

Inequality and the disappearing large firm wage premium

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I. Introduction

The large-firm wage premium, which goes back over 100 years to Moore (1911), is shrinking. The correlation between firm size (in logs) and wages (in logs) dropped by 55% between 1978 and 2013. In this paper we examine the Social Security Administration Master Earnings File covering from 1978-2013, and the Current Population Survey (CPS) from 1968 to 2015, finding three factors account for this.

First, the fall in the large firm wage premium has been driven almost entirely by the drop in the firm fixed effect from an Abowd et al. (1999) [AKM] style model. Large firms traditionally hire higher ability employees - which shows up in a positive correlation of firm size and the worker fixed-effect. We see this in our data from 1980 onwards, but this correlation remains largely unchanged until 2013. So the drop in large-firm wage premium is not driven by a fall in the quality of employees, but instead by a fall in the firm fixed-effect. That is, the pay *premium* which large firms are offering appears to have shrunk in absolute terms.

Second, most of the fall in the large-firm wage premium occurred within industries. Although industries with a historically large firm-size premium like manufacturing shrunk while those with smaller size premium like services and retail expanded,

the shift in industry composition can only account for about 20% of the overall reduction in the large-firm wage premium. Within-industry factors explain the remaining 80% of the decline.

Third, we find that the fall of the large firm wage premium mitigated against the rise of inequality. Had the large-firm wage premium remained constant, the rise in inequality over the period 1980 to 2013 would have been 20% greater. This is due to both a reduction in the variance of wage premiums and the covariance of wage and firm wage components across firm size classes.

Our paper builds on a long literature going pointing out that large firms pay a higher wages (e.g. Brown and Medoff (1989)). The size of this premium has also historically been substantial, for example with Oi and Idson (1999) reporting the wage gap due to firm size being 35%, similar to the gender gap of 36% and greater than the black-white wage gap of 14%. These firm-size wage gaps are potentially an important driver of inequality given the recent focus on cross-firm variation in pay as a driver of overall inequality (e.g. Card et al. 2013 and Song et al. 2015).

This literature offers four leading explanations rationale for pay premium in large firms. First, large firms may employ different workers - for example, they may be higher skilled, more experienced or harder working because of complementarities in input quality and productivity (e.g. Verhoogen 2008). However, despite adding extensive controls for employee characteristics like education and demographics the large-firm wage premium falls by only about 50% (e.g Brown and Medoff 1989), suggesting selection on observables cannot easily explain entirely this gap. Furthermore, as we show in section (IV) while worker fixed-effects are correlated with firm size they

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only account for roughly 1/3 of the large firm pay gap. Second, larger firms may be more unpleasant to work in, suggesting the pay premium is a compensating differential. However, as Katz and Summers (1989) show, larger firms have a far higher number of applicants per vacancy and lower quit rates, suggesting the jobs are more desirable in general. Larger firms also have higher work-life balance and other employee satisfaction metrics (Bloom et al. 2011) suggesting that while compensating differentials may be an important driver of overall pay differences across jobs (e.g. Sorkin 2017) it cannot account for the majority of the large-firm pay gap. Third, larger firms may earn higher rents from, for example, greater market power. However, measures of industry concentration and market power do not correlate well with large-firm differentials - for example, US manufacturing operates in a highly tradable and competitive product market, especially post 2000 with the entry of Chinese imports, but still has one of the highest levels of large-firm pay differentials across all sectors. Related to this union power may force rent extraction from firms, possibly to the long-run detriment of their survival. But again the evidence is weak in that the cross-industry level of the large-firm pay premium is uncorrelated with union density. Finally, a literature following Burdett and Mortensen (1998) has argued that search frictions can lead to large-firm pay premiums due to effectively random variations across firms in their hiring strategy. In these models a range of pay-rates are equally profitable, so that firms are equally likely to adopt any of these, so that the pay-size relationship is arbitrary. While these models are mathematically attractive they impose a number of very strong assumptions.

II. Data

We use two different datasets in this paper.

Social Security Administration Earnings Master File: The main source of data used in this paper is the Master Earnings File (MEF), which is a confiden-

tial database compiled and maintained by the U.S. Social Security Administration (SSA). The MEF contains a separate line of record for every individual that has ever been issued a U.S. Social Security number. In addition to basic demographic information (sex, race, date of birth, etc.), the MEF contains labor earnings information for every year from 1978 to (as of this writing) 2013. Earnings data in the MEF are based on Box 1 of Form W-2, which is sent directly from employers to the SSA. Data from Box 1 are uncapped and include wages and salaries, bonuses, tips, exercised stock options, the dollar value of vested restricted stock units, and other sources of income deemed as remuneration for labor services by the U.S. Internal Revenue Service.

Because earnings data are based on the W-2 form, the data set includes one record for each individual, for each firm they worked in, for each year. Crucially for our purposes, the MEF also contains a unique employer identification number (EIN) for each W-2 earnings record. Because the MEF covers the entire U.S. population and has EIN records for each job of each worker, we can use worker-side information to construct firm-level variables. In particular, we assign all workers who received wage earnings from the same EIN in a given year to that firm. Workers who hold multiple jobs in the same year are linked to the firm providing their largest source of earnings for the year. The resulting matched employer-employee data set contains information for each firm on total employment, wage bill, and earnings distribution, as well as the firm's gender, age, and job tenure composition. Since we do not have information on hours or weeks worked, we measure individual annual earnings (or their total wage bill) rather than wage rates. We only include workers earning above a minimum threshold of \$3,770 defined as minimum wage for one quarter of full time work (13 weeks by 40 hours) to minimize the effect of variation in hours worked.

Current Population Survey: The CPS runs a monthly survey on between 150,000 to 200,000 workers every month. In

March of each year they ask workers about their prior hours, weeks worked and earning in the previous year which we use to define earnings. From 1987 onwards the public release files of the CPS also provides an indicator for firm size, classified as less than 100 employees, 100 to 500 employees, 500 to 1000 employees and 1000+ employees. The CPS also provides a series of demographic, industrial and educational data.

A. What Is a Firm?

Throughout the paper, we use employer identification numbers (EINs) as the boundary of a firm. The EIN is the level at which companies file their tax returns with the IRS, so it reflects a distinct corporate unit for tax (and therefore accounting) purposes. Government agencies, such as the Bureau of Labor Statistics commonly use EINs to define firms.¹ They are also often used in research on firms based on administrative data. This is often not the same, however, as the ultimate parent firm. For example, the 4,233 New York Stock Exchange publicly listed firms in the Dunn & Bradstreet database report operating 13,377 EINs, or an average of 3.2 EINs each.² Although it is unclear what level of aggregation is appropriate in order to define a “firm,” we feel the EIN is a reasonable concept reflecting a unit of tax and financial accounting. An EIN is a distinct concept from an “establishment,” which typically represents a single geographic production location and is another commonly used unit of analysis to study the behavior of “firms” (e.g., this is the definition used by Barth et al. 2016, who study inequality using U.S.

¹See U.S. Department of Labor, Bureau of Labor Statistics, “Business Employment Dynamics Size Class Data: Questions and Answers,” <http://www.bls.gov/bdm/sizeclassqanda.htm>, questions 3 and 5.

²Typically, 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 Online divisions. As another example, Stanford University has four EINs: the university, the bookstore, and the main hospital and children’s hospitals.

Census data). Around 30 million U.S. establishments in the Longitudinal Business Database in 2012 are owned by around 6 million EIN firms, so an establishment is a more disaggregated concept.

III. Results

A. Overall firm size earnings correlations

Figure (1) shows a time series of the large-firm wage premium (LFWP)—defined as the coefficient on log firm size in a regression of log earnings on log firm size. We see a strongly declining relationship between firm size and wages, dropping from around 0.09 in 1980 to under 0.04 in 2013. This is a sizable drop, and implies that in 1980 working for a large firm with 10,000 employees (about the 75th percentile of employment-weighted firm size distribution) compared to a small firm of 100 employees (about the 25th percentile) would be associated with about 60% higher earnings, while by 2013 this premium would have dropped to around 25%. Therefore, the LFWP has been roughly cut in half since the early 1980s.

IV. An Econometric Model of Worker and Firm Wage Differences

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).³ We will divide our time period into five seven-year periods and estimate a separate model for each period p . The regression model we estimate in each period is

$$(1) \quad y_t^{i,j} = \theta^{i,p} + X_t^i \beta^p + \psi^{j,p} + \epsilon_t^{i,j},$$

where $\theta^{i,p}$ captures earnings related to fixed worker characteristics (such as returns to formal schooling or to innate ability), β^p captures the effect of time-varying worker characteristics (in our case, a polynomial in

³To simplify notation, we leave the dependence of the identity of the firm on the worker implicit, such that $j \equiv j(i, t)$.

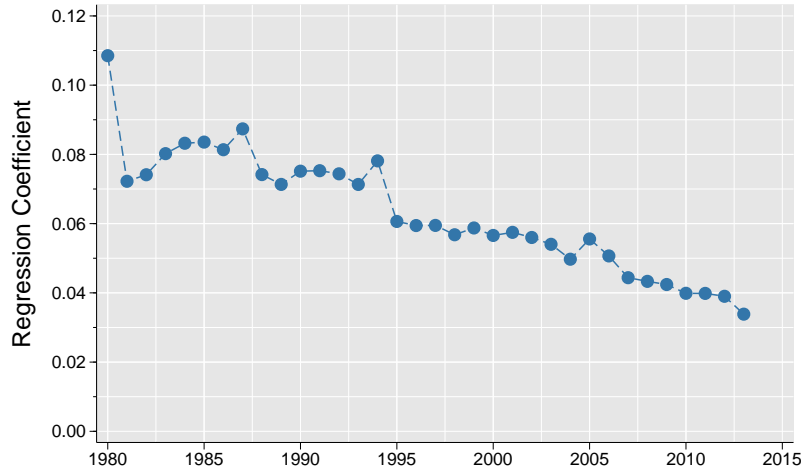


FIGURE 1. REGRESSION COEFFICIENT OF EARNINGS ON FIRM SIZE

age and year effects), and $\psi^{j,p}$ captures persistent earnings differences related to firm j (such as sharing of rents or compensating differentials). The residual, $\epsilon_t^{i,j}$, captures purely transitory earnings fluctuations. In addition, the residual will also contain any worker-firm specific (match) components in earnings, which we will denote by $m^{i,j}$.

The AKM model has proven to be an empirically successful extension of the standard human capital earnings function and has developed into the workhorse model for incorporating firm components into traditional earnings regressions. Clearly, this model is likely to be a simplification of firms' role in the setting of earnings, since in its basic form it does not allow for worker-firm interactions or for time-varying firm-specific components. Despite these reservations, Song et al. (2015) present evidence that the model appears to summarize a range of key patterns in our data surprisingly well. Hence, we believe that there is sufficient support for the model to treat it as a useful diagnostic device to better understand the patterns underlying the changes in firm and worker components of wage over time.

We estimate equation (1) separately for five adjacent seven-year intervals beginning in 1980 and ending in 2013. 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 (1) is done on the largest set of firms connected by worker flows. To maximize the number of observations in the connected set, we do not impose a restriction on firm size and do not exclude the public sector.⁴ Because of limitations in computing power, we estimate worker and firm effects separately for men and women (finding similar results for both gender groups). As we lack data on hours of work, our estimates of worker and firm effects may capture systematic differences in labor supply between workers and firms. However, Song et al. (2015) show that the results are robust across a range of labor supply sample restrictions.

A. Results from the AKM estimations

Figure (2) presents a visual representation of our main results. In each panel we show average log earnings by firm size class (blue line, circles). Firms are assigned to eight firm size classes with the smallest firms employing at most ten workers and the largest employing over 15,000. We also plot the average values of worker and firm earnings components estimated using the AKM estimation equation (1) – in particular the firm fixed-effect (red line, trian-

⁴Although included in the estimation, public sector jobs are excluded from the empirical analysis.

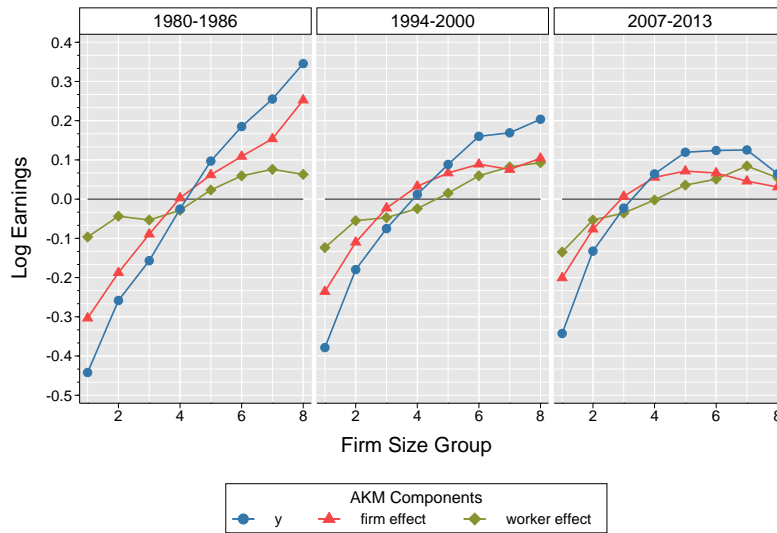


FIGURE 2. MEAN AKM COMPONENTS BY FIRM SIZE AND TIME PERIOD

Notes: Firm size groups: 1=1-10, 2=10-50, 3=50-250, 4=250-1K, 5=1-2.5K, 6=2.5-10K, 7=10-15K, 8=15K+. Age/year effects and the residual term are omitted.

	Dependent Variable:				
	Log Earnings (1)	Worker Effect (2)	Firm Effect (3)	Age Effect (4)	AKM Residual (5)
Interval 1: 1980-86	0.080	0.016	0.057	0.007	0.001
Interval 5: 2007-13	0.039	0.019	0.021	-0.002	0.001
Change Share (Percent)	-0.041 -	0.003 (-7.5)	-0.036 (86.8)	-0.008 (20.2)	0.000 (0.5)

TABLE 1—CHANGE IN LFWP REGRESSION COEFFICIENTS BY AKM COMPONENTS

gles) and worker fixed-effect (olive line, diamonds). Time-variant worker characteristics and the residual component are omitted to highlight the key forces driving the changes over time. Each panel displays these results for a different seven-year interval. This figure shows a couple of the key results. First, the major driver of the large firm premium in earlier time periods is the firm fixed-effect, which accounted for around 70% of the LFWP from 1980 to 1986. That is, the same workers appear to get paid more to work in larger firms. Another 20% of the large firm premium is driven by selection effects—workers in larger firms have superior worker fixed-effects. The second main finding is that the reduction in the large firm wage premium has almost entirely been driven by the drop in the firm fixed-effect premium by firm size. In particular, average earnings have fallen notably for the largest firm size group (15,000+ employees), driven almost entirely by the drop in the firm fixed-effect. So, the fall in the large firm wage premium appears to be driven by firms of 1,000 employees or more no longer paying above market salaries to their workers.

In table (1) we formally decompose the change in the large firm wage premium into its constituent AKM wage components. Given equation (1), log earnings is additively separable into the AKM components. Therefore, the coefficients in regressions of AKM components on log firm size mechanically add up to the total coefficient of log earnings on log firm size. The decomposition confirms the message of figure (2). The decline in the relationship between firm fixed-effects and firm size accounts for 87% of the total decline in the large firm premium. Another factor is a fall in the return to time-varying worker characteristics at large firms—contributing 20% to the total decline in the large firm wage premium. As these characteristics include year and age effects, this result suggests that larger firms are becoming relatively younger.⁵ In contrast, selection of worker types by firm

size has remained relatively stable over the period. In fact, large firms are slightly more likely to hire high-wage workers in the most recent period. This modest compositional upgrading mitigates the decline of the LFWP—accounting for an 8% increase.

B. Industry analysis

In order to better understand the decline of the LFWP, we turn to an industry analysis. Table (2) presents the initial level and changes of both employment and the LFWP by nine broad industries. A few patterns are evident. First, we find a general decline in the LFWP within most industries. In fact, manufacturing is the only industry for which the LFWP did not decline. Second, we find large shifts in employment away from manufacturing, an industry with a high initial LFWP, into the services sector, an industry with a low LFWP. Industry codes are not assigned to new firms in the SSA data set past the year 2002, therefore, there is also a surge in employment to “unclassified” industries.

Given both within-industry changes in LFWPs and large sectoral shifts in employment, we produce a decomposition to quantify the relative contributions of between- and within-industry factors on the decline in the LFWP. Although the details are left for the online appendix, our main result is that within-industry changes in the LFWP can account for 80% of the decline whereas between-industry factors account for only 20%. Therefore, the declining LFWP is not merely a reflection of sectoral employment shifts and, therefore, suggests broad changes in the pay policies of large firms throughout the economy.

C. The large-firm wage premium and inequality

As large firms have historically paid significantly higher wages, it is important to understand the implications of a fall in large firm wage premium for changes in inequality. Figure (2) suggests declines in the LFWP will also reduce inequality as the wage gradient across firms flattens. Furthermore, given that the decline is driven

⁵We are able to directly confirm that workforces of large firms have become relatively younger.

	Large Firm Premium 1980-86 (1)	Change in Large Firm Premium (2)	Employment 1980-1986 (millions) (3)	Change in Employment (millions) (4)
Manufacturing	0.094	0.003	85.9	-37.1
Mining	0.104	-0.004	5.6	-2.9
Transportation	0.096	-0.046	26.4	-1.9
Construction	0.095	-0.015	26.0	-1.8
Agriculture	0.049	-0.014	7.1	-1.0
Wholesale Trade	0.060	-0.008	19.7	-0.3
Retail Trade	0.044	-0.051	34.1	2.7
Finance & Insurance	0.057	-0.024	16.5	4.6
Services	0.054	-0.044	53.4	55.3
Unclassified	0.110	-0.048	11.2	79.8

TABLE 2—CHANGE IN LFWP AND EMPLOYMENT BY INDUSTRY

by falling firm wage premiums at large firms which employ high-wage workers, the LFWP premium may further reduce inequality as the reductions in firm pay are directed toward high-wage workers. On the other hand, if the LFWP is declining differentially across worker groups through worker-firm specific components of pay, the declining LFWP may actually contribute to rising inequality.⁶

In order to quantify the decline in the LFWP on changes in inequality, we employ a simple variance decomposition of log earnings across five broad firm size classes. The between component of this decomposition quantifies the role of firm size with respect to total wage variation. Panel A of table (3) presents the main results. Column (1) shows that firm size can account for a modest share of total wage variation. The between component accounts for 0.048 of a total wage variance of 0.791—or around 6% of total wage variance. Column (3) shows that wage variance across firm size classes declined over time—consistent with the intuition that a decline in the large firm wage premium reduces inequality. In fact, column (4) shows that inequality would have been about 20% higher had the large firm wage premium not declined. Panel B shows that the reduction in inequality is due to a

decline in the variance of firm wage premiums as well as a decline in the covariance of firm and worker fixed-effects. The decline in the covariance results from the fact that large firms tend to employ high-wage workers and that this relationship has remained stable over time. Panel C shows the important factors for rising inequality that are not explained by firm size. Similar to the aggregate results in Song et al. (2015), we see that rising variance of worker fixed-effects and covariance between firm and worker fixed-effects are the leading factors driving within-firm-size inequality.

V. Why is the Large Firm Wage Premium Declining?

Although our findings are largely descriptive, we quickly examine some competing hypotheses for the decline in the LFWP to guide future research. Our main results are that the LFWP is declining due to reductions in firm pay premiums that largely occur within industries. One hypothesis which is consistent with these findings is that a broad trend towards rising outsourcing has reduced the size of the largest, most successful firms and hence distorted the relationship between firm size and firm wage premiums. Goldschmidt and Schmieder (2017) find evidence that workers employed in business service jobs face a 10-15% decline in wages when their jobs are outsourced to contractors or temp agen-

⁶Unless these worker-firm specific components of pay are exogenous to worker mobility, then these component lie outside the scope of our simple AKM model.

	Interval 1 1980-1986 (1)	Interval 5 2007-2013 (2)	Interval 1 to 5 Change Share (3) (4)	
<i>Panel A: Between-/Within-Firm Size Class Variance Decomposition</i>				
Total Variance	0.791	0.918	0.127	-
Between Variance	0.048	0.021	-0.027	-20.9
Within Variance	0.743	0.897	0.154	120.9
<i>Panel B: AKM Components of Between-Firm Size Class Variance</i>				
Var Worker Effect	0.004	0.005	0.001	0.7
Var Firm Effect	0.026	0.010	-0.016	-12.5
Cov Worker-Firm Effect	0.015	0.008	-0.007	-5.6
<i>Panel C: AKM Components of Within-Firm Size Class Variance</i>				
Var Worker Effect	0.429	0.546	0.117	92.3
Var Firm Effect	0.142	0.125	-0.017	-13.6
Cov Worker-Firm Effect	-0.063	0.009	0.072	56.6
N (millions)	330.63	413.23	82.59	-

TABLE 3—BETWEEN-/WITHIN-FIRM SIZE CLASS VARIANCE DECOMPOSITION

Notes: Firms are groups into 5 classes based on the size of their workforce: 1 to 20, 21 to 100, 101 to 1000, 1001 to 10000, and over 10000.

cies. This result suggest that large firms outsource to reduce labor costs. Consequently, firms that pay large premiums may be reducing their size. Katz and Summers (1989) find a large increase in the incidence of alternative work arrangements in the US.

Consistent with the outsourcing story, we find suggestive evidence that low-skill workers are facing wage pressure in large firms. Figure (3) plots the regression coefficient of the AKM match component on log firm size by worker fixed effect (WFE) quartile. The regression coefficient on the bottom quartile of WFE workers is declining over time. This means that low-wage workers are receiving smaller firm wage premiums over time at large firms.

In addition to outsourcing, there are other hypotheses that may explain the decline in the LFWP which should be investigated. If firm-specific wage premiums result from rent-sharing arrangements, then increasing focus on corporate governance and efficiency in large firms may have led them to more closely align pay with market rates. Firm-specific wage premiums may in part reflect compensating differentials for non-wage amenities. If large firms are offering more amenities relative to small firms in recent decades, for example healthcare, then we may see a decline in the LFWP.

VI. Conclusion

Large firms have paid a significantly higher wage for more than a century, but over the last thirty years this large firm premium has started to disappear. We show that the decline is largely due a reduction in wage premiums at large firms holding worker composition constant. Furthermore the decline cannot be explained by sectoral changes in employment as the majority of the change occurs within industries. Finally, we find that the reduction in the large firm wage premium has mitigated against potentially larger increases in inequality.

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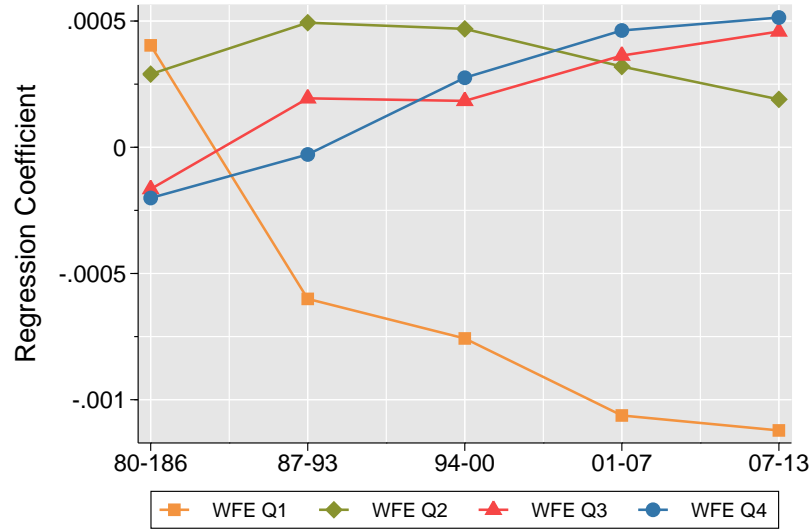


FIGURE 3. RELATIONSHIP BETWEEN FIRM SIZE AND AKM MATCH COMPONENT BY WFE QUARTILE

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Supplemental Online
Appendix

APPENDIX: DECOMPOSING THE LARGE FIRM WAGE PREMIUM

We are interested in estimating the large-firm wage premium which is the coefficient β_t in the following simple regression model:

$$y_{it} = \alpha_{it} + \beta_t x_{it} + \epsilon_{it}.$$

For random variables x_{it} , y_{it} and industry I_{it} the law of total variance states:

$$\text{Cov}(x_{it}, y_{it}) = E[\text{Cov}(x_{it}, y_{it}|I_{it})] + \text{Cov}(E[x_{it}|I_{it}], E[y_{it}|I_{it}]).$$

This is the standard between/within variance decomposition where the first term represents the within component and the second term represents the between component. Therefore, we can write the regression coefficient as:

$$\beta_t = \frac{\text{Cov}(x_{it}, y_{it})}{\text{Var}(x_{it})} = \frac{E[\text{Cov}(x_{it}, y_{it}|I_{it})] + \text{Cov}(E[x_{it}|I_{it}], E[y_{it}|I_{it}])}{E[\text{Var}(x_{it}|I_{it})] + \text{Var}(E[x_{it}|I_{it}])}.$$

Given that the expression is not additively separable, we propose to decompose the change in the regression coefficient by varying each set of components sequentially. Thus, when assessing the change in β_t between intervals one and five, we create counterfactual regression coefficients for the 5th interval by holding either the between- or within-industry components constant. The order in which the components are varied matters and thus we have a pair of estimates. *Sequence 1* refers to the case with between components change first and then the within components change. *Sequence 2* refers to the opposite case, in which the within components change first. The two sequences provide bounds for the within/between components.

Table (A1) shows that the large firm premium fell 0.041 log points between the 1980-1986 interval and the 2007-2013 interval. To put this number into context a worker moving from a 100 employee firm to a 10,000 employee firm would earn 18.9 log points less in 2007-2013 than had he moved in 1980-1986. Panels A and B of Column (1) show that 78 to 80% of the change in the regression coefficient comes through the between-industry components. This result is robust to excluding the unclassified industry. In this case the bounds for the within-industry components range from 73 to 77%. The results are also fairly consistent across intervals with a contribution of the within-industry component of 114%, 90%, and 83% for differences between the 1st and the 2nd, 3rd, and 4th intervals, respectively.

In addition to the decomposition of the total large-firm wage premium, Table (A1) also provides a decomposition of each of the constituent AKM components of the large-firm wage premium. Note that these components are additively separable as:

$$\begin{aligned} \beta^y &= \frac{\text{Cov}(x_{it}, y_{it})}{\text{Var}(x_{it})} = \frac{\text{Cov}(x_{it}, \alpha_i + \psi_{j(it)} + x'_{it}\beta + r_{it})}{\text{Var}(x_{it})} \\ &= \frac{\text{Cov}(x_{it}, \alpha_i)}{\text{Var}(x_{it})} + \frac{\text{Cov}(x_{it}, \psi_{j(it)})}{\text{Var}(x_{it})} + \frac{\text{Cov}(x_{it}, x'_{it}\beta)}{\text{Var}(x_{it})} + \frac{\text{Cov}(x_{it}, r_{it})}{\text{Var}(x_{it})} \\ &= \beta^\alpha + \beta^\psi + \beta^{x\beta} + \beta^r. \end{aligned}$$

The majority of the change in the firm size premium is due to a reduction in the covariance between firm fixed-effects and firm size. In fact, column (3) shows that 87% of the fall in the large firm premium can be attributed to firm fixed effects. Furthermore, in both sequences, changes in firm fixed-effects are the key driver of both within- and between-industry reductions in the large-firm wage premium. A secondary factor is a contribution of 20% from the age and year effect components. This is the result of large firms employing

TABLE A1—DECOMPOSITION OF LFWP INTO WITHIN-/BETWEEN-INDUSTRY COMPONENTS

	Dependent Variable:				
	Log Earnings (1)	Worker Effect (2)	Firm Effect (3)	Age Effect (4)	AKM Residual (5)
Total Change Share (Percent)	-0.041 -	0.003 (-7.5)	-0.036 (86.8)	-0.008 (20.2)	0.000 (0.5)
<i>Panel A: BT-/WI-Industry Component, Sequence 1</i>					
Within-Industry Change Share (Percent)	-0.008 (20.0)	0.005 (-12.9)	-0.012 (28.1)	-0.002 (4.9)	0.000 (-0.1)
Between-Industry Change Share (Percent)	-0.033 (80.0)	-0.002 (5.5)	-0.024 (58.7)	-0.006 (15.3)	0.000 (0.5)
<i>Panel B: BT-/WI-Industry Component, Sequence 2</i>					
Within-Industry Change Share (Percent)	-0.009 (21.8)	0.005 (-12.9)	-0.012 (29.5)	-0.002 (5.3)	0.000 (-0.1)
Between-Industry Change Share (Percent)	-0.032 (78.2)	-0.002 (5.5)	-0.023 (57.3)	-0.006 (15.0)	0.000 (0.5)

a relatively younger workforce. Column (2) shows that worker composition actually works in the opposite direction—responsible for a small rise in the large firm premium. Therefore, although the large premium premium is falling, mean worker quality has slightly improved in large firms. Column (5) shows that the contribution of the residual is negligible.