact that lower-educated workers may have had higher wages at high-wage firms suggests this might have been an area of worker-firm match components in earnings. This is compatible with our main AKM analysis that showed such match components are present but their contribution to explaining changes in the variance of earnings is limited. A better understanding of wage setting for lower-wage workers at larger employers is a fruitful avenue for future research.



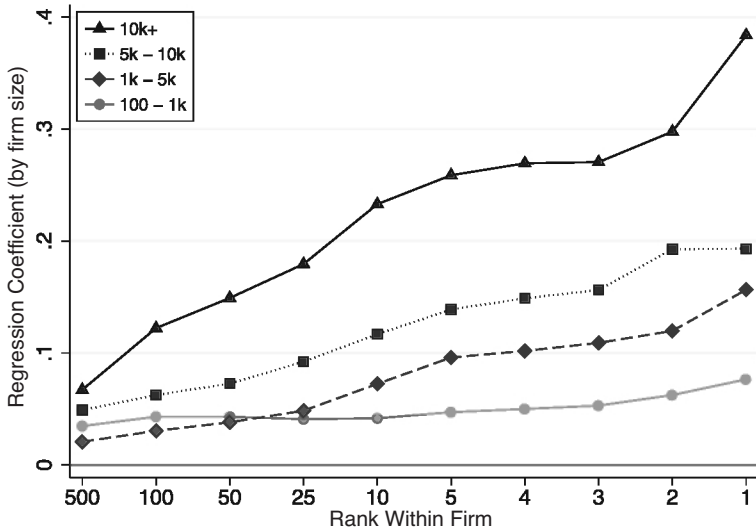


FIGURE VIII

## Earnings Responsiveness to the S&amp;P 500 Returns

Only employed individuals aged 20 to 60 are included in all statistics, where employed is defined as earning the equivalent of minimum wage for 40 hours per week in 13 weeks. Individuals and firms in public administration or educational services are not included. Each data point represents a regression coefficient; the dependent variable for each regression is the change in average log earnings from year  $t$  to  $t + 1$  among those at the given rank or percentile within their firm, for firms of given sizes (100 to 1k, 1k to 5k, 5k to 10k, and 10k+ employees). The coefficient shown is on the log change in the S&P 500 during year  $t$ . There are 35 observations in each regression: one a 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.

surprising that the top 50 employees accounted for only 3% of the increase in within-firm variance in mega firms over the sample period. (The top five employees accounted for less than 1% of the increase.) The reason is that by definition, there are not that many of them—making up only 35,000 of the 20 million employees in mega firms—so they have little impact on the increasing within-firm inequality. In contrast, the top-earning 10% of employees, a group that contains a much wider group of managers, technicians, and other highly paid individuals in large firms, accounted for 46% of the rise in within-firm inequality.

## VI. CONCLUSIONS

Using a massive, matched employer-employee database that we construct for the United States, we documented four stylized facts. First, the rise in earnings inequality between workers over the past three decades is strongly associated with their employers. Two-thirds of the increase in the variance of log earnings from 1981 to 2013 can be accounted for by a rise in the dispersion of average earnings between firms and one-third by a rise in the differences in earnings between workers within firms.

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

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

Fourth, the rise in within-firm inequality is concentrated in large firms with 1,000+ employees (and even more so in mega firms). This is driven by a fall in the earnings premium in large firms for median- and lower-paid employees and by rising earnings for the top 10% of employees.

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

leading to greater cross-firm segregation by worker skill level. Studying this and other channels is an important area for further research.

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

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#### SUPPLEMENTARY MATERIAL

An [Online Appendix](#) for this article can be found at [The Quarterly Journal of Economics](#) online. Data and code replicating tables and figures in this article can be found in [Song et al. \(2018\)](#), in the Harvard Dataverse, [doi:10.7910/DVN/QVVMHOM](https://doi.org/10.7910/DVN/QVVMHOM).

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