Firming Up Inequality*

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Abstract

Using a massive new matched employer-employee database that we construct for the United States, we show that the rise in earnings inequality between workers over the last three decades has primarily been a between-firm phenomenon. Over two-thirds of the increase in earnings inequality from 1981 to 2013 can be accounted for by the rising variance of earnings between firms and only one-third by the rising variance within firms. This rise in between-firm inequality was particularly strong in smaller and medium sized firms (explaining 84% for firms with fewer than 10,000 employees). In contrast, in the very largest firms with 10,000+ employees almost half of increase in inequality took place within firms, driven by both earnings declining for employees below the median and rising sharply for the top 100 or so best-paid employees. Finally, examining the mobility of employees across firms we find that the increase in between-firm inequality has been driven by increased employee segregation—high- and low-paid employees are increasingly clustering in different firms.

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

JEL Codes: E23, J21, J31

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1 Introduction

The dramatic rise in U.S. wage inequality since the 1970s has been well documented. An enormous body of theoretical and empirical research has been conducted over the past two decades in an attempt to understand the causes of this trend. While much has been learned from these analyses, several major questions remain unanswered. An important set of open questions concerns the link between wage inequality on the worker side to trends in the behavior of the firms and industries that employ these workers. A major difficulty with studying questions of this sort has been the lack of a comprehensive, matched employer-employee data set in the United States that covers the period of rising inequality, beginning with the 1970s.

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

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

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

\footnote{For detailed reviews of these trends as well as of theoretical models designed to study them, see, among others, Katz and Autor (1999) and Acemoglu and Autor (2011).}
at the individual level (rather than household) and are not capped (top- or bottom-coded), which allows us to examine both the bottom and top of the individual earnings distribution. As an administrative records database, there is little measurement error, and our sample size of about 100 million individuals per year enables us to do detailed analysis of industry, demographic, and regional groups.

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

Our second result is that this dominance of between-firm inequality in explaining overall inequality trends is also seen in very fine subsets of the overall economy. It holds true within broad—as well as very narrow—industry groups, within different firm size groups (with the exception of very large firms—discussed in a moment), within U.S. regions and counties, for different demographic groupings (age and gender), and by different measures of inequality (variance of log earnings, trends and long-differences of income percentiles). It also holds true for the sample of continuing firms only and using 5-year average measures of earnings.

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

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

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

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

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

In the U.S., Davis and Haltiwanger (1991) were among the first to draw attention to the fact that rising inequality among workers was closely mirrored in rising inequality among establishments, building on a long literature documenting the existence of establishment wage differentials (see, for example, Groshen (1991)). However, Davis and Haltiwanger (1991) lacked data on wages within firms, which limited the scope of their analysis to between-firm data. Kremer and Maskin (1996) also highlighted the issue of rising inequality between firms and laid out an elegant model to explain this in terms of offsetting effects of task asymmetry and task complementarity. Closest to our work, Barth et al. (2014) use the Longitudinal Employer-Household Dynamics data for nine state between 1992 to 2007 as a source of U.S. employer-employee matched data. They also find a large share (about 2/3 in their analysis) of the rise in earnings inequality can be attributed to the rise in between-establishment inequality.

Our paper extends this by doubling the sample period back to include the 1980s and post 2007 to the Great Recession; and including all U.S. states which is important for analyzing top-end pay since the top 1% are heavily concentrated in Northeast states like Connecticut, New Jersey and New York which are not in their main dataset. We also focus on firms rather than establishments, which allows us to study pay inequality in larger multi-establishment firms and include their corporate headquarters, which is important given the striking different in our data between smaller and larger firms.

The paper is organized as follows. Section 2 describes the data set and the construction of the matched employer-employee data set, presents summary statistics from the sample, and discusses the methodology. Section 3 presents the main results. Section 4

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2Preliminary work by Abowd et al. (2016) also use the Longitudinal Employer-Household Dynamics data to analyze trends in inequality within and between firms, and finds similar results.
decomposes the change in earnings inequality in components related to changes in firm average earnings and worker segregation. Section 5 provides additional findings as to the sources of increases in between-firm inequality, and Section 6 concludes.

2 Data

The main source of data used in this paper is the Master Earnings File (MEF), which is a confidential database compiled and maintained by the U.S. Social Security Administration (SSA). The MEF contains a separate line of record for every individual that has ever been issued a U.S. Social Security Number. In addition to basic demographic information (sex, race, date of birth, etc.), the MEF contains labor earnings information for every year from 1978 to (as of this writing) 2013. Earnings data in the MEF is based on Box 1 of Form W-2, which is sent directly from employers to the SSA. Data from Box 1 is uncapped, and includes wages and salaries, bonuses, tips, exercised stock options, the dollar value of vested restricted stock units, and other sources of income deemed as remuneration for labor services by the U.S. Internal Revenue Service. Because of potential measurement issues prior to 1981 (see Guvenen et al. (2014a)) we start our analysis from 1981. All earnings are converted to 2013 real values using the Personal Consumption Expenditures deflator.

Because earnings data are based on the W-2 form, the data set includes one record for each individual, for each firm they worked in, for each year. Crucially for our purposes, the MEF also contains a unique employer identification number (EIN) for each W-2 earnings record. Because MEF covers the entire U.S. population and has EIN records for each job of each worker, we can use worker side information to construct firm-level variables. In particular, we assign all workers who received wage earnings from the same EIN in a given year to that firm. Workers who hold multiple jobs in the same year are linked to the firm providing their largest source of earnings for the year. The resulting matched employer-employee data set contains information for each firm on total employment, wage bill, and earnings distribution, as well as the firm’s gender, age, and job tenure composition. Since we do not have information on hours or weeks worked, we measure individual annual earnings (or their total wage bill) rather than wage rates. As

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3The MEF has previously been used by, among others, Davis and Von Wachter (2011) and Guvenen et al. (2014b), who describe further details of the data set. Kopczuk et al. (2010) use the 1% CWHS extract of SSA data to conduct an extensive analysis of long run trends in mobility.
In Figure 1a, we plot the income distribution in real terms in 1981 and 2013. Looking at 2013 we observe a strikingly wide distribution of individual labor income—ranging from about $9,800 a year at the 10th percentile, to $36,000 at the median, $104,000 at the 90th percentile and $316,000 at the 99th percentile. These figures are somewhat lower than data on earned income from, for example, Piketty and Saez (2003) primarily because they are based on individual (rather than household) values; see Figure A.14. Comparing the 1981 and 2013 distributions we can also see the increase in inequality as the 2013 distribution is increasingly pulling away from the 1981 distribution in the upper income percentiles, most notably for the top 1% in Figure 1b.

2.1 What is a Firm?

Throughout the paper, we use Employer Identification Numbers (EINs) as the boundary of a firm. The EIN is the level at which companies file their tax returns to the IRS, so it reflects a distinct corporate unit for tax (and therefore accounting) purposes. EINs are commonly used to define firms by government agencies, such as the Bureau of Labor...
Statistics. They are also often used in research on firms based on administrative data. This is often not the same, however, as the ultimate parent firm. For example, the 4,233 NYSE publicly listed firms in the Dunn & Bradstreet database report operating 13,377 EINs, or an average of 3.2 EINs each. While it is unclear what the correct level of aggregation is to define “the firm”, we feel the EIN is a reasonable concept reflecting a unit of tax and financial accounting. An EIN is a distinct concept from an “establishment”, which typically represents a single geographic production location and is another commonly used unit of analysis to study the behavior of “firms” (e.g., this is the definition used by Barth et al. (2014) who study inequality using U.S. Census Data). There are around 30 million U.S. establishments in the Longitudinal Business Database in 2012 owned by around 6 million EIN firms, so an establishment is a more disaggregated concept. As Abowd et al. (2016) show, 84% of the increase in cross-establishment inequality can be accounted for by firms, so firms are an appropriate unit of analysis.

2.2 Benchmarking the Master Earnings File Against Other Data Sets

Aggregating wages and salaries from all W-2 records over all individuals in the MEF yields a total wage bill of $6.8 trillion dollars in 2013. The corresponding figure from the National and Income Product Accounts (NIPA) is $7.1 trillion, so these are very close; see Figure A.1a for the two series over time.

The total number of individuals in the MEF who received W-2 income in a given year (our measure of total employment) also closely tracks total employment in the Current Population Survey (CPS). In 2013, for example, the MEF measure contains 155 million workers, while the CPS indicated that, on average, 144 million individuals were employed at any given time. The difference is likely due to the fact that 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

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4See http://www.bls.gov/bdm/sizeclassqanda.htm, questions 3 and 5.
5Typically, this is because large firms file taxes at a slightly lower level than the ultimate parent firm. For example, according to Dunn & Bradstreet, Walmart operates an EIN called “Walmart Stores” which operates the domestic retail stores, with different EINs for the Supercenter, Neighborhood Market, Sam’s Club and On-line divisions. As another example Stanford University has four EINs: the university, the bookstore, and the main hospital and children’s hospitals.
include them. Figure A.1b shows total employment in the MEF and CPS; these two series track each other well over time.

There are 6.1 million unique firms (EINs) in the MEF in 2013, each associated with at least one employee. This number is slightly higher than the 5.8 million firms (with employees) identified by the Census Bureau’s Statistics of U.S. Businesses data set. In addition, as shown in Figure A.1c, the trends in each of these data sets are similar over time (at least since 1988, when the Census data begins).

2.3 Baseline Sample

We restrict our baseline sample to individuals aged 20 to 60 who work full time, where “full time” is defined as earning at least that year’s minimum wage for one quarter full time (so for 2013, 13 weeks for 40 hours at $7.25 per hour, or $3,770). These restrictions reduce the effect on our results of individuals who are not strongly attached to the labor market. We also restrict to firms (and workers in firms) with 20+ employees to help ensure that within-firm statistics are meaningful. We exclude firms (and workers in firms) in the government or educational sectors, as organizations in those sectors are schools and government agencies rather than what economists think of as firms. This yields a sample of on average 72.6 million workers and 477,000 firms per year, rising from 55.5 million and 371,000 in 1981 to 85.2 million and 517,000 in 2013 respectively. As we show in the appendix none of our results are sensitive to these assumptions—in particular, the results look similar using the all ages, all firm sizes, all industries (Figure A.9), and minimum earnings thresholds up to full time (2080 hours) at minimum wage (Figure A.10). Some statistics describing the sample are shown in Table I. More details about the data procedures are discussed in Appendix B.

3 Inequality Within and Between Firms

3.1 Rising Between-Firm Inequality

The key result in this paper—that rising inequality between workers is primarily a between (rather than within) firm phenomenon—can be shown graphically in a number of ways. We first examine a decomposition of variances over time. We then look at earnings percentiles which is a similar approach to examining yearly changes in inequality over time, but focusing on particular key percentiles of the earnings distribution. Finally,
Table I – Percentiles of various statistics from the data

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

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

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

3.1.1 Simple Variance Decomposition

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

\[
y_{t,i} = \bar{y}_i^j + [y_{t,i,j} - \bar{y}_i^j],
\]

\(^6\)For notational convenience we suppress the dependence of the subscript \( j \) on worker \( i \).
Figure 2 – Decomposition of Variance in Annual Earnings Within and Between Firms: All, Smaller, and Larger Firms

(A) Overall decomposition

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

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

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

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

$$\text{var}_i(y_t^{i,j}) = \text{var}_j(\overline{y}_t^j) + \text{var}_i(y_t^{i,j} | i \in j).$$

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

3.1.2 Tracking Select Percentiles

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

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

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

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7I.e., the line shows $\delta_{\text{firm}} = E[\tilde{y}_{2013} \mid i \in Q_{2013,q}] - E[\tilde{y}_{1981} \mid i \in Q_{1981,q}]$, 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 $i$. 

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

(A) Individuals

(B) Their Firms

(C) Individuals/Their Firms

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

the cross-section, but that the inequality of the persistent worker component of earnings has also shown a substantial increase.
3.1.3 Inequality Across Percentiles

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

First, we start with individuals in the baseline sample in 1981 and group them into percentile bins on the basis of their income in 1981. Then we calculate the average of log real earnings (in 2013 dollars) for each percentile bin. Let $P_{t,x}$ denote this average for percentile bin $x$ in year $t$. We then repeat the same procedure for 2013 (now for individuals who satisfy sample selection in that year). The blue line marked with diamonds (labeled “Indv Total Earnings”) in Figure 4 plots $P_{2013,x} - P_{1981,x}$ for all percentile groups $x = 1, 2, ..., 99, 100$ against the percentile number $y$ on the horizontal axis. So, for example, we see that between 1980 and 2013 the 50th percentile of earnings has increased by 12 log points (13 percent) from about $32,000 to $36,000. The upwards slope of the individual line highlights the rise in individual earnings inequality—earnings at higher percentiles have risen at a faster rate, and this rise grows steadily as you move up the
income percentiles.

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

Finally, the green line marked with squares (labeled “Indv Earnings/Firm Average”) is based on the residual earning measure, $y_{i,j}^t - \bar{y}_j^t$. Specifically, we compute the average of $y_{i,j}^t - \bar{y}_j^t$ across all workers within a percentile in each year.\(^8\) We then plot the change between in this statistic in 1981 and 2013. For example, in 1981, individuals in the 50th percentile of individual earnings had average log earnings 0.05 higher than their firms’ mean earnings (corresponding to about 106% of their firms’ mean earnings). In 2013, individuals in the 50th percentile had average log earnings 0.03 lower than their firms’ mean earnings (corresponding to about 103% of their firms’ mean earnings). We plot the difference of –0.02 at the 50th percentile. Note that this “Individual/Firm” line will be mechanically equal to the difference between the “Individual” line and the “Firm” line.

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

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

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\(^8\) Notice that in all likelihood, the workers we average over are employed in different firms and each residual is computed with respect to a worker’s own employer.
demographic group gains or loses relative to the firm average for all employees. When we examine the whole population, or subsets of the population that, for each firm, include either everyone or no one at that firm, the green line’s weighted average taken over all percentiles must be zero. The key finding from this figure is that the green line is almost flat across all percentiles, indicating that within-firm inequality has remained nearly constant over the entire population of workers.

3.2 Robustness of Results

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

First, given the different trends in rents and amenities identified by Moretti (2013) and Diamond (2016) maybe this increase in between-firm inequality simply reflects regional variation? To investigate this we re-ran our analysis within each county and took the average (Figure A.2) and within each Census region (Figure A.3), finding very similar results. In case these trends reflects changes in demographics Figure A.4 reports the graphs by age breakdowns (20s, 30s, 40s and 50s), and by gender, with again the results looking broadly similar for each subgroup. Another possible driver could be variations by industry---maybe differential trends due to trade, technology or other industry factors are driving the firm results (e.g. Autor et al. (2013) and Pierce and Schott (2016))? However, the results are also similar within broad industry SIC 1-digit categories as shown in Figure A.5, and also on average within narrow SIC 4-digit categories as shown in Figure A.6.

We also experimented with different measures of the firm average earnings, using the log of average earnings (rather than the average of log earnings), firm median earnings, average of log earnings among only those in the bottom 95%, and calculating firm-average log earnings leaving out the individual themselves; we once again finding very similar

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

10For age and gender graphs, to improve comparability between them and with the firm statistics, sorting into percentile bins is based on the overall population.
results (see Figure A.7). We examined a panel of continuing firms in case our results are being driven by the selection of firms, and see again very similar results (see Figure A.8). We varied our definition of full-time earnings from 520 hours at 2013 minimum wage to 260, 1040, and 2080 hours and again find broadly similar results (see Figure A.10). Finally, we compare in Figure A.11 changes in 5-year (rather than 1 year) earnings in case the results are driven by changes in temporary (rather than permanent) earnings, but see very similar results.

We also considered other robustness issues around healthcare and self-employment income. On healthcare perhaps rising firm earnings inequality is offset by an increase the generosity of firm health-care insurance that as a flat entitlement to all employees provides a progressive compensation component. In fact, as Burkhauser and Simon (2010) show, employer-provided (but not Government) health insurance is about as unequally distributed as earnings among the bottom eight income deciles. In fact, Kaestner and Lubotsky (2016) show that employer-provided health insurance actually increases inequality. The reason is higher paid employees are more likely to be in firms offering generous health-care packages, have higher firm coverage rates, pay lower premiums and are more likely to enroll.11 Regarding self-employment the IRS Statistics of Income report that in 2012 while 16.5% of individuals reported self-employment income on Schedule C and 1099 forms it accounted for only 3.2% of all income, most of which is concentrated in employees of smaller firms. Hence, in our 20+ employee sample self employment income is too small to play a major role in shaping inequality.

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

3.3 Firm Size

When we break firms down by size—defined by the number of employees according to our full-time and age definitions (earning above 520 hours times minimum wage in the year and aged 20 to 60)—we see some difference between “smaller to large firms” (those with

11 The part of healthcare that has reduced inequality is Medicaid and Medicare, which is strongly progressive and has increased in generosity (Burkhauser and Simon, 2010). However, since this is independent of the employee-firm match this does not influence our analysis.
fewer than 10,000 employees) and the “mega-firms” (those with 10,000+ employees). Figures 2b and 2c plot the decomposition of variance for these two groups. We see in Figure 2b that in smaller to large firms—which contain over 70% of employees and over 99% of firms—inequality is almost entirely (84%) due to between-firm variation. In comparison, increases in inequality in the mega-firms—which account for about 30% of employees and only about 700 firms—is still mostly (58%) between firms but also has a large (42%) within-firm component.

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

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

### 3.4 The Top 1%

Much of the recent policy and media attention around inequality has focused on the top 1% of earners, following in particular the pioneering early work of Piketty and Saez (2003). Interestingly, it turns out that while the top 1% looks generally similar in terms of the role of firms accounting for the majority of the rise in inequality between workers, there are also some differences in the top 0.5%. To show this, Figure 6 plots the cross-sectional percentiles graph for just the top 1%, breaking this into 100 subdivisions of 0.01% each (since the entire population is about 70 million workers, each 0.01% thus represents about 7,000 people).

We see in Figure 6 that up until about the 99.5% point—which is an earnings threshold
Figure 5 – Change in Within-Firm Distribution of Annual Earnings: Smaller and Larger Firms

(A) Workers at Firms with 100 to 1000 employees

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

Notes: Only firms and individuals in firms of the listed size are included. Only full-time individuals aged 20 to 60 are included in all statistics, where full-time is defined as earning the equivalent of minimum wage for 40 hours per week in 13 weeks. Individuals and firms in public administration or educational services are not included. Statistics shown are based on the average log earnings among those at the given rank or percentile within their firm. All values are adjusted for inflation using the PCE price index.
Figure 6 – Rise in inequality of annual earnings between 1981 and 2013 among top 1% of earners

Notes: See notes for Figure 3.

of around $450,000 in 2013 (see Figure 1b)—increases in individual earnings from 1981-2013 within each percentile point have been matched almost fully by the increases in earnings of their firms. However, in the top 0.5% and particularly the top 0.1% there is such a steep increase in earnings between 1981 and 2013 that these rises have outpaced their colleagues. For example, the 99.95th percentile reveals individual earnings growth of 102 log points (178%) while the firms these employees are in have increased their average pay by only 73 log points (106%), generating a 29 log point gap.\(^\text{12}\)

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

\(\text{12}\)Most of this divergence between top workers and their firms occurred between 1981 and about 1988; since then, earnings of even those at the top of the top 1% has risen similarly to their firms.

20
The Role of Worker Sorting and Segregation

As we have seen, the increase in inequality observed over the last 35 years in the U.S. is primarily a between-firm phenomenon. But this could come from two different sources. First, a “widening firm premium” story: firms may be increasingly unequal in their earnings because some firms had become economic “winners” and are sharing the increased profits with their workers, while other “loser” firms are not.\textsuperscript{13} Second, a “worker segregation” story: workers may be increasingly segregation among firms, so that high-ability workers are clustering in some firms and low ability workers in other firms. As we show below, the worker segregation story appears to account for almost the entire increase in between-firm inequality.

4.1 Econometric Model of Worker and Firm Effects

To analyze the worker and firm movements in earnings we closely follow the Card et al. (2013) [henceforth CHK] implementation of the model introduced by Abowd et al. (1999) [henceforth AKM] and solved by Abowd et al. (2002).\textsuperscript{14} We will divide our time period into five seven-year periods, as further discussed below, and estimate a separate model for each period \( p \). The regression model we estimate in each period is

\[
y_{ijt}^{i,j} = \theta_{i}^{i,p} + X_{i}^{i} \beta^{p} + \psi_{i}^{j,p} + \epsilon_{i}^{i,j},
\]

where \( \theta_{i}^{i,p} \) 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 restricted cohort effects), and \( \psi_{i}^{j,p} \) captures persistent earnings differences related to firm \( j \) (such as sharing of rents or compensating differentials). The residual, \( \epsilon_{i}^{i,j} \), captures purely transitory earnings fluctuations. In addition, the residual will also contain any worker-firm specific (match) components in earnings, which we will denote by \( m_{i}^{i,j} \).

The AKM model has proven an empirically successful extension of the standard human capital earnings function, and has developed into the work-horse model for incorporating

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

\textsuperscript{14}To simplify notation we leave the dependence of the identity of the firm on the worker implicit, such that \( j = j(i) \). Note that while most of the literature uses the model to analyze daily or hourly wages, we follow an increasing number of papers that analyze earnings. We discuss the potential role of labor supply differences below.
firm components into traditional earnings regressions. Clearly, this model is likely to be a simplification of firms’ role in the setting of earnings, since in its basic form it does not allow for worker-firm interactions, or time-varying firm-specific components (something we discuss in Appendix C). Despite these reservations, we confirm the model appears to summarize a range of key patterns in our data surprisingly well. Hence, we feel there is sufficient support for the model to treat it as a useful diagnostic device to better understand the patterns underlying the stark changes in the between-firm component over time.

The estimates of the parameters of the econometric model in equation (3) can be used to further decompose the within- and between-firm components of the variance. Ignoring time-varying worker characteristics $X_i^p$ for now and variation across periods (dropping $p$), the firm-worker decomposition is

$$\text{var}(y_{i}^{i,j}) = \text{var}(\psi^j) + \text{cov}(\theta^j, \psi^j) + \text{var}(\theta^j) + \text{var}(\theta_i - \theta^j) + \text{var}(\epsilon_{i}^{i,j}),$$

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

\(^{15}\)Note that one can rewrite the within-firm component as $\text{var}(\theta_i - \overline{\theta}^j) = E_j\{\text{var}(\theta^i| i \in j)\}$, i.e., as the worker-weighted mean of the firm-specific variances of the worker effect (and similarly for $\text{var}(\epsilon_{i}^{i,j})$).
4.2 Implementation of Regression Model Using SSA Data

We estimate equation (3) separately for five adjacent seven-year intervals beginning in 1980 and ending in 2013.\textsuperscript{16} As is well known, firm fixed effects are identified by workers moving between firms, and hence can only be estimated relative to an omitted firm. Estimation of equation (3) is done on the largest set of firms connected by worker flows. We impose the same restrictions on the data as in our descriptive analysis, with three exceptions. To maximize the number of observation in the connected set, we do not impose a restriction on firm size and do not exclude the education and public sector. Because of limitations in computing power, we estimate worker and firm effects separately for men and women (finding similar results for both gender groups). All other restrictions, including imposing a minimum earnings threshold, are the same as described in Section 2.

While 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.\textsuperscript{17} Given the nature of our data, such differences can arise both because of variation at the intensive margin (i.e., hours worked) and 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.\textsuperscript{18} However, it is worth noting that under the plausible assumption that job moves occur randomly within a year there is no mechanical reason why labor supply effects should introduce a bias into our estimates of firm effects.

We tried various ways to address the potential effect of systematic labor supply differences in our findings. We have experimented by imposing increasingly stringent lower earnings restrictions. Using retrospective data from the CPS, one can show that this tends to

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

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

\textsuperscript{18}For example, systematic differences in the propensity to take part-time jobs or to be unemployed would load onto the worker fixed effect. If firms offer different hours packages or offer seasonal work, this could load onto the firm effect as well. If high-hour workers (or stable workers) are increasingly sorted into high-hour firms (or stable firms), labor supply can also affect the nature of sorting. If job moves are partly triggered by changes in hours worked, labor supply effects could also contribute to a failure of the CRM assumption.
eliminate part-time or part-year workers. Our results are robust to variation in this restriction; see, for example, Figure A.10. Since our analysis based on the CPS also shows more stringent earnings cutoffs eliminate low-wage full-time or full-year workers, we use a less stringent restriction in our main sample. In addition, we have also tried to isolate full-year to full-year job transitions by only comparing earnings in years before and after job moves that were flanked by two years of positive earnings at the employer. Again, our results were robust to this more stringent specification. CPS data do not reveal any trend in the aggregate variance of weekly hours worked or weeks per year worked over time. Given the robustness of our findings and the stability in trends in the variance of time worked, we are confident that our main results are mainly driven by changes in the variance of wages, not hours or days worked.\footnote{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 about 5 of 7 years in each period. This number is very similar to numbers reported by CHK (Table I) for full-time men in Germany.}

Estimating the model requires a set of identification assumptions, which given the prior literature on this we do not discuss in detail in the paper and relegate to Appendix C. Since the estimated firm effects will capture any systematic differences in earnings of movers before and after the job move, to associate estimated firm effects with true underlying firm-specific differences in pay, we have to assume that conditional on worker and firm effects, job moves do not depend systematically on other components, in particular worker-firm specific job match effects (the conditional random mobility (CRM) assumption). After reviewing the evidence, we join an increasing number of papers whose results indicate the AKM model can be estimated without systematic bias (e.g., AKM, CHK, and Abowd et al. (2016)).

Following CHK, we summarize several pieces of evidence in favor of the CRM assumption and against an important role of match effects in explaining rising inequality. First, we find the goodness of fit of the model has increased over time from an $R^2$ of 74\% (1980-1986) to an $R^2$ of 81\% (2007-2013), driven by both a reduction in the root mean squared error (RMSE) and an increase in the variance of earnings. If the rise in sorting of workers to firms we find had resulted from an increasing role of complementarities (i.e., match effects), we would have expected the RMSE to rise and goodness of fit of the model without match effects to decline over time (see Appendix Table C2).

Second, to check whether adding a match-specific component would substantially increase the fit of the model, we directly included a match effect ($m_{ij}$) in the model.
While, not surprisingly, allowing for a match effect reduces the RMSE and increases the adjusted $R^2$ by about the same amount each period, to $82\%-87\%$, the standard deviation of match effects declines somewhat over time. If the increasing covariance of worker and firm effects we find reflected a rising importance of worker-firm complementarities omitted from the model, this would imply the standard deviation of match effects should rise (see Appendix Table C2).\textsuperscript{20} Third, since violations of the separability assumptions in the AKM model would likely cause large mean residuals for certain matches (say, where highly skilled workers are matched to low-wage establishments), we directly examined the distribution of average residuals by 100 cells of estimated firm and worker effects. For most cells, the mean residual is very small, below 0.02, and shows few systematic patterns (see Appendix Figure A.16).

Finally, if the model is correctly specified, on average workers changing from one firm to another should experience earnings changes corresponding to the estimated firm effects. In Figure A.17, we divided firms into quartiles according to their estimated firm effects, and recorded the mean earnings of workers moving between the four firm-type classes in the years before and after the job change.\textsuperscript{21} On average, the patterns of earnings changes is approximately symmetric for switches between firm groups, and there are no signs of systematic earnings declines or increases before or after job changes, both of which are consistent with the CRM assumption. Overall, despite being an obvious abstraction from reality, we conclude that our model constitutes a useful tool for a better understanding of trends in earnings inequality in our data.

4.3 Decomposing the Change in the Variance of Earnings

Table 2 presents results for the the variance decomposition of earnings (equation 4) for our 5 periods, as well as for the change from period 1 (1980-1986) to period 5 (2007-2013). There are two key findings. First, in all periods, about half of the level of the variance of log annual earnings is explained by the variance of person effects, which at $48\%-53\%$

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

\textsuperscript{21}To deal with the fact that we do not know the specific time of the move, we followed workers from two years before the year $t$ in which we observe the move (i.e., from year $t-2$ to $t-1$), to two years after the year succeeding the move (from year $t+2$ to $t+3$). To further try to approximate transition between “full-time” jobs, we only look at workers who remained at the firm in the two years before and two years after the move. Since we are following workers for six years, we adjust earnings for flexible time trends.

25
is by far the biggest component. The two other within-firm components, the variance of time-varying worker characteristics (7 – 10%) and the variance of residuals (12% – 16%) together explain roughly another 20% of the variance. Firm-related components together (the variance of fixed effects, and their correlation with worker effects and worker characteristics) explain about 20 – 25% of the level variance.

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

To learn more about the rise in the covariance of worker and firm effects, the first two panels of Figure 7 displays the joint distribution among deciles of worker and firm effects in 1980-1986 and 2007-2013, while the third panel shows the difference between them. The change in the pattern of sorting is striking. Over time there has been a substantial shift of middle-decile individual individuals towards middle and lower decile firms, while top-two decile individuals have shifted towards top-decile firms. Hence, this increased sorting of workers has occurred across the entire firm and worker distribution.

Table 3 contains additional key results. First, consistent with our descriptive work in Section 3, we see in columns (1) to (6) that once we drop firms with 10,000 employees or more that the share of inequality accounted for by the between-firm component rises to 87.4% (row labeled “Between-Firm Variance”). Breaking this down we see that about half of this (42.6%) comes from the increased dispersion average individual effects and the other half mostly comes from increased employee sorting across firms (33%), with some small additional contributions from the covariance of individual characteristics at the firm level (6.3% + 3.6% = 10.2% in total). If we drill down further into this group of firms in the right panel keeping only firms with 1000 employees or less (columns 7 to 12) we find the increase in inequality is entirely (102.1%) explained by a rise in the between-firm component. This comes about equally from two sources—the increased variance of the average worker effect (52.5%) and the increasing covariance of worker and firm effects (31.9%), plus a small additional contributions from the firm effects (4.9%) and employee characteristics 7.1% + 5.2% = 12.3%.

\textsuperscript{22}This number is quite close to the corresponding statistic quoted in Subsection 3.1. However, statistics in this section may differ from those in Section 3.1 because of small differences in sample selection and time periods analyzed.
Figure 7 – Distribution of workers among deciles of worker and firm fixed-effects

(A) 1980-1986

(B) 2007-2013

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

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

Finally, Table 3 also shows that larger firms experienced more substantial growth in inequality within firms. Given a similar absolute increase in between-firm inequality, this implies larger firms experienced stronger increases in overall earnings inequality.
than smaller firms. Interestingly, initially large firms appear to have had lower within-firm inequality than smaller firms. This is consistent with the view that large firms may have compressed wages, at least for the bottom end of their workforce. Yet, by the end of our sample period there is no difference in earnings inequality between large and small firms (row 1).

5 Explaining Trends on Within- and Between-Firm Inequality

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

5.1 Accounting for Between-Firm Inequality

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

One explanation that fits these findings is rising overall inequality is driven by skill-biased technical change, while rising outsourcing is constraining the impact on within firm inequality. This rise in outsourcing is potentially being driven by a combination of the falling costs of outsourcing (due to improving information-communications technology), by a desire to limit the extent of inequality within firms due to concerns over fairness (e.g. Akerlof and Yellen (1990) and Weil (2014)), and by the push by businesses to focus on “core competencies” (Hamel and Prahalad, 1990). This would lead firms to re-organizing away from full-service production towards a focused occupation structure. So, for example, large engineering firms like General Electric would outsource both lower

\footnote{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.}

\footnote{While the concept of “core-competencies” may not be well known in economics this is an extremely popular idea in the business and consulting world, with the Hamel and Prahalad (1990) article that coined the term having been received over 80,000 citations by May 2016.}
skill activities (e.g. catering, cleaning and security) as well higher skill activities (IT, legal services and human resources) to firms like Sodexo, ISS, Accenture and Oracle. At the same time firms like General Electric have increased employment in core activities by hiring more engineers and scientists (which is why firm size has not shrunk alongside outsourcing). Hence, occupations are increasingly concentrating within firms (Handwerker (2016)) and industries as shown in Figure (8).

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

There are of course other possible stories, and distinguishing between these is an important task for future research. We briefly discuss two others which seem empirically plausible. One was proposed by Kremer and Maskin (1996) highlights how in an assignment model that if firms operates a technology with complementarities between workers (or tasks) but where some tasks are more critical than others, then increasing worker skill heterogeneity can lead to worker segregation. A second model, by Acemoglu (1999), features search frictions, and firms decide what type of job to open before meeting a worker. When worker skills are similar, a pooling equilibrium emerges where firms create “middling” jobs. With higher skill dispersion, it becomes optimal for firms to open good and bad jobs, suitable for high and low skill workers respectively, leading to a separating equilibrium. Both of these models have appealing features and can generate increasing segregation and sorting. An exciting future research avenue is to test the implications of these models formally against the new empirical facts documented in this paper.

### 5.2 Accounting for Within-Firm Inequality

We saw in Section 3 that within-firm inequality is also rising, but only within very large firms, due to both falling earnings in the bottom half of the earnings distribution and rapidly rising earnings in the top 1%. In this section we examine these two factors in turn.
5.2.1 Stagnating Earnings for Lower-Paid Workers in Large Firms

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

One fact that helps to explain this is that the lower percentile earnings in large firms has converged \textit{from above} with smaller firms. So, for example, in 1981 the median paid

\textsuperscript{25}This is related to the general debate over the collapsing large-firm wage premium (see, for example, the recent survey in Cobb et al. (2016)).
employee in 10,000+ employee firms was paid 40 log points more than the median paid employee in firms with fewer than 10,000 employees, but this gap has shrunk to 5 log points by 2013.  

To examine this convergence in pay for lower-earning employees in large firms we used the CPS, which since 1987 has information on firm size. We found no evidence for a changing mix of employee types across firm sizes over time, so this fall in median pay in large firms is not due to a change in employee mix. However, as shown in Figure 9 we do find that the earnings premium for low-skilled employees (high-school or less) in large firms (1000+ employees using the CPS definition) compared to small firms (fewer than 100 employees) has fallen by over half from 35% in 1987 to 15% in 2013. In comparison the highest-skilled employees (those with 2 or more years of post-graduate education) have seen this earnings premium fall far less, from 19% in 1987 to 12% in 2013. Hence, the earnings premium for low skilled employees in large firms has fallen by 20% in the last 27 years (1987-2013), potentially accounting for much of the 35%
difference in median earnings growth between the very largest firms and the rest over the last 33 years (1981-2013) seen in the SSA data.

5.2.2 Rising Earnings in the Top 1%

The other striking exception from the between-firm inequality result in Section 3 was the large gap between earnings growth of the top 1% and the rest of the firm, particularly among the top 0.25% paid employees. This top 0.25% rising pay phenomenon was particularly striking in the largest (10,000+ employee) firms. To help explain this, Figure 10 plots the coefficients from regressions of the yearly change in log earnings for top earners at different positions in firms of different sizes on the annual returns on the S&P500 plus controls for GDP growth and unemployment. For example, the top right point with a triangle marker on the yellow “10k+” line indicates that the top-paid employee in firms with 10,000 or more employees saw their log earnings annual change related to S&P returns with a coefficient of 0.38. That is, for every 10% the S&P 500 rose their earnings rose by 3.8%. Figure 10 shows how the earnings of the top paid employees
at the 10,000+ employee firms have exceedingly high coefficients: 0.38 for the top-paid employee (presumably the CEO), 0.3 for the second highest paid employee (presumably the CFO) down to 0.15 for the 50th highest paid employee (a very senior manager). In comparison, top-paid employees in firms of 100 to 1000 employees saw a compensation connection with the returns on the S&P500 of about 0.08.

One explanation for these results is that 10,000+ employee firms are more likely to be publicly listed, and publicly listed firms tend to reward their senior executives with stock-options and stock-grants. Moreover, this stock-based remuneration (which is included in the W2 earnings figure as long as options are exercised) has been rising over time. For example, in 2014 the annual compensation of the top-5 executives in Execucomp—which spans about the top 1,800 largest U.S. firms by market capitalization — was 48% from stock-options and stock-awards, up from 15% in 1993 (the first full year of Execucomp data). Alongside this rising stock payment to senior executives there has been a 19 year stock-market bull-run, with real returns averaging 9.5% between 1981 and 1999. As Figure 5 shows we see the senior executives at the largest firms received extremely generous pay increases over this 1981-1999 period, and since 2000 (a period of low stock returns) move roughly in-line with the rest of their firm.

Thus, it appears that the top 50 or so executives in the largest U.S. firms have experienced rapidly rising earnings—far outstripping their colleagues—in part due to a rising level and generosity of stock-based compensation. Simply applying the magnitudes of the 680% real increase in the S&P over the period 1981–1999 to the average 0.25 coefficient on the S&P returns in Figure 9, yields a real cumulative pay increase of 170%, which is similar to the earnings gains of up to 200% this group made over the same period (see 5). One outstanding question this analysis raises, however, is why these stock-driven pay rises have been permanent, rather than one-off high earnings payouts during the years of unexpectedly strong S&P 500 performance. One recent paper offering an explanation on this is Shue and Townsend (2016) who report that S&P500 firms tend to give executives similar numbers of stock options each year, despite these options rising in value with the firms stock price. Hence, historic rises in the S&P500 tend to get locked in to future equity pay levels.
6 Conclusions

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

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

Second, this dominance of rising between firm inequality in accounting for the increase in overall inequality is an extremely robust stylized fact. It holds within narrowly defined industries, within counties, by employee demographic (age and gender), by firm type (continuing or entrant/exiting firm), by sub-period, and by definition of earnings (1-year or 5-year). This is also an international phenomena, with similar patterns in every other countries for which detailed worker-firm earnings data is available (Brazil, Germany, Sweden and the UK).

Third, examining the sources of this increase in between-firm inequality we find it has been mainly driven by increased employee segregation. That is, highly paid employees are increasingly clustering in high-wage firms with other high-paid workers, while low paid employees are clustering in other firms. Similarly, we also see segregation of employees by occupation and skills in the US and other countries whenever we can measure this. This raises the question as to what is driving this dramatic increase in worker segregation across firms. While our results are speculative, our belief is outsourcing plays an important role in allowing firms to constraint inequality within firms and focus on core-competency activities, spinning of non-essential activities like cleaning, catering, security, accounting and HR. Since firm size is slowly growing over this period firms are not atomizing, instead they appear to be reorganizing around a more concentrated set of occupations, leading to great cross firm segregation by earnings and education. However, our evidence on this explanation is tentative and this is an area that would benefit from further research.
Finally, this increase in between-firm inequality raises a question over its impact on individual welfare. We believe increased firm segregation is worrying for three reasons. One concern is that firms play an important role in providing employee healthcare and pensions, so rising earnings segregation will flow through into rising health and retirement inequality. Second, given the importance of work-experience to long-run earnings growth, if employees gain experience more rapidly working with higher ability colleagues, then rising segregation will dynamically increase inequality. Finally, increased segregation itself may make it obscure the underlying inequality making it harder to appropriate address this issue with future policy.
References


Table 2: Detailed Decomposition of the Rise in Earnings Inequality Between- and Within-Firms

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Var(log(y))</td>
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<td>0.861</td>
<td>0.921</td>
<td>0.915</td>
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<td>100</td>
<td>100</td>
<td>100</td>
<td>100</td>
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<tr>
<td>Between-Firm Components</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Var(m_we_f)</td>
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<td>0.106</td>
<td>0.121</td>
<td>0.131</td>
<td>0.143</td>
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<td>Share of Total</td>
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<td>12.4</td>
<td>14.0</td>
<td>14.2</td>
<td>15.6</td>
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<tr>
<td>Var(firm effect)</td>
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<td>0.115</td>
<td>0.099</td>
<td>0.110</td>
<td>0.108</td>
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<tr>
<td>Share of Total</td>
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<td>13.5</td>
<td>11.5</td>
<td>12.0</td>
<td>11.9</td>
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<tr>
<td>Var(m_xb_f)</td>
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<td>0.013</td>
<td>0.012</td>
<td>0.009</td>
<td>0.010</td>
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<td>Share of Total</td>
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<td>1.4</td>
<td>1.0</td>
<td>1.1</td>
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<tr>
<td>2cov(m_we_f,firm)</td>
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<td>0.035</td>
<td>0.049</td>
<td>0.060</td>
<td>0.065</td>
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<td>4.1</td>
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<td>6.5</td>
<td>7.1</td>
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<tr>
<td>2cov(m_we_f,m_xb_f)</td>
<td>0.015</td>
<td>0.022</td>
<td>0.021</td>
<td>0.021</td>
<td>0.025</td>
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<tr>
<td>Share of Total</td>
<td>2.0</td>
<td>2.5</td>
<td>2.4</td>
<td>2.3</td>
<td>2.8</td>
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<tr>
<td>2cov(firm,m_xb_f)</td>
<td>0.020</td>
<td>0.025</td>
<td>0.021</td>
<td>0.022</td>
<td>0.024</td>
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<td>Share of Total</td>
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<td>2.5</td>
<td>2.4</td>
<td>2.6</td>
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<tr>
<td>Between Firm Variance</td>
<td>0.260</td>
<td>0.315</td>
<td>0.323</td>
<td>0.354</td>
<td>0.375</td>
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<td>Share of Total</td>
<td>34.7</td>
<td>36.8</td>
<td>37.5</td>
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<td>Within-Firm Components</td>
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<td></td>
<td></td>
<td></td>
<td></td>
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<tr>
<td>Var(diff_we_f)</td>
<td>0.272</td>
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<td>0.348</td>
<td>0.341</td>
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<td>36.2</td>
<td>37.7</td>
<td>37.8</td>
<td>37.2</td>
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<td>Var(diff_xb_f)</td>
<td>0.048</td>
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<td>0.055</td>
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<td>8.8</td>
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<td>6.1</td>
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<td>Var(diff_r_f)</td>
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<td>0.158</td>
<td>0.149</td>
<td>0.156</td>
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<tr>
<td>Share of Total</td>
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<td>17.2</td>
<td>16.9</td>
<td>14.9</td>
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<td>2cov(diff_we_f,diff_xb_f)</td>
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<td>0.011</td>
<td>0.008</td>
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<tr>
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<tr>
<td>Within Firm Var</td>
<td>0.488</td>
<td>0.540</td>
<td>0.538</td>
<td>0.567</td>
<td>0.540</td>
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<tr>
<td>Share of Total</td>
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<td>62.5</td>
<td>61.6</td>
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<td>Raw Decomposition</td>
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<td></td>
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<tr>
<td>Between Firm Var</td>
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<td>0.315</td>
<td>#DIV/0!</td>
<td>0.354</td>
<td>0.375</td>
</tr>
<tr>
<td>Share of Total</td>
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<td>36.8</td>
<td>#DIV/0!</td>
<td>38.4</td>
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<td>0.540</td>
<td>0.538</td>
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<tr>
<td>Share of Total</td>
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<td>62.5</td>
<td>61.6</td>
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<tr>
<td>Segregation Index</td>
<td>Var(m_we_f)/Var(we)</td>
<td>0.235</td>
<td>0.255</td>
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<td>0.273</td>
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<tr>
<td>Share of Total</td>
<td></td>
<td></td>
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</tr>
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Notes:
- log(y) - natural log of annual earnings
- m_we_f - mean worker effect across firms
- m_xb_f - mean Xb across firms
- m_r_f - mean residual across firms
- diff_we_f - difference of worker effect from mean worker effect across firms
- diff_xb_f - difference of Xb from mean xb across firms
- diff_r_f - difference of the residual from the mean residual across firms

Estimates are from the baseline 100% sample - 520 hrs at minimum wage, male, age 20-60, with normalization: age'=age-40)/40.

Raw decomposition refers to the between and within firm variance composition simply on log wages, rather than using the CHK components.
### Table 3: Decomposition of the Rise in Earnings Inequality Between- and Within-Firms by Firm Size

<table>
<thead>
<tr>
<th>Var. Component</th>
<th>Sample Excluding Firms with Greater than 10,000 Employees</th>
<th>Sample Excluding Firms with Greater than 1,000 Employees</th>
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<tr>
<td>Var(log(y))</td>
<td>0.774 100</td>
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<td>Between-Firm Variance</td>
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<td></td>
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<tr>
<td>Var(m_we_f)</td>
<td>0.100 12.9</td>
<td>0.159 17.4</td>
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<tr>
<td>Components</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Var(firm effect)</td>
<td>0.114 14.7</td>
<td>0.116 12.7</td>
</tr>
<tr>
<td>of Variance</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Var(m_xb_f)</td>
<td>0.009 1.1</td>
<td>0.009 1.0</td>
</tr>
<tr>
<td>2cov(m_we_f,firm)</td>
<td>0.007 0.9</td>
<td>0.053 5.8</td>
</tr>
<tr>
<td>2cov(m_we_f,m_xb_f)</td>
<td>0.013 1.7</td>
<td>0.022 2.4</td>
</tr>
<tr>
<td>2cov(firm,m_xb_f)</td>
<td>0.017 2.2</td>
<td>0.022 2.4</td>
</tr>
<tr>
<td>Between Firm Variance</td>
<td>0.260 33.6</td>
<td>0.381 41.7</td>
</tr>
<tr>
<td>Within-Firm Variance</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Var(diff_we_f)</td>
<td>0.291 37.6</td>
<td>0.339 37.2</td>
</tr>
<tr>
<td>Components</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Var(diff_xb_f)</td>
<td>0.049 6.3</td>
<td>0.053 5.8</td>
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<tr>
<td>of Variance</td>
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<tr>
<td>Var(diff_r_f)</td>
<td>0.161 20.8</td>
<td>0.139 15.2</td>
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<tr>
<td>2cov(diff_we_f,diff_xb_f)</td>
<td>0.013 1.7</td>
<td>0.002 0.2</td>
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<tr>
<td>Within Firm Variance</td>
<td>0.514 66.4</td>
<td>0.532 58.4</td>
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<tr>
<td>Raw Decomposition</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Between Firm Var</td>
<td>0.259 33.5</td>
<td>0.381 41.7</td>
</tr>
<tr>
<td>With Firm Var</td>
<td>0.514 66.5</td>
<td>0.531 58.3</td>
</tr>
<tr>
<td>Segregation Index</td>
<td>Var(m_we_f)/Var(we)</td>
<td>0.255 0.319</td>
</tr>
</tbody>
</table>

**Notes.**
- \( \log(y) \) - natural log of annual earnings
- \( m_{we\_f} \) - mean worker effect across firms
- \( m_{xb\_f} \) - mean Xb across firms
- \( m_{r\_f} \) - mean residual across firms
- \( diff_{we\_f} \) - difference of worker effect from mean worker effect across firms
- \( diff_{xb\_f} \) - difference of Xb from mean xB across firms
- \( diff_{r\_f} \) - difference of the residual from the mean residual across firms

Estimates are from the baseline 100% sample - 520 hrs at minimum wage, male, age 20-60, with normalization: \( \text{age}' = \frac{\text{age}-40}{40} \).

Raw decomposition refers to the between and within firm variance composition simply on log wages, rather than using the CHK components.
| 7 Year Interval | All full-time men, age 20-60 | | Individuals in largest connected set | |
|----------------|------------------------------|------------------------------|---------------------------------|
|                | (1) Number worker/yr. obs.  | (2) Number workers | (4) Mean | (5) Median | (6) Std. dev. | (7) Number worker/yr. obs. | (8) Number workers | (10) Mean | (11) Median | (12) Std. dev. |
| 1980-1986      | 336,095,166                 | 66,253,680                  | 10.381  | 10.505  | 0.868  | 332,624,208        | 65,311,438        | 10.3   | 79       | 10.506  | 0.865  |
| Ratio: largest connected/all | 99.0                     | 98.6                         | 100.0   | 100.0   | 99.6   | 98.9  | 98.5  | 100.0   | 100.0   | 99.6   |
| 1987-1993      | 378,061,870                 | 71,852,732                  | 10.355  | 10.473  | 0.929  | 373,806,862        | 70,802,234        | 10.354 | 10.474  | 0.925  |
| Ratio: largest connected/all | 98.9                     | 98.5                         | 100.0   | 100.0   | 99.6   | 98.7  | 98.4  | 100.0   | 100.0   | 99.7   |
| 1994-2000      | 408,883,618                 | 76,590,263                  | 10.421  | 10.514  | 0.931  | 403,724,055        | 75,365,461        | 10.421 | 10.515  | 0.928  |
| Ratio: largest connected/all | 98.7                     | 98.4                         | 100.0   | 100.0   | 99.7   | 98.4  | 98.1  | 100.0   | 100.0   | 99.8   |
| 2001-2006      | 431,749,460                 | 81,950,386                  | 10.484  | 10.578  | 0.961  | 425,006,770        | 80,409,315        | 10.485 | 10.581  | 0.960  |
| Ratio: largest connected/all | 98.4                     | 98.1                         | 100.0   | 100.0   | 99.8   | 98.1  | 97.8  | 100.0   | 100.0   | 99.9   |
| 2007-2013      | 422,334,068                 | 82,761,555                  | 10.487  | 10.566  | 0.958  | 414,466,857        | 80,920,372        | 10.489 | 10.570  | 0.956  |
| Ratio: largest connected/all | 98.1                     | 97.8                         | 100.0   | 100.0   | 99.9   | 98.1  | 97.8  | 100.0   | 100.0   | 99.9   |
| Change from first to last interval | 0.106                  | 0.061                        | 0.089   | -0.83   | 0.069  | -0.80 | 0.063 | 0.092  |

Notes:
### Table C2: Estimation Results for AKM Model, Fit by Interval

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<tr>
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<th>Interval 1</th>
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<th>Interval 3</th>
<th>Interval 4</th>
<th>Interval 5</th>
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<tr>
<td><strong>Sample</strong></td>
<td>(1)</td>
<td>(2)</td>
<td>(3)</td>
<td>(4)</td>
<td>(5)</td>
</tr>
<tr>
<td># Worker Effects</td>
<td>65,311,438</td>
<td>70,802,234</td>
<td>75,365,461</td>
<td>80,409,315</td>
<td>80,920,372</td>
</tr>
<tr>
<td><strong>Summary</strong></td>
<td># Firm Effects</td>
<td>5,206,888</td>
<td>5,733,422</td>
<td>5,884,023</td>
<td>5,889,906</td>
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<tr>
<td><strong>Statistics</strong></td>
<td>Sample size</td>
<td>332,624,208</td>
<td>373,806,862</td>
<td>403,724,055</td>
<td>425,006,770</td>
</tr>
<tr>
<td></td>
<td>SD(log(y))</td>
<td>0.865</td>
<td>0.925</td>
<td>0.928</td>
<td>0.960</td>
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<tr>
<td><strong>Summary of</strong></td>
<td>SD(WE)</td>
<td>0.596</td>
<td>0.644</td>
<td>0.667</td>
<td>0.692</td>
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<td><strong>AKM Parameter</strong></td>
<td>SD(FE)</td>
<td>0.346</td>
<td>0.339</td>
<td>0.314</td>
<td>0.332</td>
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<tr>
<td><strong>Estimates</strong></td>
<td>SD(Xb)</td>
<td>0.238</td>
<td>0.278</td>
<td>0.297</td>
<td>0.254</td>
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<tr>
<td>Between Firm Variance</td>
<td>0.030</td>
<td>0.080</td>
<td>0.116</td>
<td>0.131</td>
<td>0.141</td>
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<td>Corr(WE,XB)</td>
<td>0.113</td>
<td>0.084</td>
<td>0.027</td>
<td>0.084</td>
<td>0.091</td>
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<td>Corr(FE,Xb)</td>
<td>0.124</td>
<td>0.133</td>
<td>0.115</td>
<td>0.129</td>
<td>0.143</td>
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<tr>
<td>RMSE(residual)</td>
<td>0.438</td>
<td>0.445</td>
<td>0.431</td>
<td>0.442</td>
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<tr>
<td>Adj R²</td>
<td>0.743</td>
<td>0.768</td>
<td>0.784</td>
<td>0.788</td>
<td>0.812</td>
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<tr>
<td><strong>Comparison</strong></td>
<td>RMSE(match residual)</td>
<td>0.369</td>
<td>0.374</td>
<td>0.360</td>
<td>0.369</td>
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<tr>
<td><strong>Match Model</strong></td>
<td>Adj R²</td>
<td>0.817</td>
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<td>SD(match effect)</td>
<td>0.260</td>
<td>0.266</td>
<td>0.264</td>
<td>0.267</td>
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</table>

**Notes:**
- A 100% sample of the SSA Master Earnings File. Male only, ages 20-60, over 520 hours worked at minimum wage.
- Age is normalized as age=(age-40)/40 as in CHK.
- We include an unrestricted set of year dummies and quadratic and cubic terms in age.
- We do not interact 5 education dummies with other covariates as in CHK.
- The dependent variable is log annual earnings at main job.
- Annual earnings are adjusted for inflation with the PCE deflator at base year 2013.
<table>
<thead>
<tr>
<th>Total Variance Component</th>
<th>Share of Total (1)</th>
<th>Share of Total (2)</th>
<th>Share of Total (3)</th>
<th>Share of Total (4)</th>
<th>Share of Total (5)</th>
<th>Share of Total (6)</th>
<th>Share of Total (7)</th>
<th>Share of Total (8)</th>
<th>Share of Total (9)</th>
<th>Share of Total (10)</th>
<th>Change from 1 to 5 (h)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Var(log(y))</td>
<td>0.748</td>
<td>0.855</td>
<td>0.861</td>
<td>0.921</td>
<td>0.915</td>
<td>0.167</td>
<td>100</td>
<td></td>
<td></td>
<td></td>
<td></td>
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<tr>
<td>Components of Variance</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
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<td></td>
</tr>
<tr>
<td>Var(WE)</td>
<td>0.355</td>
<td>0.415</td>
<td>0.445</td>
<td>0.479</td>
<td>0.483</td>
<td>0.128</td>
<td>47.5</td>
<td></td>
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<td></td>
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<tr>
<td>Var(FE)</td>
<td>0.120</td>
<td>0.115</td>
<td>0.099</td>
<td>0.110</td>
<td>0.108</td>
<td>-0.011</td>
<td>16.0</td>
<td></td>
<td></td>
<td></td>
<td>-6.6</td>
</tr>
<tr>
<td>Var(Xb)</td>
<td>0.057</td>
<td>0.077</td>
<td>0.088</td>
<td>0.065</td>
<td>0.065</td>
<td>0.009</td>
<td>7.6</td>
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<td></td>
<td>5.3</td>
</tr>
<tr>
<td>Var(residual)</td>
<td>0.151</td>
<td>0.158</td>
<td>0.149</td>
<td>0.156</td>
<td>0.136</td>
<td>-0.015</td>
<td>20.3</td>
<td></td>
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<td>-9.2</td>
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<tr>
<td>Between Firm Variance</td>
<td>0.012</td>
<td>0.035</td>
<td>0.049</td>
<td>0.060</td>
<td>0.065</td>
<td>0.052</td>
<td>1.6</td>
<td></td>
<td></td>
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<td>31.4</td>
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<tr>
<td>2*Cov(WE,Xb)</td>
<td>0.032</td>
<td>0.030</td>
<td>0.011</td>
<td>0.029</td>
<td>0.033</td>
<td>0.001</td>
<td>4.3</td>
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<td>0.3</td>
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<tr>
<td>2*Cov(FE,Xb)</td>
<td>0.020</td>
<td>0.025</td>
<td>0.021</td>
<td>0.022</td>
<td>0.024</td>
<td>0.004</td>
<td>2.7</td>
<td></td>
<td></td>
<td></td>
<td>2.2</td>
</tr>
<tr>
<td>Notes:</td>
<td></td>
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</tr>
<tr>
<td>• Var(log(y)) - variance of annual earnings, Var(WE) - variance of worker fixed effects, Var(FE) - variance of firm fixed effects, Var(Xb) - variance of residual</td>
<td></td>
<td></td>
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</tbody>
</table>

**Counterfactuals**

1. No rise in Corr(WE,FE) | 0.748 | 0.833 | 0.825 | 0.874 | 0.864 | 0.116 | 69.5 |
2. No fall in Var(FE)     | 0.748 | 0.861 | 0.889 | 0.933 | 0.930 | 0.182 | 109.3 |
3. Both 1 and 2           | 0.748 | 0.838 | 0.849 | 0.885 | 0.877 | 0.129 |

**Notes:**

* Var(log(y)) - variance of annual earnings, Var(WE) - variance of worker fixed effects, Var(FE) - variance of firm fixed effects, Var(Xb) - variance of residual
Supplemental Online Appendix
A Appendix: Additional Figures

A.1 Sensitivity and Robustness

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

(A) Total earnings

(B) Total employment

(C) Total firms

Notes: SSA data includes all entries in the MEF. National Income and Product Accounts (NIPA) data is from the St. Louis Federal Reserve Bank’s FRED service, series A576RC1, “Compensation of Employees, Received: Wage and Salary Disbursements.” Current Population Survey (CPS) total employment shows the yearly average of the monthly employment numbers in the CPS. This data is from the Bureau of Labor Statistics Table LNS12000000. Census firms shows the total number of firms reported by the Census Bureau’s Statistics of U.S. Businesses data set, available at http://www.census.gov/econ/susb/historical_data.html. All data are adjusted for inflation using the PCE price index.
Figure A.2 – Robustness: Controlling for Geography at County Level

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

(A) Northeast

(b) Midwest

(c) South

(d) West

Notes: See notes for Figure 3. Regions are based on Census region definitions. Percentiles are based on only those individuals in the given region.
Figure A.4 – Robustness by demographic (age group and gender)

(A) Age: 20 to 29

(B) Age: 30 to 39

(C) Age: 40 to 49

(D) Age: 50 to 60

(E) Men

(F) Women

Notes: See notes for Figure 3. Percentiles are based on all individuals, regardless of age or gender.
Figure A.5 – Robustness by industry: results by SIC 1-digit industry

(A) Agriculture, Mining, Construction & Other

(B) Manufacturing

(C) Utilities

(D) Trade

(E) Finance, insurance and real estate

(F) Services

Notes: See notes for Figure 3. Industries are based on definitions from https://www.osha.gov/pls/imis/sic_manual.html. Percentiles are based on only those individuals employed in the given industry.
Figure A.6 – Robustness by industry: averaged across analysis within SIC 4-digit industry

![Graph]

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

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

![Graph]

Notes: See notes for Figure 3. Individual statistics are the same for all lines; firm statistics are calculated differently, as indicated.
Figure A.8 – Continuing firms only

Notes: See notes for Figure 3. Only firms (and individuals in those firms) that are in the sample in both 1981 and 2013 are included in the analysis.
Figure A.9 – Less-restrictive sample selection

(A) All ages

(B) All firm sizes

(C) All industries

(D) All ages, firm sizes, and industries

Notes: See notes for Figure 3. Sample selection criteria are relaxed as indicated.
Figure A.10 – Different definitions of full-time workers

(A) 6.5 weeks

(B) 26 weeks

(C) 52 weeks

Notes: See notes for Figure 3. Minimum earnings thresholds are adjusted to the equivalent of 40 hours per week at minimum wage for the given number of weeks.
Figure A.11 – Five year average earnings: comparing 1981-1985 vs 2009-2013

![Graph showing log change in average earnings across different percentiles.](image)

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

Figure A.12 – Other restrictions

(a) 100% sample

![Graph showing log change in average earnings across different percentiles.](image)

(b) Winsorizing at Execucomp maximum

![Graph showing log change in average earnings across different percentiles.](image)

Notes: See notes for Figure 3.
A.2 Other figures

**Figure A.13** – Cumulative firm size distribution

(A) Unweighted

(B) Weighted by employment

Notes: Only full-time individuals aged 20 to 60 are included in all statistics, where full-time is defined as earning the equivalent of minimum wage for 40 hours per week in 13 weeks. Individuals and firms in public administration or educational services are not included. Both graphs are inverse cumulative distribution functions. Figure A.13a shows the fraction of firms below a given size; Figure A.13b shows the fraction of individuals at firms below a certain size. For disclosure reasons, Figure A.13b does not report the top 3 percentiles.
Figure A.14 – Comparison to Piketty and Saez (IRS data)

(A) 90th Percentile

(B) 95th Percentile

(C) 99.5th Percentile

(D) 99.9th Percentile

Notes: Piketty and Saez (2003) data is based on Table B3 in http://eml.berkeley.edu/~saez/TabFig2014prel.xls. All values are adjusted for inflation using the PCE price index. For SSA data, only individuals in firms with at least 20 employees are included. Only full-time individuals aged 20 to 60 are included in all SSA statistics, where full-time is defined as earning the equivalent of minimum wage for 40 hours per week in 13 weeks. Individuals and firms in public administration or educational services are not included in SSA data.
Figure A.15 – Earnings and firm size

(A) Individual earnings and average firm size

(B) Correlation between firm size and wage

Notes: Only firms and individuals in firms with at least 20 employees are included. Only full-time individuals aged 20 to 60 are included in all statistics, where full-time is defined as earning the equivalent of minimum wage for 40 hours per week in 13 weeks. Individuals and firms in public administration or educational services are not included. Firm statistics are based on the average of mean log earnings at the firms for individuals in that percentile of earnings in each year. For each percentile in Figure A.15a, statistics are based on individuals in that percentile of earnings in each year. Correlation in Figure A.15b is calculated at the firm level in each year, and is weighted by firm size.

B Appendix: Data Procedures

B.1 Social Security Administration Data

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

The first step we take with this data is to exclude individuals who did not have a reasonably strong labor market attachment in a given year from the analysis for that year. More concretely, we consider an individual to be full-time in a given year and include in the analysis if, summing across all jobs, he/she earns at least the equivalent of 40 hours per week for 13 weeks at the minimum wage (so $3,770 in 2013). (As discussed above, we also conducted robustness checks with other threshold levels, which show similar results; see Figure A.10.) This condition ensures that we are focusing on data about individuals with a reasonably strong labor market attachment, and that our results are comparable to other results in the wage inequality literature, such as Juhn et al. (1993) and Autor et al. (2008). The data from any individual earning
below this threshold in a given year is excluded from all results for both firms and individuals in that year.

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

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

In order to analyze a representative sample of individuals in a computationally feasible way, we analyze a one-eighth representative sample of all U.S. individuals from 1978 to 2013 (except in the firm and worker fixed effects analysis, in which we use a 100% sample). Results are robust to using a 100% sample; see Figure A.12a. The sample is organized as a longitudinal panel, in the sense that once an individual is selected into the sample, he/she remains in the sample until he/she dies. In particular, an individual is in our sample if the MD5 hash of a transformation of their Social Security Number begins with a zero or one; because MD5 hashes are hexadecimal numbers, this will select one in eight individuals. MD5 is a cryptographic algorithm that deterministically turns any string into a number that is essentially random. It is designed so that a slightly different input would lead to a completely different output in a way that is essentially impossible to predict. Because it took cryptographic researchers several years to figure out a way that, under certain circumstances, MD5 is somewhat predictable, this algorithm is certainly random enough for our purposes. Thus whether one individual is included in our sample is essentially independent of whether some other individual is included, regardless of how similar their SSNs are.

We top-code all variables of interest above the 99.999th percentile to avoid potential problems with disclosure or extreme outliers. Variables are top-coded with the average value (or geometric average value, as appropriate) of all observations within the top 0.001%. Variables are top-coded immediately before analysis. An exception is in analysis of top income ranks within firms, as in Figures 5 and 10, which could be more affected by top-coding; for these analyses, we top-code at the maximum value in Execucomp for the given year (or, before 1992, the average
of the maximum values between 1992 and 1994). Top-coding at the 99.999th percentile has no visible effect on the main analysis: see Figure A.12b for results top-coding at the maximum value in Execucomp. Finally, we adjust all dollar values in the data set to be equivalent to 2013 dollars with the Personal Consumption Expenditure (PCE) price index.\footnote{http://research.stlouisfed.org/fred2/series/PCEPI/downloaddata?cid=21}

B.2 Current Population Survey Data

C Appendix: The Abowd, Kramarz and Margolis decomposition

C.1 Identifying Assumption

Estimation of the firm effects in equation (3) crucially relies on earnings changes of workers switching employers. Hence, the estimated firm effects will capture any systematic differences in earnings of movers before and after the job move. This includes the difference in firm effects between the sending and receiving firm, but also potential differences in average fixed worker-firm match effects, or systematic transitory earnings changes leading up to or following a job change. Hence, to associate estimated firm effects with true underlying firm-specific differences in pay, one has to assume that conditional on worker and firm effects, job moves do not depend systematically on other components. This assumption, often referred to as the conditional random mobility (CRM) assumption, and its relation to economic models of job mobility, is discussed at length in AKM and CHK, among others, and we will not review the theoretical arguments against or in favor here.

On a fundamental level, whether the CRM assumption is conceptually or empirically plausible or not, the estimation of the parameters in equation (3) is done by Ordinary Least Squares, and hence one relies on “random” variation provided by nature, not on known sources of manipulation. To ensure our core assumption and findings are plausible, following CHK, we will provide several pieces of corroborating evidence below. This includes event studies of the effect of worker mobility, the goodness of fit of the model, the value added of allowing for worker-firm match effects, and the properties of the residuals. After a careful review, we conclude from this evidence that there appear to be no large, systematic worker-firm or transitory components influencing job mobility. We thus join an increasing number of papers whose results indicate the AKM model can be estimated without systematic bias (e.g., AKM, CHK, Barth et al. (2014), Abowd et al. (2016)). Nevertheless, we are well aware of the limitations of the model, and incorporate it into our overall approach. Among other measurements, we will separately estimate worker-firm component in earnings $m_{ij}$, and use it to directly assess potential departures from the basic model for our discussion of earnings inequality.

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

In addition, the estimate of the covariance term \( \text{cov}(\theta^i, \psi^j) \) is likely to be downward biased, because the sampling error in the worker and firm effects are negatively correlated. We do not attempt to construct bias-corrected estimates of these components. Instead, we follow the literature and focus on trends in the estimated moments assuming that the bias from sampling errors is similar over time. Finally, firm effects are identified up to the difference with respect to an omitted reference firm. Hence, one can only obtain comparable estimates of firm effects for firms that are connected by worker flows. Following AKM and CHK, we estimate equation (3) on the greatest connected set of workers, which in our case comprises close to 98% of all observations (see Table C1).

### C.2 Model Fit

Table C1 shows basic characteristics for the full sample as well as for observations in the connected set, separately for each of our five time periods. In the following, we will focus our discussion on men. Unless otherwise noted, the results for women are similar. For space reasons, the results for women are in an appendix. Table C1 shows that in all five periods, approximately 98% of workers are in in the greatest connected set. As a result, the mean, median, and standard deviation of earnings in the connected set are very similar to the overall sample. If one compares the number of observations with the number of workers, one obtains that the average worker is in the sample about 5 of 7 years in each period. This number is very similar to numbers reported by CHK (Table I) for full-time men in Germany.

Table C2 displays basic statistics from the estimation. The table delivers a snapshot of the basic findings, as well as important diagnostic checks. In terms of basic findings, the table shows how the standard deviation of worker effects has risen over time, especially in the early 1980s. The standard deviation of firm effects has remained stable. In contrast, the correlation of worker and firm effects rose almost five fold from our first period, 1980-1986, to our last period, 2007-2013. The table also shows that the RMSE has remained stable, and has at best declined somewhat over time. If the rise in sorting of workers to firms had resulted from an increasing role of complementarities (i.e., match effects), we would have expected the goodness of fit of the model without match effects to decline over time. Instead, the RMSE drops at the same time as the variance of earnings increases. As a result, the adjusted \( R^2 \) increases from 74.1% in 1980-1986 to 81.2% in 2007-2013.

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28The age-earnings gradient in SSA data flattens out around age 40. The worker effect is biased because it absorbs the time-invariant effect of age (i.e., age at start of the sample, which is effectively a cohort effect). Note that for the analysis of changes in the variance of worker effects over time, the normalization has no effect on the trend as long as the age distribution of the population and the return to age are roughly stable over time. The firm effects is not affected by the normalization. The covariance of worker and firm effects may be affected insofar as workers are sorted into firms by age.

29Andrews et al. (2008) show that the degree of negative correlation declines with the number of movers that is used to identify firm effects. We indeed find that the level of the covariance rises with our sample size. However, the gradient over time is unaffected.

30The correlation of observable worker characteristics (mainly age) with worker and firm effects has a U-shaped pattern—declining to a low point during the economic book of the late 1990s, and returning to similar levels by the end of the period.
While the goodness of fit based on worker and firm effects and age is quite high, at around 80%, there is room left for additional components. To check whether adding a match-specific component would substantially increase the fit of the model, the bottom of the table shows basic statistics of a model that also allows for a match effect ($m_{ij}$). Not surprisingly, allowing for a match effect reduces the RMSE and increases the adjusted $R^2$, by about the same amount each period, to 82 – 87%. However, the standard deviation of match effects declines somewhat over time. As noted by CHK, this is consistent with an interpretation of the match effects as uncorrelated random effects. If instead they were specification errors caused by incorrectly imposing additivity of the person and establishment effects, one would expect the standard deviation of match effects to rise and the relative fit of the AKM model to deteriorate over time as the covariance of worker and firm effects increases in magnitude.

As additional check on the appropriateness of the basic AKM specification of model (3), we examined average regression residuals for different groups of worker and firm effects. Violations of the separability assumptions in the AKM model would likely cause large mean residuals for certain matches, say, where highly skilled workers are matched to low-wage establishments. To search for such potential interactions, we followed CHK and divided the estimated person and establishment effects in each interval into deciles, and computed the mean residual in each of the 100 person-firm decile cells. Figure A.16b shows the mean residuals from the cells using data from period 2007–2013. For most cells, the mean residual is very small, below 0.02, and shows few systematic patterns. Only for cells with either low worker effects or low firm effects do residuals appear larger. It is interesting to note that this pattern is quite similar to those found by CHK (Figure VI), who report larger mean residuals for the lowest worker and firm effect groups. Hence, in both Germany and the U.S. separability appears a good description for all worker and firm groups but for the bottom end. Figure A.16c shows the change in mean residuals within cells over time. The changes are of opposite signs of the deviations in A.16b, implying that the absolute magnitude of deviations has declined over time. Hence, overall, the goodness of fit of the model has improved from the first to the last period in our sample.

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

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31Not surprisingly given the presence of labor supply effects, the mean residuals in Figure A.16 are on average larger than those shown CHK (Figure VI).
earnings for flexible time trends. Overall, we conclude that despite the fact we are modeling information on annual earnings rather than daily or hourly wages, our model delivers a good approximation of the underlying earnings process.

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

Tables 2 and 3 have shown that the substantial between-firm component of the rise in earnings inequality in the United States from the early 1980s to today can be attributed almost entirely to sorting (a rise in the correlation of worker and firm effects) and segregation (a rise in the variance of mean worker effects between firms). We have also found that these patterns are particularly pronounced for moderately sized firms (i.e., for employment size less or equal to 1000). In this section, we will use our estimated worker and firm effects from implementing equation (3) to assess how workers are sorted into high-wage firms and large firms, and how this has changed over time. We will also describe the changing patterns of firm and worker effects by firm size and industry.

To learn more about the pattern of sorting, the first two panels of Figure 7 displays the joint distribution among deciles of worker and firm effects in 1980-1986 and 2007-2013. The cross-sectional sorting patterns displayed in the figure are striking. Consider first the early 1980s shown in Figure 7a. One can see that most workers are in medium to high fixed-effect firms. Yet, lower fixed-effect workers are over-represented at lower fixed-effect firms; workers with fixed effects in the middle range are over-represented at middle to high fixed-effect firms; and high fixed-effect workers are over-represented at high fixed-effect firms. However, one also sees that low to medium fixed-effects firms have modes at both low and high fixed effects workers, presumably reflecting a distribution of lower-skilled production workers and managerial employees.

The distribution for the years 2007–2013 displayed in Figure 7b show these pattern have changed substantially over time. Figure 7c shows the net change of density of the two distributions at corresponding deciles. Overall, there has been a substantial shift in the distribution away from the two highest firm categories towards middle to lower fixed-effect firms. Yet, this shift did not occur uniformly across worker groups. It is the middle of the worker fixed-effect distribution that predominantly left high-wage firms, such that high-wage workers are now over-represented at the top firms. This pattern is augmented by a move of the highest fixed-effect workers to higher-paying firms.

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

Figures 7 and ?? confirm the evidence from the variance decomposition that sorting has increased, and show which workers and firms appear most affected. A striking finding is that the

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32Note that the definition of the deciles differ between the two time periods. Yet, since the distribution of firm effects has changed little, the deciles of firm effects are roughly comparable over time.
the incidence and composition of workers at high-wage firms has been changing substantially. Since high-wage firms are likely to be in part large firms, and we have found large firms to play a special role in the evolution of inequality, we use our data to examine the incidence of worker and fixed effects separately by firm size. These results are shown in Figures A.18 and A.19 for three firm size groups (firms with number of workers in range 1 – 100, 101 – 9999, and 10,000+).

From Figure A.18 it is clear that on average, high-wage firms tend to be larger. However, over time, Figure A.18c shows that large employers have experienced a substantial shift out of high-wage firms to middle and lower-wage firms. Figure A.19 shows that among larger firms, the decline was accompanied by an increase in the incidence of high wage workers at larger firms. In addition, especially employers with more than 10,000 employees saw a reduction in workers in the middle of the worker fixed-effects distribution. Hence, this confirms that larger firms have become, on average, workplaces that pay less and employ a more unequal set of workers.

To examine potential differences in sorting patterns, we have also examined the joint distribution of firm and worker fixed effects within each size class. These figures are displayed in our appendix. The results show that the pattern of sorting is quite similar among our two larger firm size classes, and reflects the pattern shown in Figure 7 – there is a substantial net shift in the mass of workers from high-wage firms to middle-wage firms. The bulk of this shift is comprised of middle-wage workers. In contrast, high-wage workers have left middle-wage firms to move to the top firms. In contrast, the distribution of low-wage workers has changed less. These results corroborate our finding from Table 2 that the differences in the sources of inequality growth by firm size is not the between-firm component, whose levels evolve similarly, but rather the within-firm component of inequality.

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

Overall, the findings from the figures corroborate and strengthen our core results from the detailed variance composition in Table 3. There is a clear pattern of increasing sorting of higher-wage workers into higher-wage firms over time. In particular, from the early 1980s to today, high-wage firms appear to lose middle-wage workers to middle-wage firms, and in turn gain more high-wage workers. These patterns partly correspond to shifts between firm-size classes. Fewer middle-wage workers work at very large employers, at the same time as these employers are increasingly composed of lower-wage firms. Yet, within firm-size classes the patterns of sorting is similar as for the full sample, and characterized by a substantial shift between firm-size classes and substantial redistribution of workers. Overall, these findings hint at a substantial reorganization of U.S. businesses over the last 40 years. This reorganization has had profound consequences for both the level and the nature of earnings inequality.
FIGURE A.16 – Regression residuals by firm fixed effect decile

(A) 1980-1986

(B) 2007-2013

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

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

(A) Firms ranked by earnings: 1980-1986

(B) Firms ranked by earnings: 2007-2013

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

(D) Firms ranked by earnings: 2007-2013

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

(A) 1980-1986

(B) 2007-2013

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

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

(a) 1980-1986

(b) 2007-2013

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

Notes: