Aligning Inequalities

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July 26, 2019

Abstract

Drawing on US linked occupation-workplace data, we show that half of rising wage inequality since 1999 is due to rising correlation between workplace and occupation premiums. Fewer middle-skill occupations are employed at high-paying workplaces and high- and low-skilled workers are more likely to be employed at corresponding high- and low-paying workplaces. What drives this increased alignment between potentially independent systems of organizational and occupational stratification? We show that it is primarily not due to entry and exit of establishments, but instead due to shifting occupational composition and workplace premiums within establishments. These results demonstrate an understudied way that organizations affect the earnings distribution: not by changing aggregate inequality in workplace or occupational premiums, but by aligning these two stratification systems.

Keywords: Wage Inequality, Stratification, Organizations, Variance Decomposition

*This research was conducted with restricted access to Bureau of Labor Statistics (BLS) data. The views expressed here do not necessarily reflect the views of the BLS or the U.S. government. Thank you for helpful comments from Paul Osterman, Chris Winship and the participants at the HBS Nerdlab and the MaxPo “Firms, Sectors and States” seminar. Please direct correspondence to wilmers@mit.edu, Massachusetts Institute of Technology, Sloan School of Management.
1 Introduction

Rising inequality wage inequality has reshaped the US earnings structure since 1980. Most research focuses on increasing inequality either between occupations or between high- and low-paying workplaces. Yet, at the micro-level organizations both organize tasks into jobs and set pay relative to other employers. When a manufacturing plant upgrades, it might increase the skill intensity of work and also increase pay even relative to other employers of similar workers (Fernandez 2001). When a mental hospital substitutes lower-paid social workers for psychologists, it might pay those social workers more than the market rate for that occupation, in hopes of selecting for higher skilled substitutes (Abbott 1988). In outsourcing, a high-wage employer may shift a category of low-skilled workers, like janitors or security guards, into a lower-paying contractor (Dube and Kaplan 2010; Ochsenfeld 2018). When scientific management roiled the steel industry in the early twentieth century, pay premiums attributable to skill declined, while those attributable to organization were increased (Braverman 1974). Craftsmen became relatively high-paid operators.

When employers make these decisions about skill composition and firm premiums, they bring two macro-level systems of stratification into more or less alignment. A janitorial job, low in the ranking of occupation or skill, can either be similarly low in the firm premium ranking, contracted out to a , or benefit from working for a large corporations, where collective bargaining, reputation and selection provide pay premiums even for low-level employees. In this paper, we claim that the recent rise in US wage inequality is due in large part to increased alignment between inequalities in skill premiums and firm premiums.

We build on prior research on rising wage inequality, which has focused primarily on the contribution to inequality made by changes in gaps between occupations and between firms. First, skill-biased technological change has increased demand for high-skilled workers at the expense of middle-skill workers (Goldin and Katz 2008; Autor and Dorn 2013). This research focuses on pay differences between broad occupation and skill groups. Similarly, sociological research on occupational closure and licensing finds that changing occupation premiums can also spring from institutional constraints (Weeden 2002).

Other research focuses on pay differences across organizations, rather than across occupations. An organization may pay employees more or less than competitors pay, even for the same job type. This can come from differences in institutionalized pay practices across organizations or from organizations sharing some part of their economic rents or profits with their employees (Barth, Bryson, Davis, and Freeman 2016; Card, Heining, and Kline 2013). Between-organization inequality can also stem from redistribution of rent across industries, as in the growth of large buyers or financialization (Wilmers 2018; Tomaskovic-Devey and Lin...
A changing distribution of firm premiums could also spring from shifts in non-wage amenities and other compensating differentials across the economy (Sorkin 2018).

Of course, inequality could also increase below the broad level of organizations and occupations. This could be located in growing gaps among co-workers doing the same job, perhaps due to the rise of performance pay (Lemieux, MacLeod, and Parent 2009). It could also stem from increased gaps among co-workers of different skill levels, as the decline of unions allows managers and professionals to wrest surplus from production workers (Piketty and Saez 2003; Rosenfeld 2006).

This rich body of research establishes occupations and organizations as core determinants of wage inequality. But it says little about how these stratification systems relate to each other. All of these theories assume that economic inequality is driven by increased dispersion across the core stratification institution—occupation, firm, hierarchical level. Yet understanding inequality requires exploring how membership in multiple roles allows pay premiums and how these pay premiums can become more or less dispersed.

Insofar as inequality alignment has been considered previously, it has focused on skill sorting, outsourcing and industry changes. Increased skill sorting across organizations can drive inequality under theories of o-ring production, where productivity hinges on a firm’s weakest employee (Kremer 1993; Song, Price, Guvenen, Bloom, and von Wachter 2018). Many organizations, claiming to focus on employing only workers in their core competency, have contracted out low-skilled work, like janitorial, security and logistics (Dube and Kaplan 2010). This contracting-out process shifts low-skilled occupations to poorly paying employers. The decline of manufacturing employment, which provides relatively highly paying jobs for low-skilled workers, could also increase inequality in part by increasing alignment.

In the following, we draw on restricted-use data from the Bureau of Labor Statistics and implement the first ever decomposition of US inequality trends that accounts simultaneously for occupation and workplace contributions to inequality. We first present the data and the basic variance decomposition that motivates our analysis. We then present our key hypotheses about the determinants of increased alignment and test them by studying workplace-level changes in covariance over time.

2 Data

Our study makes use of the 1999-2017 years of the Occupational Employment Statistics Survey (OES), collected by the Bureau of Labor Statistics (BLS). The OES combines a census of U.S. Postal Service, federal government executive branch, and state government workplaces, with a semiannual probability sample of local governments and nonfarm establishments in the private sector. Establishments in the private sector and local government are drawn from a sampling frame of 7.6 million establishments identified through states’
unemployment insurance records. Every six months, the BLS assembles a new version of this sampling frame, removing establishments that have been sampled in any of the prior five rounds of the OES.

The sampling frame is, furthermore, stratified into more than 150,000 cells defined by metropolitan or nonmetropolitan statistical areas and industry. Schools and casinos are also stratified by ownership. Within each stratum, the largest establishments are sampled with certainty every 6-panel cycle, while smaller establishments have probability of selection approximately proportional to size. Following this procedure, the BLS surveys approximately 200,000 establishments semiannually, excluding federal and USPS workplaces.

The total combined 3-year sample ending in May 2017 comprised approximately 1.2 million establishments with a 72.0% response rate; this accounted for 82 million workers out of 141 million in the United States. The BLS imputes staffing distributions for nonresponders or incomplete responders via a nearest-neighbor hot deck procedure: the proportionate employment by occupation in a workplace is copied from the most recent respondent in the same industry, state, and ownership cell with the closest reported employment. Neighbors are selected from those workplaces sharing the nonresponder’s 5- or 6-digit NAICS level, though this restriction is loosened when needed until a match is found. In our main analysis, we include only privately-owned establishments and omit those with imputed data.

The OES records wages as the hourly averages of base rate pay and supplementary pay, including cost-of-living allowances and commissions. While wages are reported at the individual level for most USPS, state, and federal workers, for most other employers wages are aggregated into twelve wage ranges and reported as the mean within each of these ranges. Because wages are aggregated by range, the variance of within-workplace wages in the OES data, even when weighted by the number of workers in each range and the appropriate sampling weights, will underestimate the true variance of wages.

3 Inequality Trends by Organization and Occupation

We measure inequality as the variance of log earnings across all workplace-occupation cells. This is a standard approach in the sociology and labor economics literature (Mouw and Kalleberg 2010; Lemieux 2006; Van Heuvelen 2018, for example), and it allows us to decompose total inequality in a year into the components occurring between and within groups such as occupations or workplaces.

If the observations are assigned to groups $g$, we can decompose the total variance of the log-earnings $y$ into a between-group component and a within-group component (Western and Bloome 2009, 296). Suppose $y$ equals the sum of a fixed effect for its group $g$ and an error term with mean zero; then, the variance of $y$ can be written as the sum of the variance of the fixed effects and the average of the variance of the errors
within each group $g$. That is,

$$V(y) = V(E[y \mid g]) + E[V(y \mid g)]$$

(1)

This model can be put to use to examine any set of groups $g$ that split up the $y$. Western & Bloome (2009, 318), for example, decompose earnings inequality by education category. Mouw & Kalleberg (2010) decompose earnings inequalities by occupation:

$$V(y) = V(E[y \mid occupation]) + E[V(y \mid occupation)]$$

They define occupations that are roughly equivalent the 2-digit SOC level. Van Heuvelen (2018) decomposes male, female, and household income by “big” classes and “small” classes, defined at the occupation level. Van Heuvelen finds that the small-class WGI explains about 60% to 70% of the total variance in the years between 1970 and 2011, and around 60% of the increase in variance during this period (Van Heuvelen 2018, 1065).

To assess the relative importance of different aggregations of occupations, we conduct decompositions at 2, 3, and 4 occupation-code levels. Similarly, we produce decompositions at the workplace level and at the 2, 3, and 4 NAICS-code levels. Finally, we decompose variance by a 4-group aggregate of SOC occupation codes, which we term “skill”, and again by an aggregation of 2-digit NAICS codes into 21 major industry groups. We re-estimate the model at each year, allowing the skill-group averages, for example, to vary over time.

Figure 1: BGI and WGI components for occupation and workplace decompositions, 1999-2017.
Because we estimate our decomposition at the occupation-workplace level, thereby ignoring the spread of earnings within those cells, we can expect that our BGI estimates make up a larger share of total variance in a given year than they would if calculated on individual-level earnings. Moreover, the increase in skill-group BGI explains about 76% of the increase in total variance from 1999 to 2016, while the increase in industry BGI explains about 55%. Note that refining from the 3-digit SOC level to the 4-digit does not drastically change our results. In any given year, the two BGIs never differ by more than 0.1 percentage points of total variance. Note that the 3-digit SOC codes define 96 occupational groups.

The above decomposition are calculated one at a time using Equation 1, which allows only one vector of groups $g$. This requires us to estimate separate one-way fixed effect models such as $y_{i,t} = \alpha_{\text{occ}(i),t} + \epsilon_{i,t}$ for occupation and $y_{i,t} = \beta_{\text{workplace}(i),t} + \zeta_{i,t}$ for workplace, where $\alpha_{\text{occ}(i),t}$ is the fixed effect of $i$’s occupation in year $t$, $\beta_{\text{workplace}(i),t}$ is the workplace fixed effect, and $\epsilon_{i,t}$ and $\zeta_{i,t}$ are mean-zero error terms. However, this approach ignores the possibility that workplace and occupation fixed effects are related to one another. We therefore specify a two-way fixed effect model where a workplace-occupation cell’s earnings are the sum of an occupation fixed effect, a workplace fixed effect, and a mean-zero error term:

$$y_{i,t} = \alpha_{\text{occ}(i),t} + \beta_{\text{workplace}(i),t} + \eta_{i,t}$$  \hspace{1cm} (2)

After estimating this model, we can decompose the earnings variance in year $t$ as:

$$V(y_{i,t} \mid t) = V(\alpha_{\text{occ}(i),t} \mid t) + V(\beta_{\text{workplace}(i),t} \mid t) + 2 \times Cov(\alpha_{\text{occ}(i),t}, \beta_{\text{workplace}(i),t} \mid t) + V(\eta_{i,t} \mid t)$$ \hspace{1cm} (3)

Our approach is similar to the popular earnings model specified in Abowd, Kramarz, and Margolis (1999), in which log earnings are the sum of an individual fixed effect, a workplace fixed effect, and an error term. However, it differs in two important respects. First, ours allows both sets of fixed effects to vary by year, permitting us to trace the changing earnings premiums of particular occupations or workplaces over time. Second, our model can be estimated more robustly. The AKM model relies workplace-switching individuals to properly identify the fixed effects, and the resulting estimates are only as reliable as the bipartite graph linking workers to workplaces is strong. Identification in our model relies on workplaces that have multiple occupations (and vice-versa), which is more likely to obtain.

Workplace explains the greatest share of the variance, between 33% and 39% in all years, down from about 60% in the one-way model. 3-digit occupation is the next largest component at about 32% of variance.
in most years. While both workplace and occupation steadily increase over time as shares of variance in their respective one-way layout (see Fig. 1), in the two-way design they remain fairly steady in all years. Instead, it is the covariance term that increases dramatically, from less than 10% of total variance in 1999 to over 17% in 2016. The increase in covariance accounts for almost 54% of the total increase in variance, whereas the increase in workplace variance and occupation variance account for only about 23% each.

Figure 3: Correlation between workplace and occupation FEs, 1999-2017.

The increase in the covariance component is reflected in the rapid rise in the correlation between workplace FE and occupation FE, which doubles from 1999 to 2016. A series of simulations suggest that, under conditions similar to the OES, the estimates of correlation are on average a tenth of a percent low; so, the
estimates presented in Fig. 3 are a reliable indication that correlation has steadily and dramatically increased in the past two decades.

AKM-style studies of administrative data – in, for example, Germany (Card, Heining, and Kline 2013) or Denmark (Bagger, Sorensen, and Vejlin 2013) – conclude that the correlation between worker fixed effects and workplace fixed effects has been increasing in many countries. Our results suggest that a similar phenomenon is taking place in the United States. However, because the standard AKM model relies on time-invariant fixed effects, changes in correlation are due solely to changes in the joint distribution of workers and workplaces. The increasing correlation in Fig. 3, on the other hand, can be explained both by changes in the joint distribution of occupations and workplaces, and by changes in the occupation and workplace fixed effects.

4 Explaining Increased Inequality Alignment

This is an ongoing analysis. In this section we first draw on the sociology of work to formulate hypotheses about the determinants of the increased alignment between occupational and organizational stratification. We then test these hypotheses using counterfactuals derived from the two-way decomposition in Equations 2 and 3.
References


