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Consolidated Advantage: New Organizational Dynamics of Wage Inequality

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Consolidated Advantage:

New Organizational Dynamics of Wage Inequality*

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Abstract

The two main sources of inequality in the US labor market—occupation and workplace—have increasingly consolidated. Workers benefiting from employment at a high-paying workplace are increasingly those who already benefit from membership in a high-paying occupation. Drawing on occupation-by-workplace data, we show that two-thirds of the rise in wage inequality since 1999 can be accounted for not by occupation or workplace inequality alone, but by their increased consolidation. This consolidation is not attributable to firm turnover or to how occupations have shifted across a fixed set of high paying firms (as in outsourcing). Instead, consolidation has resulted from new bases of workplace pay premiums. Workplace premiums associated with teams of professionals have increased, while premiums for previously high-paid blue-collar workers have been cut. Yet the largest source of consolidation is bifurcation in the social sector, whereby some previously low-paying but high-professional share workplaces, like hospitals and schools, have deskilled their jobs, while others have raised pay. Broadly, the results demonstrate an understudied way that organizations affect wage inequality: not by directly increasing variability in workplace or occupation premiums, but by consolidating these two sources of inequality.
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US wage inequality has risen persistently since the 1980s. Research explaining this trend has increasingly emphasized two causal explanations. First, because inequality has increased between occupations and skill levels (Mouw and Kalleberg 2010; Goldin and Katz 2008), researchers have pointed to rising returns to education and to occupational closure—that is, barriers to entry like occupational licensing—as drivers of inequality (Weeden 2002; Acemoglu and Autor 2011). Second, because inequality has risen between rather than within workplaces (Barth, Bryson, Davis, and Freeman 2016), researchers have attributed inequality to rising average pay at top firms with market dominance or high pay practices (Tomaskovic-Devey and Avent-Holt 2019).

What unites these prominent explanations for wage inequality is a focus on inequality between groups. They each assume that increasing inequality is due to increasing pay-offs by occupation, skill level, or workplace. Indeed, this assumption underlies most general theories of inequality, whether they emphasize inequality due to classes or occupations; whether by firm performance or between segmented product markets (Mouw and Kalleberg 2010; Wodtke 2016; Weeden and Grusky 2012). In this article, we propose an alternative theory of rising inequality. We focus not on inequality between groups, but instead on the consolidation of distinct sources of advantage—that is, the extent of correlation between multiple sources of inequality. Building on an old idea in macrostructural sociology, we demonstrate that inequality is exacerbated as distinct axes of inequality align (Blau 1977).

Specifically, we argue that recent increases in wage inequality are accounted for by increased correlation between occupation pay premiums and workplace pay premiums.[1] High-paying workplaces once employed low-skill workers in circumstances ranging from unionized manufacturing assembly jobs to maintenance and food service positions at large corporate headquarters. Moreover, previously many members of high-paying occupations—like doctors, teachers, and psychiatrists—worked in low-paying service workplaces. In this paper, we show that these cases of offsetting mismatch between occupation and workplace premiums have become more rare. Over time, the workers bene-

[1] By occupation premiums, we mean the part of a worker's pay that is common across all members of an occupation and not just due to where they work: the average pay for doctors attributable to education requirements, skill, licensing, etc. Some doctors will make less than this average, due to low experience, employment at a small, low-paying clinic or specialization in a low-paying area like internal medicine or pediatrics. Others will make more. By workplace premiums, we mean the component of pay specific to a workplace, over and above its occupational composition. Some workplaces pay more than their competitors even though they employ workers in the same occupations. As discussed further below, workplace premium differences could be due to unionization, efficiency wages, product market power or non-wage compensating differentials.

fiting from employment at a high-paying workplace are increasingly those who already benefit from membership in a high-paying occupation. We call the ensuing correlation between different sources of advantage *consolidated inequality*.

This argument extends recent research linking earnings inequality to positive worker-employer sorting (Song, Price, Guvenen, Bloom, and von Wachter 2018) and to the increased prevalence of occupationally homogenous employers (Handwerker 2018). In our analysis, we find that up to two-thirds of the rise in wage inequality since 1999 is accounted for by increased correlation between occupation pay premiums and workplace pay premiums. It is the consolidation of inequality, rather than rising variance in pay premiums associated with occupation or with workplace alone, that explains rising inequality. Moreover, this trend is not just due to entry and exit of workplaces. Changing strategic decisions about job composition and pay rates shift workplaces' occupational composition and pay premiums over time. Consolidating advantage is thus an understudied way that organizations affect inequality. For example, consider a previously low-workplace premium mental health clinic that raises pay for its largely professional employees. This raise could be applied equally to its employees and diminish both within-workplace inequality and overall inequality in workplace premiums (as a low-paying clinic moves up toward standard compensation levels). But the raise could nonetheless exacerbate overall inequality by allocating more workplace premium benefits to professional employees, who are already advantaged by occupation premiums. Even absent changes in within-workplace inequality, organizations exacerbate inequality when their pay-setting and job composition decisions heighten the correlation between occupation and workplace premiums.

This descriptive characterization of rising inequality does not explain *why* consolidation between occupation and workplace advantages increased. In a second step, we explore several organizational and labor market changes that could explain rising consolidation. The expansion of both low- and high-paid service firms—fast food alongside finance—has polarized employment opportunities and supplanted more skill-diverse manufacturing employment (Kalleberg 2011). Beyond industry composition changes, occupations can shift across workplaces. For example, outsourcing has shifted low-paid occupations like janitors and food service workers out of employment in high-paying firms (Weil 2014). Other research suggests that macro-institutional developments have changed the source of workplace premiums (Davis 2016; Cappelli 1999; VanHeuvelen 2018). For example, in the past, unions once bolstered workplace premiums for some workers in lower-paid manual occupations

(Sørensen 2000). At the other side of the occupation distribution, many professionals employed in health, education and social service organizations were underpaid due to penalties associated with gender, meaningful work and professional identity (England, Budig, and Folbre 2002; Reich 2014). While these consolidation-reducing union premiums and identity penalties have declined, the rise of superstar firms has meant increased pay at workplaces that employ high-paid teams of managers and professionals (Autor, Dorn, Katz, Patterson, and Van Reenen 2020; Lazear 2019). Consolidation is neither due to industry composition changes nor a reshuffling of occupations across high- and low-paying workplaces. Instead, the sources of workplace pay premiums have changed in ways that affect their distribution.

In this paper, we first document that consolidated inequality helps explain rising inequality and then we evaluate each of these potential sources of consolidation. Occupation-by-workplace Occupational Employment Statistics (OES) microdata allows us to estimate the first two-way occupation and workplace fixed effects model on US data. With this model, we distinguish rising inequality due to workplace, occupation or residual components from rising inequality due to the covariance of workplace and occupation. Next, to determine why consolidated inequality is increasing, we cannot directly observe ultimate causes like technological change or deunionization. Instead, we take advantage of the large sample and repeat respondents in the OES to study a panel of workplaces that appear at the beginning and end of the period. We use this panel to construct descriptive counterfactuals to capture different types of organizational changes that can drive consolidation. For example, we estimate how much less correlation would have increased if workplace premiums had not increased at establishments that employed managers and professionals at high wages.

Our findings amend prior research on inequality. Recent rising inequality is not mainly due to heightened pay-offs to occupation-wide skill (Liu and Grusky 2013) or to rising inequality between workplace pay premiums (Barth, Bryson, Davis, and Freeman 2016). It is also not due to residual or within-job inequality (Western and Bloome 2009; Tilly 1998). Instead, organizations have consolidated occupation and workplace inequalities. Our attempt to explain this trend revives a classic question in the sociology of wage-setting: under what conditions does workplace context, over and above occupational skill, affect pay? Building on prior research, we show how workplace sources of premiums for blue collar workers and penalties for pink collar service organizations have been supplanted by higher pay for already-highly paid teams of managers and professionals. The net result is that it is professionals and managers, not blue collar workers, who now benefit from workplace premiums.

We organize the paper by first introducing the idea that consolidation between occupation and workplace pay premiums can drive increased economic inequality. We then draw on prior research to motivate potential channels through which consolidated inequality could have increased over the last two decades. Next, we discuss the OES data and present our main inequality decomposition. We then propose panel counterfactual methods for studying the sources of consolidated inequality. We use these counterfactuals to quantify the contribution of each source to the overall change in consolidation since 1999. We conclude with implications of our analysis for future research on inequality, stratification and organizations.

1 Wage inequality, pay premiums and consolidation

Rising wage inequality is often attributed to rising returns to skill or to variation in pay across profitable and struggling workplaces. In this section, we argue that prior research on inequality has neglected the shifting extent of correlation between these two sources of pay premiums. We then specify several potential channels through which occupation and workplace inequality could consolidate.

Since at least 2000, occupations have accounted for an increasing share of total wage inequality (Mouw and Kalleberg 2010). Skill-biased technological change raises demand for skill and without a concomitant increase in supply of college graduates, returns to education have grown (Goldin and Katz 2008). Sociologists have emphasized that in addition to demand for broad skill groups, specific occupational communities can organize barriers to entry that protect the interest of their "micro-class" (Weeden 2002; Weeden and Grusky 2012). Together, these market and institutional theories predict that occupational pay premiums contribute to wage inequality.

At the same time as inequality between occupations has increased, inequality between workplaces has also risen (Barth, Bryson, Davis, and Freeman 2016). Employers with product market power and high profits may face collective pressure from workers to share economic rents in the form of pay premiums, particularly in a context of strong labor unions (Dencker and Fang 2016; Cobb 2016). Other employers pay efficiency wages, above those of competitors, to increase productivity or maintain teams of high-productivity workers (Krueger and Summers 1988; Kremer 1993). Beyond profit-sharing, workplace premiums and penalties can also be driven by non-wage compensating differentials (Sorkin 2018). If one workplace offers below-average pay but an inspiring social mission, it might still be able to recruit workers (Hedblom, Hickman, and List 2019; Burbano 2016). Each of these different forces—bargaining over organizational surplus, efficiency wages and compensating differentials—manifest in unequal pay premiums across different workplaces.

This prior inequality research demonstrates that both occupation and workplace affect workers' pay. But research on each of these sources of advantage often neglects the other. Little theory addresses the shifting degree of overlap between skill- and closure-driven occupation premiums and the profit-sharing or compensating differentials that hold in particular workplaces.[2] Indeed, research on rising inequality has largely neglected the insight from macrostructural sociology that overall inequality increases when different dimensions of status advantage are correlated (Blau 1977, 103). The idea of consolidated social structure has been used to study organizations and networks, but not stratification (Centola 2015; Brashears, Genkin, and Suh 2017). As such, we ask whether the *consolidation* of two sources of inequality, rather than increased variance in workplace or occupation premiums alone, accounts for rising US inequality labor market inequality.

If high-premium workplaces employ mainly managers and professionals, as in finance or consulting, inequality will be higher than if high-premium workplaces employ mainly production and maintenance workers, as in large manufacturing firms in the mid-twentieth century, like the Ford Motor Company (Raff and Summers 1987). In the latter case, workplace premiums, arising from efficiency wages or from union bargaining power, can actually reduce overall inequality, as relatively low-skill occupations benefit from it. Figure 1 provides schematic examples of how inequality increasing through consolidation works differently than inequality increasing due to changes in underlying occupation or workplace pay premiums. In the first example, an increase in the pay-off to skill raises occupation premiums for high-skilled workers in both high-paying firms (a software engineer at a profitable technology company) and low-paying firms (a child psychologist at a low-

[2]In labor economics, recent research with US linked employer-employee data finds that high-wage workers are increasingly sorted into high-wage firms (Song, Price, Guvenen, Bloom, and von Wachter 2018). Studies in Germany (Card, Heining, and Kline 2013), Denmark (Bagger, Sørensen, and Vejlin 2013) and Sweden (Hakanson, Lindqvist, and Vlachos 2015) also find that the correlation between high-wage workers and high-wage firms has risen in recent decades. Assuming that part of this apparent worker-ability sorting is associated with occupation sorting, then these findings provide suggestive evidence that correlation between occupation and workplace premiums could be an important source of rising inequality.

paying school). In the second example, occupation premiums stay constant, but become increasingly correlated with workplace premiums. In this consolidation example, a previously high-paid, low-skill manufacturing worker faces a decrease in workplace premiums, while the child psychologist enjoys an increase in pay due to increased workplace premium. These examples illustrate how it is not only the extent and variance of workplace premiums that matters for inequality, but their distribution across workers in different occupations. In appendix A.1, we simulate how consolidated inequality can exacerbate overall inequality, even absent increases in the underlying variance of workplace or occupation premiums.

[Figure 1 about here.]

Put generally, consolidation increases when more workers are employed in jobs that match premiums: when low-occupation workers are employed at low-premium workplaces or when high-occupation workers are employed at workplaces with high workplace premiums. In contrast, inequality deconsolidates when more workers are employed in mismatched, or off-diagonal, jobs. As noted above, these off-diagonal jobs range from high-paying, often-unionized, employers of blue-collar workers to low-paying social service entities employing high-skilled professionals. Likewise, food service and janitorial workers at high-paying corporate headquarters combine high workplace premiums with low occupation premiums. Depending on whether they match or mismatch with occupation premiums, workplace premiums can either offset or exacerbate occupation-based advantages.

2 Industry composition, outsourcing, or new sources of premiums?

The contribution of workplace and occupation premiums to inequality thus hinges on their joint relationship. However, an increase in occupation and workplace correlation can come from several distinct types of changes. In addition to distinguishing consolidated advantage from inequality in occupation or workplace premiums, we also ask what drives recent consolidation. Understanding ultimate causes of consolidated inequality requires considering several potential channels of change: industry composition changes, shifting occupations across workplaces, and changing sources of workplace premiums.

2.1 Growth of a polarized service sector

First, the rise of the service sector has meant a polarization of employment opportunities (Kalleberg 2011). Growth in personal services, retail, and restaurant sectors increases employment at establishments with low workplace premiums and low average occupation composition. At the other end of the labor market, high-end services harbor many managerial and professional jobs in high-premium workplaces. The expansion of the finance industry due to deregulation is the most prominent example (Krippner 2011). In these processes, employment shares increase in jobs like the low-paid cook and the high-paid software engineers in Figure 1. When employment grows in these matched low- and high-wage sectors, inequality consolidation increases.

2.2 Shifting occupations across workplaces

Second, beyond changes in employment shares by industry, existing workplaces have also become more occupationally homogeneous (Handwerker 2018). Companies face pressure to focus on their core competencies, leading them to shed unrelated business lines (Davis, Diekmann, and Tinsley 1994). For example, many corporate headquarters, dominated by managerial and professional employees, have eliminated IT and basic human resources processing jobs (Weil 2014). The result is that high workplace premium establishments have increasingly shed technical and clerical employment, while maintaining executives and professionals. Similarly, high-paying firms have contracted out service jobs like janitors, food service and security guards (Goldschmidt and Schmieder 2017; Ochsenfeld 2018). In these core competency focus and outsourcing processes, existing workplaces change their occupational structure by excluding peripheral occupations. When rising skill segregation increases occupation premium by workplace premium matching, this trend can contribute to consolidated inequality.

At the same time, technological change has led to occupational upgrading in many high-paying production workplaces (Caroli and Van Reenen 2001; Fernandez 2001). If high workplace premium establishments that were previously composed of low and middle occupation jobs (such as the manufacturing worker in Figure 1) increasingly shift to hiring engineers and programmers, then consolidated inequality increases as these workplaces move up in the occupation distribution. In this case, the underlying tasks performed in certain high-paying workplaces have changed. Even absent any outsourcing or contracting, the share of high premium occupations benefiting from high premium workplaces could increase.

Together, these occupational change processes all involve shifting occupations across workplaces, whether by carving out low-premium occupations from high-paying workplaces or by upskilling and replacing them with higher-end occupations.

2.3 Changed sources of workplace pay premiums

Just as certain occupations can be removed from workplaces with high pay premiums, high pay can be cut at workplaces with certain types of workers. Specifically, high-paying jobs for workers in low and middle premium occupations—those that previously offset consolidated inequality—have faced wage cuts. Previously, blue collar workers in manufacturing, mining, utilities, and transportation were often able to extract above-market pay. But amidst anti-worker policy changes, deunionization, and economic globalization, many employers of these workers cut their workplace pay premiums. Deregulation and the collapse of union density and wages in interstate trucking provides the starkest example (Viscelli 2016). But a combination of policy changes (Hacker and Pierson 2010; Alderson and Nielsen 2002), shifting market power (Wilmers 2018), and employer anti-union campaigns (Kochan, Katz, and McKersie 1994; Bronfenbrenner 2009), eroded the collective bargaining regime that undergirded premiums for blue-collar workers. This confluence of negative pressures has led researchers to generalize about widespread destruction of economic rents for workers in these sectors (Sørensen 2000).

Group-based bargaining is not the only source of off-diagonal, mismatched jobs. Previous research also finds occupational polarization within the "caring economy" (Dwyer 2013). There are two broad explanations for this within-industry polarization. First, barriers to female employment locked high-skill women in low-paying schools, hospitals and social service agencies (England, Budig, and Folbre 2002; Duffy 2011). Second, when managers and professionals work in low-paid sectors, some sacrifice pay for social impact (Besley and Ghatak 2018). Both of these sources of pay penalties have eroded in recent years. Women have entered male-dominated occupations and firms (Stainback and Tomaskovic-Devey 2012). Likewise, a new emphasis on cost control, monitoring and rationalization has challenged old logics of care provision and social purpose in healthcare, education and non-profits more broadly (Reich 2014; Mehta 2013; Hwang and Powell 2009). Insofar as these changes mean that employers can no longer employ cheap, but highly skilled professionals and managers, it drives bifurcation in the social sector. Some cost-minimizing employers reorganize operations to reduce reliance on expensive professional employees (Galperin 2020). Others will retain those employees, but be forced to increase pay premiums to levels consistent with other sectors. The net result of the decline in ascriptive penalties (Busch 2017) and bifurcation in the social sector will be consolidated inequality.

While these collective action and ascriptive workplace pay differences have declined, pay premiums for top teams of managers and professionals have increased. These "superstar" teams have enjoyed substantial productivity and pay increases over the last two decades (Song, Price, Guvenen, Bloom, and von Wachter 2018; Lazear 2019; Davis 2016). Theorists have attributed these productivity increases to technological change that boosts the returns to collaboration in high-skilled teams (Kremer 1993). Moreover, as product markets have grown more integrated, some star firms succeed and pay their workers more than their laggard competitors (Autor, Dorn, Katz, Patterson, and Van Reenen 2020; Dunne, Foster, Haltiwanger, and Troske 2004). In these theories, firm-based wage premiums result from distinctively productive combinations of highly skilled employees. However, rising pay for groups of high-skill workers need not stem from high productivity (Weeden and Grusky 2014). For example, one study found a substantial role for micro-level bargaining power in setting pay in finance (Godechot 2016). Likewise, high pay could reflect not human capital but social capital, consistent with organizational research on team performance (Reagans and Zuckerman 2001). Regardless of the specific reasons for high pay among top professional firms, note that this channel remains distinct from a pure increase in average pay for professional and managerial occupations, which would be reflected in increased inequality in occupation premiums, not in consolidation. For example, insofar as technological change increases overall demand for managers and professionals, this would increase the pay-off to workers in those occupations in general. Instead, the process hypothesized here means that a specific subset of high-occupation workers, employed in high pay premium workplaces, have reaped increasing pay over and above the average for their occupation.

Whereas industry composition and shifting occupations imply that the sources of workplace premiums are roughly constant over time, the decline of bargaining power, declining identity-based penalties and the rise of top teams all imply that the very sources of workplace premiums have changed. Determining which of these trends accounts for consolidated advantage is critical to understanding the nature of recent increases in inequality. But, before operationalizing these potential sources of consolidation, we first discuss our data and assess the overall contribution of occupation and workplace correlation to rising inequality.

3 Data

We analyze restricted-use microdata from 1999-2017 from the Occupational Employment Statistics Survey (OES), collected by the Bureau of Labor Statistics (BLS). The OES is fielded to provide official annual estimates of occupational wages and employment levels (BLS 2008). The OES surveys around 400,000 establishments per year, sampled from the population of private and public sector workplaces.[3] The survey is administered to employers, managers and human resource managers. Each respondent is asked to report all occupations employed in their establishment and to indicate the number of employees in each occupation who receive pay in each of 12 pay intervals. The data include no information about individual worker characteristics beyond pay, occupation and establishment information. The OES is thus useful for studying occupation- and workplace-related pay changes, but we cannot adjust for individual characteristics like education, race or gender. This limitation of the data means that the occupation and workplace premiums we estimate should be interpreted as broadly summarizing pay effects due to skill, education, and other characteristics correlated with occupation and workplace. We consider this limitation further in the robustness section.

Despite the lack of worker-level characteristics, we proceed with analysis because the OES is the only source of US wage data that includes both workplace and occupation characteristics. Prior research on occupation premiums has focused on household surveys of workers, which include no workplace information beyond industry (Mouw and Kalleberg 2010). Research on workplace premiums has drawn on administrative data, which, in the US, include no occupation identifiers (Barth, Bryson, Davis, and Freeman 2016; Song, Price, Guvenen, Bloom, and von Wachter 2018). These data limitations have prevented simultaneous analysis of trends in occupation and workplace premiums and by extension have narrowed theory away from considering consolidated inequality. We obtained access to the OES via a data sharing agreement that made the authors of this paper

[3]The survey has a response rate of around 70 percent. In the resulting sample, the median job has 14 workers. The median workplace, weighted by employment, employs 61 workers and includes 8 occupations.

temporary agents of the BLS.

In the main analysis, we exclude public sector employers to focus on dynamics in the private sector. The main trends and results are similar, but accentuated, when we include public sector employers. We also exclude imputed observations, following prior research on inequality trends. We discuss the OES sampling procedure, imputation and weighting in more detail in appendix A.2.

Versions of this survey on occupational employment have been fielded since 1971. But, wage data have only been collected since 1996. Moreover, the first few years of pay data collection used different intervals and different occupation categories (Spletzer and Handwerker 2014). To avoid these changes, we start our analysis with the 1999 survey, following previous research (Handwerker 2018). This also allows us to use a relatively consistent set of 3-digit Standard Occupation Codes (SOC) throughout the analysis (up to 5-digit occupation details are available).

The OES records wages as a total of base rate pay and supplementary pay, including cost-of-living allowances, tips, production bonuses, incentive pay, piece rates, and commissions. It excludes several types of nonstandard bonuses, like holiday bonuses and stock grants, along with all non-wage benefits and perquisites. Respondents can enter information based on hourly wages or on full-time equivalent annual salary. To reduce respondent burden, the OES survey form collects wage data in 12 pay ranges (see a detail of the OES in Figure A.2 in appendix A.3). These range intervals are spaced around 0.23 log points apart and are adjusted 3 times during the period we study (see Figure A.3 in appendix A.3). To derive single wage values for each observation, we assign midpoints from the bounds of the first 11 intervals, and the conditional expectation of a Pareto distribution for the top-code interval. The interval filter in the OES could affect both the estimated overall variance of wages and the decomposition of variance into component parts. Nonetheless, prior research using the OES shows that its level and trend in wage variance is similar to that recorded by the Current Population Survey (CPS) (Spletzer and Handwerker 2014). In appendix A.3 and the robustness section, we conduct supplementary analyses with continuous wage employer-employee data from 17 European countries to assess the impact that intervalizing wage data has on wage variance decompositions. We find that estimates from continuous and interval-filtered wage data are remarkably similar.

In appendix A.5 we compare basic one-way variance decomposition results in the OES to those found in other US data. Both between-workplace inequality and between-occupation inequality are increasing in the OES, as they are in the Current Population Survey (for occupation) and the Social

Security Administration and Longitudinal Employer-Households Dynamics data (for workplace). In the next section, we ask whether these descriptive trends, showing rising inequality between workplace and between occupations, persists after controlling both workplace and occupation simultaneously. This simultaneous analysis of workplace and occupation then allows us to assess their degree of consolidation.

4 Inequality trends by workplace and by occupation

In this section, we present our first set of findings, which decompose rising inequality into components due to occupation and workplace premiums and to their consolidation. We use the unique availability of both occupation and workplace codes in the OES to fit a two-way fixed effect model including both occupation and workplace. We model log earnings $\ln y_{j,t}$ of a job j consisting of occupation o located at workplace w at time t as:

$$\ln y_{j,t} = \alpha_{o,t} + \beta_{w,t} + u_{j,t}. \tag{1}$$

Here, $\alpha_{o,t}$ is the fixed effect of occupation o at time t, $\beta_{w,t}$ is the fixed effect of workplace w, and $u_{j,t}$ is a residual. $\beta_{w,t}$ captures the average extent to which a workplace pays more or less than the standard rate for its occupations. A successful hedge fund, for example, might consistently pay its workers more than the going rate for their occupations, in which case it has a high workplace fixed effect. Similarly, an occupation's fixed effect captures the average extent to which workers in that occupation are compensated more or less than others, controlling for workplace premium effects: at the hedge fund, a financial analyst will still be paid more than an administrative assistant. Note that unlike worker-firm two-way fixed effects models (Abowd, Kramarz, and Margolis 1999), we allow workplace and occupation fixed effects to vary by year (see appendix A.6 for additional comparison to worker-firm fixed effects models).

After estimating the two-way fixed effects regression model, we can decompose the variance in log-earnings in year t as:

$$\mathbf{V}(\ \ln y_{j,t} \mid t) = \mathbf{V}(\alpha_{o,t} \mid t) + \mathbf{V}(\beta_{w,t} \mid t) + 2\mathbf{Cov}(\alpha_{o,t}, \beta_{w,t} \mid t) + \mathbf{V}(u_{j,t} \mid t) \tag{2}$$

where variance components include those due to variance in occupation premiums ($\mathbf{V}(\alpha_{o,t} \mid t)$), workplace premiums ($\mathbf{V}(\beta_{w,t} \mid t)$) and within-workplace residuals ($\mathbf{V}(u_{j,t} \mid t)$). Because both sets of fixed effects $\alpha_{o,t}$ and $\beta_{w,t}$ are estimated conditional on each other, the part of the variance due to their overlap is not included in either vector of fixed effects. To recover the full variance of the sum $\alpha_{o,t}+\beta_{w,t}$, we therefore need to include the covariance between them ($\mathbf{Cov}(\alpha_{o,t}, \beta_{w,t} \mid t)$). We repeat this decomposition for each year t to obtain a time series for each of the four variance components in Equation 2. These correspond to variance in occupation premiums, variance in workplace premiums, a residual variance and the component due to the covariance between occupation and workplace premiums.

[Figure 2 about here.]

Figure 2 shows the main results from these models. While in the one-way models both between-workplace and between-occupation variance increase over time (see Figure A.8 in the appendix), in the two-way model they remain fairly steady across all years. Neither rising variance in occupation premiums nor rising variance in workplace premiums alone explains much of the increasing inequality trend. The residual variance component, a combination of workplace-specific occupation premiums and within-job inequality, does not change over time. Instead, it is the covariance that increases sharply from 1999 to 2017. The increase in covariance accounts for almost two-thirds of the total growth in inequality, whereas the small increases in variance in workplace premiums and occupation premiums account for only about 12 percent and 23 percent, respectively. Figure 3 shows that this increase in covariance is due to a rise in correlation between workplace fixed effects and occupation fixed effects, which doubles from 0.14 to 0.28 between 1999 and 2017. Workplace and occupation have become increasingly consolidated.[4]

[Figure 3 about here.]

The two-way variance decomposition demonstrates that the largest driver of rising wage inequality since 1999 is increased covariance between occupation and workplace fixed effects. In other words, the majority of increased wage inequality since 1999 occurs because high-wage workplaces

[4] This consolidation is a secular trend, persisting through the 2008 recession and beyond. This differs from the overall trend in log-earnings variance, which slows and declines in the post-2012 economic recovery. The recent decline in variance in the OES is due mainly to declining variance in occupation premiums during the recovery.

are more likely to employ people in high-wage occupations while low-wage workplaces are more likely to employ those in low-wage occupations. There are fewer people in the kinds of off-diagonal jobs discussed above, like lower-skill workers in unionized, high-pay workplaces and higher-skill social services professionals in gender-segregated and low-paying workplaces. Note however that this cross-sectional decomposition reveals little about why consolidated inequality increased during this period. The following section introduces methods to address this question.

5 Methods to decompose inequality consolidation

So what drives this consolidation between occupation and workplace pay premiums, the core source of recent rises in US wage inequality? To tease apart the sources of change in consolidation, we follow a cohort of establishments that appear in the OES both at the beginning and the end of our data.[5] We then ask about the impact on consolidated inequality of various types of workplaces restructuring their occupational composition, growing or shrinking their total employment, or changing their workplace premiums. Using counterfactual analyses that fix particular changes for specific groups of establishments, we isolate the key drivers of consolidated inequality. In the following section, we operationalize specific substantive sources of consolidation, but first we introduce the general approach and descriptive findings here.

Specifically, we decompose the correlation between the workplace premium β_w and establishment average $\overline{\alpha_{o,t|w}}$ of the occupational premiums α_o within establishment w:[6]

$$Corr(\overline{\alpha_{o,t|w}}, \beta_{w,t} \big| \omega_{w,t}) = \frac{\sum_w \omega_{w,t} \overline{\alpha_{o,t|w}} \beta_{w,t}}{\sqrt{\sum_w \omega_{w,t} \left(\overline{\alpha_{o,t|w}}\right)^2} \sqrt{\sum_w \omega_{w,t} \left(\beta_{w,t}\right)^2}}, \tag{3}$$

where the normalized weight $\omega_{w,t}$ is proportional to the product of the sampling weight of workplace

[5]In practice, we do this by including establishments that appear in the OES in both the period from 1999 to 2005 and in the period from 2012 to 2017. We denote these two six-year periods by $t = 0$ and $t = 1$, respectively. When an establishment appears multiple times during a single period, we select the earliest instance in the period $t = 0$ and the latest instance in the period $t = 1$. In robustness checks we try different starting periods and a different within-period selection procedure. Patterns are consistent with the main results.

[6]While the data used in Equation 2 is at the job level, we cannot formulate longitudinal counterfactuals for jobs that are newly introduced to a workplace after period 0 or completely removed by period 1. Instead, we switch our unit of analysis from the job level to the establishment level. Average occupational premiums within a workplace can change due either to a change in a workplace's occupational composition or to an economy-wide shift in the occupational premiums associated with the jobs at a workplace. In the appendix A.8 we compare trends between workplace- and job-level units of analysis.

w and the total employment at w.[7] We calculate this correlation for the same set of workplaces at the beginning and end of the period, as $t = 0$ or $t = 1$. This equation illustrates how changes in correlation can come from three sources: the mix of occupations within workplaces, captured by $\overline{\alpha_{o,t|w}}$; the relative sizes of workplaces, $\omega_{w,t}$; and the level of workplace fixed effects, $\beta_{w,t}$.

In addition to this decomposition of types of changes, we divide workplaces into different groups according to their starting level of occupation and workplace premiums. We define starting groups of workplaces by crossing 3 categories from each of the workplace premiums and average occupation premiums. The crossed tertiles define sets of workplaces that track substantive differences in industry and occupation composition. For the cell lowest in workplace pay premiums and in average occupation premiums, the most common industries are accommodation, food service and retail. These workplaces employ cooks, food service workers and sales clerks. In contrast, establishments with low average occupation premiums and high workplace premiums commonly employ production, transportation and administrative support workers. These establishments are typically in manufacturing, warehousing and transportation industries. Among high occupation premium establishments, those with low workplace premiums are predominantly healthcare and social services, professional and technical services and education. These establishments employ managerial and professional employees like doctors, social workers and teachers. However, they pay relatively little. In contrast, workplaces in the high occupation and high workplace premium cell are in professional and technical industries, healthcare and finance.

This design allows us to obtain counterfactual correlation trends by reevaluating Equation 3 after fixing within-workplace occupation averages, workplace fixed effects, or workplace weights at their period-0 levels for some subset of establishments. For example, if the highest-paying third of establishments had retained their period-0 workplace fixed effects, then the counterfactual correlation at period 1 is:

$$Corr(\overline{\alpha_{o,1|w}}, \beta_{w,CF} \big| \omega_{w,1}) = \frac{\sum_w \omega_{w,1} \overline{\alpha_{o,1|w}} \beta_{w,CF}}{\sqrt{\sum_w \omega_{w,1} \left(\overline{\alpha_{o,1|w}}\right)^2} \sqrt{\sum_w \omega_{w,1} \left(\beta_{w,CF}\right)^2}}, \quad (4)$$

[7] In the counterfactual analyses we present below, we fix total workplace employment, but leave sampling weights unchanged. This captures the pure effect of changing establishment size, rather than shifts in sampling or in composition due to establishment entry and exit. We define panel weights, compare job- and establishment-level trends and discuss establishment entry and exit in the robustness section and appendix A.8.

where the counterfactual workplace fixed effects, $\beta_{w,CF}$, equal the period-0 fixed effects $\beta_{w,0}$ for the top third of workplaces and the period-1 fixed effects $\beta_{w,1}$ for all other workplaces. If the resulting counterfactual is close to the true correlation of $\overline{\alpha_{o,t|w}}$ and $\beta_{w,t}$ at $t = 1$, then this would mean that changes in the top third of workplace premiums do not explain much of the real growth in correlation. On the other hand, a large difference between counterfactual and true correlations suggests that the operationalized mechanism—changes in workplace premiums at the top third of workplaces—accounts for a great deal of the increase in correlation. By fixing out a particular channel of change for a particular group of establishments, we can identify the main channels by which inequality consolidated.

6 Sources of consolidated inequality

Possible explanations for inequality consolidation fall into three main groups: compositional polarization of low- and high-end service industries; shifting occupational compositions of certain workplaces; and changes in workplace pay practices within industries. In the framework of Equation 3, these primarily affect correlation through establishment size ($\omega_{w,t}$), establishment occupational composition (reflected in $\overline{\alpha_{o,t|w}}$) and workplace premium ($\beta_{w,t}$), respectively. In this section, we first provide a full set of basic descriptive panel counterfactuals and we then operationalize and test the specific theoretically motivated channels of consolidation proposed above.

7 Broad channels of consolidation

Figure 4 panel (a) shows how fixing changes in workplace premiums or average occupational premiums, within a given occupation and workplace tertile, affects the overall correlation trend. Within each cell, the top (bottom) number indicates the change in the correlation trend if no establishments in that cell had increased (decreased) their average occupational composition. The left (right) number indicates the counterfactual change if no establishments had reduced (increased) their workplace premiums. Panel (b) shows how preventing establishments in that cell from growing (top) or shrinking (bottom) would impact the total change in correlation. These counterfactuals allow us to locate the impact of these changes in different parts of the joint distribution of workplaces and occupations. For example, premium changes in workplaces with low establishment premiums and high occupational averages (top left of panel (a)) are important. If we prevent these establishments from increasing workplace premiums or from decreasing average occupational premiums, we reduce the total correlation increase of 0.104 by 0.024 and 0.026, respectively.

[Figure 4 about here.]

Some key changes also occur in the top right cell, which contains workplaces that begin in the highest third of workplace premiums and the highest third of average occupation premiums. By counterfactually blocking workplaces in this cell from increasing their establishment premiums, we reduce the total correlation growth by 0.024 points. Finally, establishments with low and medium occupation averages and high workplace premiums (the off-diagonal bottom left cell) are also influential. Preventing high workplace premium and low occupation establishments from reducing workplace premiums decreases correlation growth by 0.016 points.

In addition to fixing workplace and occupation premiums, we can also restrict changes in employment across establishments. Each cell of panel (b) of Figure 4 shows how preventing establishments in that cell from growing (above) or shrinking (below) would impact the total change in correlation. Again, the top right cell is important: keeping establishments in this cell from growing limits the total increase in correlation by 0.028. Preventing establishments in the bottom left cell—those with low establishment premiums and low occupational averages—from growing restrains the increase in total correlation by 0.014. These two counterfactuals indicate that, as on-diagonal, matching premium workplaces grew in size, they contributed to the growth in total correlation.

More broadly, Figure 4 reveals important patterns in the influence of different changes over the correlation trend. Correlation increases as workplaces move away from mismatched areas—like low workplace premiums coupled with high average occupation premiums—and toward the dashed diagonal line running from the lower left to the upper right the figure. Changes in occupation (workplace) premiums are influential when their workplace (occupation) premium is already extreme. This follows from our multiplicative correlation measure of inequality consolidation: a change multiplied by an extreme value will be magnified, while one paired with a value near the mean will be muted. Substantively, this means that changes in the corner regions are important. For establishments with occupation premiums near the mean, but high or low workplace premiums, changes in occupation composition will be influential. For establishments with middling workplace premiums, but extreme occupational compositions, changes in workplace premiums become particularly influential.

8 Specific channels of consolidation

While the counterfactuals in Figure 4 reveal the broad patterns of workplace premium and occupational reorganization driving consolidated inequality, they are limited. First, they are difficult to interpret without knowing exactly which industries and which occupations are changing. Second, they only fix channels of correlation within one occupation-workplace cell at a time. Some theories of consolidated inequality imply multiple simultaneous changes. For example, in outsourcing, low-premium workplaces in catering, building services and security increase their share of low-skilled occupations while high-premium workplaces reduce their employment of such workers. So, we next test the specific channels of inequality consolidation theorized above. Table 1 summarizes the operationalization of these specific channels, which we discuss in turn.

[Table 1 about here.]

Table 2 shows counterfactual correlation trends in the establishment panel observations, in which each of these key, specific channels of consolidation are blocked. The panel sample starts with a correlation between workplace premiums and workplace-level average occupation premiums of 0.38 in the first period (1999 to 2005) and increases to 0.49 by the second period (2012 to 2017). This increase is comparable to that observed in the full sample, averaging across the beginning and ending periods. Fixing all of the proposed explanations accounts for around 75 percent of the 0.10 increase in correlation. As expected, these processes together account for the bulk of the consolidated inequality trend. But which processes matter most?

[Table 2 about here.]

8.1 Industry composition and growth of a polarized service sector

First, we consider shifting industry composition. We operationalize the expansion of service establishments by fixing workplace sizes (Kalleberg 2011). On the low-wage side, this means robust job growth sectors that combine low workplace premiums with high shares of low occupation premium workers. On the high-pay side, the expansion of high-end services has generated more high workplace premium professional jobs. Firms in finance, technology and information and professional services have all expanded. Both of these trends in industrial composition have increased the number of jobs at firms with similar occupational premiums and workplace premiums, whether at the bottom or top of the earnings distribution. To calculate a counterfactual correlation in which there was no growth in low-paid services, we reweight poorly-paying food, accommodation, retail, and service-sector workplaces to reflect the number of nonroutine manual workers employed in the starting period. Similarly, we reweight well-paying workplaces in the information, FIRE, professional services and management sectors, to restrain their employment from increasing due to rising numbers of managerial and professional employees.

Table 2 indicates that fixing the low-skill employment growth in low-paying establishments in retail, food and personal services industries accounts for 7 percent of increased correlation. Fixing high-skill employment growth, of managers and professionals, at high occupation premium and high workplace premium establishments in information, FIRE, professional and technical services and management reduces correlation by 17 percent. Together, the rise of these high- and low-paying services account for around quarter of the increase in correlation during this period. Note that it is primarily the expansion of the high-end service establishments that contributes to rising correlation. This is consistent with the broad decomposition results reported above.

8.2 Shifting occupations across workplaces

Second, while the uneven employment growth involved in the expansion of polarized services would affect workplaces or industries uniformly, inequality consolidation may also stem from changing occupational composition *within* workplaces. In equation 3, changes in firm occupational composition affect the average occupation premium, $\overline{\alpha_{o,t|w}}$ at workplace. The most prominent such change comes from outsourcing, in which janitors, security guards, food service workers and logistics workers are contracted out (Goldschmidt and Schmieder 2017). We simulate a counterfactual in which outsourcing of low-premium work from did not occur by retaining the first-period share of nonroutine manual workers for medium-premium and high-premium workplaces that shed nonroutine manual work in the second period. We also counterfactually limit the employment growth of the building services, catering, warehousing, trucking and security industry establishments that contract to provide outsourced services. Results in Table 2 show that this change makes very little difference to the correlation trend, largely because the outsourcing industries are small and because few low-skill occupations were still present at high-workplace premium workplaces by the beginning of this period.

Alongside outsourcing, there has also been a broader strategic shift toward firms' core competencies, over and above the outsourcing of low-skill workers (Davis, Diekmann, and Tinsley 1994; Weil 2014). For example, a law firm hiring more lawyers and fewer administrators or payroll managers could also contribute to inequality consolidation. To capture this shift toward organizational specialization, we counterfactually retain each establishment's average occupational premium from the first period if that establishment's modal occupation increases in share. Results in Table 2 shows that fixing average occupation premiums for these firms actually offsets slightly the increase in correlation. This result indicates that the general shift toward workplace occupational homogeneity documented previously (Handwerker 2018), does not necessarily also increase the correlation between workplace and occupation premiums. For example, if a high-paying firm that employs mainly low-premium occupations moves toward occupational homogeneity by reducing managerial and professional employees, specialization actually *reduces* correlation between occupation and workplace premiums.

Beyond outsourcing and a focus on core competencies, many high-paying employers of low-skill workers have upskilled their production jobs (Caroli and Van Reenen 2001; Fernandez 2001). This form of "upskilling" can be counterfactually fixed by keeping the fraction of white-collar managerial, professional, technical and clerical employees in high workplace premium establishments in the manufacturing, mining, utilities and transportation sectors. As with outsourcing and core competencies, little of the correlation increase is accounted for by fixing the low occupation premium and high workplace premium establishments that are upskilling by shifting toward more technicians, professionals and managers. While these changes represent an important trend in their industries, they have little effect on the overall trend toward consolidated inequality.

8.3 Changed sources of workplace pay premiums

Finally, aside from differential employment growth and shifting occupational composition across high- and low-paying workplaces, the bases for workplace pay premiums can change (Davis 2016; Cappelli 1999; Sørensen 2000). First, consider blue collar employers in the manufacturing, mining, utilities and transportation sectors which start the period with high workplace premiums and low-or middle-occupation premiums. If these establishments reduce their workplace pay premiums, then consolidated inequality will increase. These beleaguered workplaces could include unionized heavy industry facing increased international competition, or airlines forced by new, non-union competitors to lower labor costs. To simulate a counterfactual without such blue-collar rent destruction, we retain the first-period firm premiums and sizes for high workplace premium establishments in the manufacturing, mining, utilities, and transportation sectors that shrink and cut wages. Table 2 shows that workplace premium cuts at these workplaces account for 7 percent of the increase in consolidated inequality during this period.

Second, we adjust for social services bifurcation, which reduces the share of low workplace premium jobs for high occupation workers. To estimate a counterfactual correlation in which social-sector deskilling did not occur, we assign the starting-period occupational average to low-premium establishments in the health, social, educational, and civic industries. To counterfactually restrain the development of the highly-paid part of the social sector, we assign the starting-period workplace premium to workplaces whose premiums increase.

On the up-market side of social services bifurcation, we fix workplace premiums for the subset of these establishments that are increasing their employment of managers and professionals. Insofar as these up-market firms increase pay premiums for their increasingly well-paid occupational mixes, this drives consolidated inequality. Indeed, fixing the pay changes at these firms accounts for 11 percent of the increase over this period, rivaling the impact of rising pay at top team high workplace premium and high occupation premium establishments.

The down-market side of bifurcation involves lowering average occupation composition. These workplaces may substitute teachers aids for teachers, nursing assistants for nurses and doctors, and mental health workers for psychiatrists. We fix the occupation premiums associated with these relatively low-paying firms that are reducing their average occupation premiums. Table 2 shows that this reduced average occupation premiums channel alone explains 12 percent of the change.

Finally, as workplace pay premiums increase at establishments that start with high workplace pay premiums and high shares of high-premium occupations, consolidated inequality increases. We fix the growing pay-offs to top teams in the information, FIRE, professional and managerial sectors by retaining the starting-period workplace premium for high workplace and occupation premium establishments whose workplace and average occupational premiums increase. In other words, for workplaces that start the period with both high workplace premiums and high shares of managerial and professional employees, we prevent workplace premiums from rising further. The counterfactual shows that these rising premiums at the top account for around 10 percent of the change during the period.

Taken together, these descriptive counterfactuals suggest that changing bases of workplace pay premiums have driven inequality consolidation. The decline of collective premiums for blue-collar workers and collective penalties for service sector professionals has occurred amidst rising workplace premiums for some teams of professionals and managers. Consistent with the latter, the most important composition change comes from the employment expansion of high-premium and high-occupation workplaces. In contrast, shifting occupations across workplaces explains relatively little of the inequality consolidation trend.

9 Robustness tests

In additional analysis, we consider a series of potential objections to our core set of findings: (1) correlation between occupation and workplace premiums is increasing; (2) this rising correlation contributes to rising wage inequality; and (3) specific organizational mechanisms drive rising correlation account of increased consolidated inequality. We summarize the tests here, but provide more detail in the appendix.

9.1 Robustness of trend in consolidation

As discussed above, the OES data provide a unique opportunity to study the joint US occupation and workplace distributions. However, the OES data contain only intervaled, not continuous wage information. We assess the robustness of the increasing trend in correlation using these intervaled data in several ways.

First, as outlined in appendix A.3, we try alternative approaches to identifying the midpoints of the intervaled wage data. In the main results presented earlier, the outcome variable consists of midpoints of the logged bounds for the first 11 intervals, and the conditional expectation of a Pareto distribution in the top interval. We test the robustness of the main results, first, by using an outcome estimated by the BLS to capture the average wage within each interval in a given state and industry. Second, we fit a left-truncated normal distribution across all 12 wage intervals for each year, and create an outcome equal to the conditional mean of the distribution within each interval. The resulting correlation trends are very close to that estimated from the midpoint-Pareto approach.

Next, to compare these midpoint-based results to estimates based on continuous wage information, we draw on additional data beyond the OES. First, we use European linked employer-employee data from the Structure of Earnings Survey (SES) data (discussed in more detail in appendix A.4). By imposing an interval filter on those data, and identifying midpoints with the strategies noted above, we can compare correlation trends derived from intervalled and continuous versions of the same data. Estimated correlations between occupation premiums and workplace premiums are strikingly similar between the intervalled and continuous estimates. Second, we use three US household surveys of workers to estimate the correlation between occupation premiums and premiums attributed to industry by state groups. These household surveys include continuous wage and earnings information, but do not include workplace information. Even substituting workplace for the industry by state groups, all 3 survey sources show increased correlation with occupation premiums over time. Together, these results from alternative data sources increase our confidence that, despite the survey's quirks, the OES trend results are reliable.

9.2 Robustness of consolidation as an explanation for increased wage inequality

These tests raise confidence that the correlation between occupation and workplace premiums is rising. But does that trend account for increasing wage inequality during this period?

The main limitation of the OES data is that it includes no information on observable worker characteristics. This means we cannot distinguish our estimated occupation and workplace premiums (and their correlation) from shifting worker composition. On the occupation side, this primarily affects our interpretation of the premiums: clearly, the premium we attribute to managers relative to production workers includes the compositional fact that managers tend to be more experienced and more highly educated than production workers. On the workplace side, unmeasured worker composition is more concerning. What looks like increased positive matching between occupations and workplaces may just be a reshuffling the highest-human capital members of each occupation into the same workplaces. Note that this process is similar to that hypothesized in the top teams theory tested above: our argument does not presuppose that workplace premiums are unrelated to worker composition. Nonetheless, the strongest version of this objection—that individual worker characteristics account for an apparent workplace premium—would make our interpretation of wage premiums as "workplace" premiums misleading.

Unfortunately, there is no US data that includes both occupation and workplace information along with observable worker characteristics. As such, we turn again to the European SES data, described in appendix A.4. Using these data, we compare two models. The first fits occupation and workplace fixed effects, as in our main analysis of the OES data. The second model adds controls for educational attainment, age and gender. Table A.1 in the appendix compares the resulting covariance between occupation and workplace premiums with and without controls for observable characteristics. The differences in the covariance trends with and without controls are very small. None of the 16 countries have more than a 0.01 log point difference in covariance between the baseline and observable controls models. However, the vast majority of these countries see much smaller changes in covariance than we observe in the US data—consistent with smaller increases in wage inequality in Europe during this period. The countries with the largest increases in covariance are also the countries with estimates most effected by the observable controls. Cyprus has a very similar covariance trajectory to the US (from 0.02 to 0.05; US 0.03 to 0.06) and adding controls for observables reduces covariance growth by 15 percent. Other countries with covariance increases, like Hungary, Lithuania and Bulgaria see covariance growth reduced by 10 to 40 percent. Based on these estimates, we think a lower bound for the US covariance contribution is 35 percent of increased inequality explained. While this lower bound is substantially lower than the two-thirds estimate given in our main analysis, it remains a substantial portion of rising inequality.

Another objection to our analysis is that we focus on occupation pay premiums and workplace pay premiums without distinguishing between workplace and industry or broad skill groups and micro-classes. Different theories of workplace and occupation premiums begin from these broader or narrower categories. Further partitioning variance trends in pay premiums allows us to check whether offsetting changes at higher and lower levels of analysis mask important shifts in inequality. We separate the workplace fixed effect $\beta_{w,t}$ into an industry average—defined at the 2-digit NAICS level for each year t—and a workplace residual term. Similarly, we aggregate the occupations into four broad skill groups each year and average the occupation fixed effects $\alpha_{o,t}$ within each group.[8]

[8] The four skill groups are: non-routine cognitive (managers or professional occupations); routine cognitive (clerical

This procedure allows us to decompose the variance in occupation premiums $\mathbf{V}(\alpha_{o,t} \mid t)$ into a component occurring between skill groups and a component occurring within skill groups; and to decompose the variance in workplace premiums $\mathbf{V}(\beta_{w,t} \mid t)$ into between-industry and within-industry components. The resulting variance components are plotted in Figure A.9 in appendix A.7.

Figure A.9 shows that the largest share of variance in any year occurs between workplace premiums within 2-digit NAICS industry; the variance between industries is half the size. Yet, both of these components hardly increase over time. Occupation, on the other hand, exhibits the reverse trend: the four broad skill groups explain more of earnings variance than do the residual occupation premiums. While the between-skill component does increase somewhat from 2000 to 2010, it decreases afterward. The within-skill-group variability in detailed occupation premiums is smaller and exhibits little rise in inequality, contrary to theories of inequality focused on idiosyncratic occupational institutions (Weeden 2002). Thus, even decomposing variance across these detailed categories, the rising covariance between occupation and workplace premiums stands out as the key driver of recent increases in wage inequality.

Finally, while we study between-group pay premiums and their covariance, a substantial line of research focuses on residual within-organization inequality, defined by shifting distribution of resources across work groups or job titles within a workplace or by within-job inequality (Tilly 1998; Baron and Bielby 1980; Wilmers 2020). To address these theories, we divide the residual component of the two-way fixed effects model into within-job (occupation by workplace) and job-specific premiums. Figure A.9 shows that neither within-job variance nor the idiosyncratic variation in occupations across workplaces (job premiums) account for a substantial portion of increased inequality during this period. Job premiums actually diminish during this period. Job premiums include, for example, idiosyncratic higher pay for a manager who exploits his production workers by paying them less than is typical for their occupation. Within-job inequality actually increases slightly during this period, perhaps consistent with the rising prevalence of merit-based and individualized pay systems (Lemieux, MacLeod, and Parent 2009). However, within-job inequality only accounts for around 7 percent of the total rise in inequality during this period. This result challenges approaches that attribute rising overall inequality to increased residual inequality among workers in the same

work); routine manual (production work); and non-routine manual (service jobs) (Acemoglu and Autor 2011).

job or among workers in the same workplace.

9.3 Robustness of mechanisms of consolidated inequality

Finally, we consider objections to the mechanisms we identify as drivers of consolidated inequality.

In the panel analysis we focus on organizational changes to occupation composition, workplace pay premiums and employment levels among establishments that exist throughout the period of analysis. This approach follows from our general theory that organizational changes are driving rising correlation. However it is possible that correlation has increased due to shifting patterns of workplace composition via entry and exit. For example, new entrants could be less matched between occupation and workplace premiums and new entrants have been declining during this period (Decker, Haltiwanger, Jarmin, and Miranda 2016). Such a pattern would parallel recent findings that workplaces have grown increasingly racially segregated due to the formation of newer, more racially homogeneous, workplaces (Ferguson and Koning 2018). Yet panel (a) of Figure A.11 in appendix A.8 shows that correlation grows very similarly among workplaces newly entering the OES, and workplaces that reappear multiple times. The rise in correlation, therefore, is not due only to entering and exiting establishments. Of course, it is still possible that establishment turnover plays some role in the trend. We discuss this possibility further in the next section.

Another issue in the main analysis is that we fix channels of consolidated inequality as if each channel is independent and causally unrelated to other sources of consolidation. However, shifts in supply and demand within labor markets are often interdependent. Our most novel source of inequality consolidation—reduced managerial and professional employees in low-paying firms in the social services sector—is particularly vulnerable to this kind of interdependent effect. If high workplace premium employers are growing, upskilling or raising pay for workers in high pay premium occupations, this increased demand may siphon those workers out of low workplace premium employers. In this case, low workplace premium employers in the social sector would still be observed to reduce their average occupation premiums, substituting lower occupation premium jobs for increasingly expensive professional and managerial workers. However, these off-diagonal changes would only be a conduit, and not an originator of consolidated inequality.

To test this alternative explanation, we set up a descriptive regression model predicting reductions in occupation premiums in the social services sector among establishments that begin the period with low workplace premiums and high average occupation premiums. Table A.2 in the appendix displays the results. Model 1 shows that the establishments more likely to reduce occupation composition begin with both higher shares of high-paid occupations and larger workplace fixed effects. They are also smaller and growing during the period. As such these workplaces are not simply losing business and routinizing as a last cost-cutting resort prior to bankruptcy. This downward shift in occupational composition occurs among growing firms. Finally, Model 3 assesses whether these dynamics are driven by changes in the cell of high workplace pay premium and high occupation pay premium establishments competing for employees with the low-paying firms modeled here. To do so, we define variables measuring the average change in occupation premiums, workplace premiums and employment levels among the high workplace and occupation premium establishments in the same commuting zones as low-pay social sector establishments. The results show, contrary to the possibility proposed above, that increasing pay, upskilling and growth in the high-paid segment of the labor market make reductions in occupation composition less likely, if anything. This result provides more evidence that bifurcation in the off-diagonal, social services sector of the labor market is an independent contributor to consolidated inequality.

In appendix A.8, we also rule out additional objections to the panel counterfactual analysis—industry representativeness, the shift from job to establishment and outliers in the pay premium distribution—and we show that a reweighting exercise on industry and skill level in the repeated cross-sectional data gives comparable results to the analogous portion of the panel analysis.

10 Discussion

We find that an increasing correlation between occupation and workplace premiums accounts for two-thirds of increased wage inequality since 1999. This result clarifies prior research on worker sorting across firms (Song, Price, Guvenen, Bloom, and von Wachter 2018). Increased assortative matching is not just worker ability sorting occurring within occupation categories. Instead, the increasing correlation between workplace and worker is reflected in shifts in occupation composition and workplace wage premiums across establishments.

We then identify a series of organizational changes that could drive increased consolidation between potentially independent bases of pay premiums. Using descriptive counterfactuals and comparing a panel of establishments present in both the early 2000s and late 2010s, we find evidence that the sources of workplace pay premiums have changed over time. Low workplace premium, high occupation composition social sector establishments are either shifting to low-paid jobs or maintaining large shares of high-premium occupations and increasing their establishment pay premiums. The result is a bifurcation that reduces the number of middle-wage, high-occupation and low-paying jobs. Rising pay for top teams and expansion of high-paying services also explain substantial portions of the rise in correlation. Pay cuts from employers of previously highly paid blue-collar workers play a supplementary role. In contrast, the occupational composition changes associated with shifting to core competencies, outsourcing and upskilling of blue collar work explain little of the increased correlation.

We also uncover several general dynamics of consolidated labor market inequality. Much analysis of wage dynamics focuses on industries in which occupation and workplace premiums match—for example, expansion of low-paying service jobs, which harbor low workplace and low occupation premiums, or increasing pay at high workplace premium professional services firms. But subtler organizational dynamics reducing shares of off-diagonal, mismatched jobs have also consolidated workplace and occupation-based inequalities. When low workplace premium health services organizations corporatize (Reich 2014), they may lose the job amenity and meaning that previously allowed them to attract high-premium professionals despite low pay. Similarly, wage cuts at high workplace premium, but blue collar, jobs in manufacturing and in transportation can follow from deunionization, deregulation or intensified product market competition. Both of these changes increase consolidated inequality. We also find that, in studying panel changes in the correlation between wage premiums, the pay premium changes most influential on the overall trend are those that occur alongside already-extreme values. For example, consider establishments with workplace-premiums near the mean that employ mainly high occupation workers. For these establishments, decreases in the workplace premium will do more to offset consolidated inequality than will a similar-magnitude deskilling of the occupational composition of the workplace. The workplace premium change is leveraged up by the starting occupation composition of the establishment. Considering the inequality-increasing channel of correlation between distinct bases of pay premiums thus draws attention to types of jobs and types of organizational changes that have not been central to prior inequality research.

These contributions should, however, be interpreted in context of limitations imposed by our data. First, the top-codes in the OES prevent analysis of inequality at the very top of the distribution. Nonetheless, despite recent interest in top income earners, our data do capture the vast bulk of workers and earnings. Second, we do not analyze pre-1999 OES data, in order to avoid large changes in occupation categories and wage interval design prior to that year (discussed in appendix A.2). The recency of our data prevents comparison with a period in which correlation did not increase. As such, it is difficult to distinguish establishment age from period and cohort in our panel analysis. If firms shift occupational composition and workplace wage premiums as they age, and do so non-linearly across the establishment life course, this could affect the interpretation of our panel decomposition. For example, if low-paying firms increasingly routinize and replace high-skill employees as they age, we might wrongly attribute off-diagonal age-based occupation composition reductions to changes between the beginning and end of the period. The similarity in correlation trends between the panel and non-panel OES samples mitigates our concern about this (discussed in appendix A.8). Still, future research should explore other data sources, including industry case studies, that allow age and period effects to be distinguished.

Third, we focus our investigation of channels of consolidated inequality on organizational changes. This approach is born out in our data: the correlation increase among stayer establishments is nearly identical to the trend in the full sample of establishments. Given the low rate of firm entry and exit during this period, and the striking within-organization changes we observe, our focus on organizational changes is well-justified. However, the OES does not allow direct analysis of establishment entry and exit. We cannot distinguish in the data between establishments that exit the survey sample and establishments that exit the economy entirely. Future research with alternative data sources should consider how firm turnover could offset or exacerbate the core dynamics observed among stayer establishments.

A final limitation of the project is that we do not observe individual workers in the data, so we cannot adjust our wage models for individual characteristics like race, gender, age or education. Prior research finds that these characteristics are correlated with both occupation and workplace premiums, but that both occupation and workplace matter for earnings even when controlling for these characteristics (Barth, Bryson, Davis, and Freeman 2016; Mouw and Kalleberg 2010). We interpret our results as descriptive of trends, rather than pinning down precise estimates of occupation and workplace pay premiums. Moreover, in robustness tests with European linked employer-employee data, we find that increases in occupation and workplace covariance persists with controls for observable characteristics. Unfortunately, no alternative US data source includes annual workplace, occupation and individual worker characteristics.

11 Conclusion

When organizations match or mismatch occupational composition and workplace pay premiums, they consolidate or offset two systems of inequality. A privatizing, low-paying mental health clinic may substitute lower-paid social workers in for psychologists (Abbott 1988). An assembly job, low in the ranking of occupation or skill, can either be similarly low in the workplace premium ranking, at a low-paying supplier, or benefit from employment at a large, unionized corporation, with pay premiums even for low-level employees (Wilmers 2018). As workers are increasingly employed in jobs matching high or low premiums across workplace and occupation, fewer workers are in jobs defined by mismatched and offsetting premiums. It is this consolidated inequality, rather than rising variance in pay premiums associated with occupation or with workplace alone, that is the dominant source of rising inequality over the last two decades.

By extension, we find that shifting pay-offs to skill, as measured by occupation premiums, do not account for much of the recent rise in inequality. This is consistent with the recent slowdown in demand for skill seen in other data (Autor 2017) and with null effects of new occupational licensing on wages (Redbird 2017). But likewise, standard theories of organizational influence on wage inequality are insufficient to account for the recent rise inequality. These theories have focused on the relative autonomy from labor market prices of within-workplace levels of inequality (Tilly 1998). The results here demonstrate that within-job inequality and idiosyncratic workplace premiums for a given occupation play little part in recent increases in overall earnings inequality. Organizations' allocation of pay across levels in an organization chart, or the extent of inequality among better- or worse-compensated co-workers in the same position, are minor factors in the overall inequality trends studied here. Instead, organizations matter as the nexus in which workplace pay premiums are linked to different occupations. Organizations either consolidate or disorder inequalities.

These results challenge researchers studying trends in earnings inequality to consider consolidated inequality. Much research on aggregate trends in wage inequality focuses on a single hypothesized structure of inequality, without attending to the shifting correlation between structures. More analogous to the problem studied here is research on how assortative mating and family structure aggregate labor earnings into more or less unequal household income distributions (Western, Percheski, and Bloome 2008). Just as households aggregate individual labor earnings into household-level income inequality, organizations aggregate occupation and workplace premiums into overall wage inequality. Bringing lessons from other stratification research areas to the study of wage inequality could be a promising extension of the approach introduced here.

Note that consolidated advantage is related, but distinct, from two prominent claims in prior sociological research. First, theorists of intersectionality and overlapping categorical inequality argue that attaining different types of advantage actually increases the pay-off of each (Tilly 1998; Cho, Crenshaw, and McCall 2013). For our argument, sources of inequality need only be additive, not multiplicative. Of course, future research could consider whether, for example, managers and professionals receive a larger wage boost from working in a high workplace premium establishment than do lower-premium occupation workers at the same establishment. But, our argument does not presuppose this and instead emphasizes that additive consolidation per se can be an important contributor to inequality. Second, theories of cumulative advantage emphasize the temporal alignment of different types of advantage: initial advantages are rewarded and compound over time (DiPrete and Eirich 2006). We emphasize instead that inequality is a function of the synchronic alignment of distinct structures of inequality. Even absent cumulative advantage, consolidated advantage can exacerbate overall inequality.

The analysis justifies renewed attention to organizational theories that account for shifting occupational composition and changing wage rates. Organizational researchers who have studied occupational composition point out sources of stickiness—like job interdependence and imprinting (Hasan, Ferguson, and Koning 2015; Beckman and Burton 2008)—that may be unevenly distributed across the population of workplaces. Likewise, firms can target high or low wage levels relative to their labor market competitors (Bewley 1999). Our findings suggest that these problems of occupational composition and relative pay setting should be theorized together. However, at the establishment-level, there is no one-size-fits-all process that will reliably erode consolidated inequality. Instead, effects of changing occupational composition or workplace premiums hinge on the current position of an organization within the broader distribution of occupation and workplace. Research could thus turn to asking, for example, under what conditions organizations can maintain mismatched occupation and workplace premiums.

We motivate our analysis of consolidated inequality as a means to understand trends in economic inequality. However, the same low-paying occupations that are increasingly siloed into low-premium workplaces may be those occupations that overrepresent women and people of color (Kmec 2003; Mandel 2013). Studies of occupational or workplace segregation often investigate the unequal distribution, by race or gender or other ascriptive characteristic, of workers along a single stratification axis—say, workplace or occupation–at a time. But, as workplace and occupation premiums align, distinct structural inequalities compound. Moreover, the increasing consolidation of organizations and occupations means that race- or gender-based occupational tracking within workplaces, long an important process of racial inequality (Sundstrom 1994; Wingfield and Alston 2014), may now account for less of total inequalities by race and gender. Attention to racial and gender inequalities within the workplace (Acker 1990) should thus be supplemented by more attention to inequalities between workplaces (Ferguson and Koning 2018).

Beyond inequality per se, the degree of consolidation in the labor market could affect opportunity, mobility and the sequence of careers. If an economy harbors only a single pathway to affluence—one that goes through certain schools, occupations and firms—we expect heightened economic exclusion and insecurity. When multiple independent sources of advantage crosscut, failure in one dimension may be offset by success in another. Multiple types of capital, cultural, symbolic or material, can undergird countervailing groups of elites (Bourdieu 1984; Milner 1994). For example, when status and political power adheres to both age and to wealth, rather than wealth alone, laws are more friendly to the poor (Zhang 2017). These are old ideas in sociological theory. Given the changes in job structure and pay established in this article, these issues are increasingly relevant to understanding inequality dynamics.

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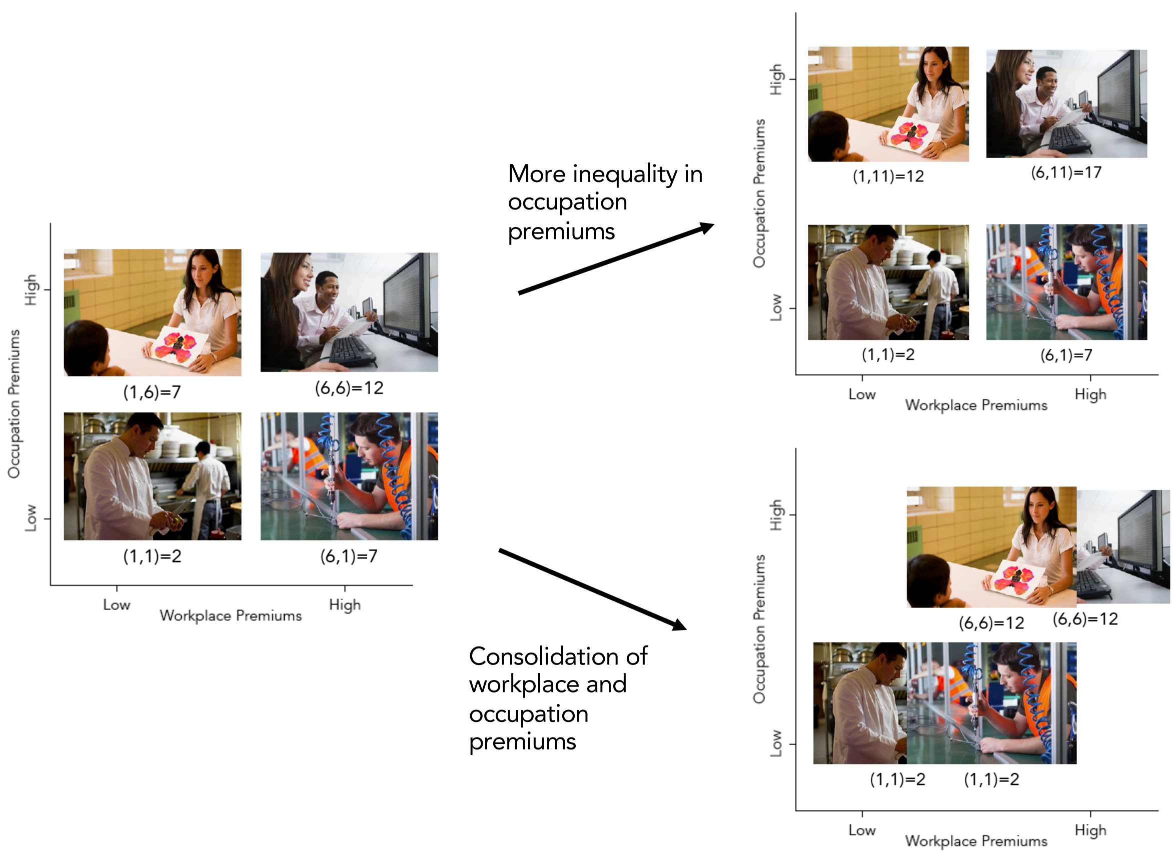
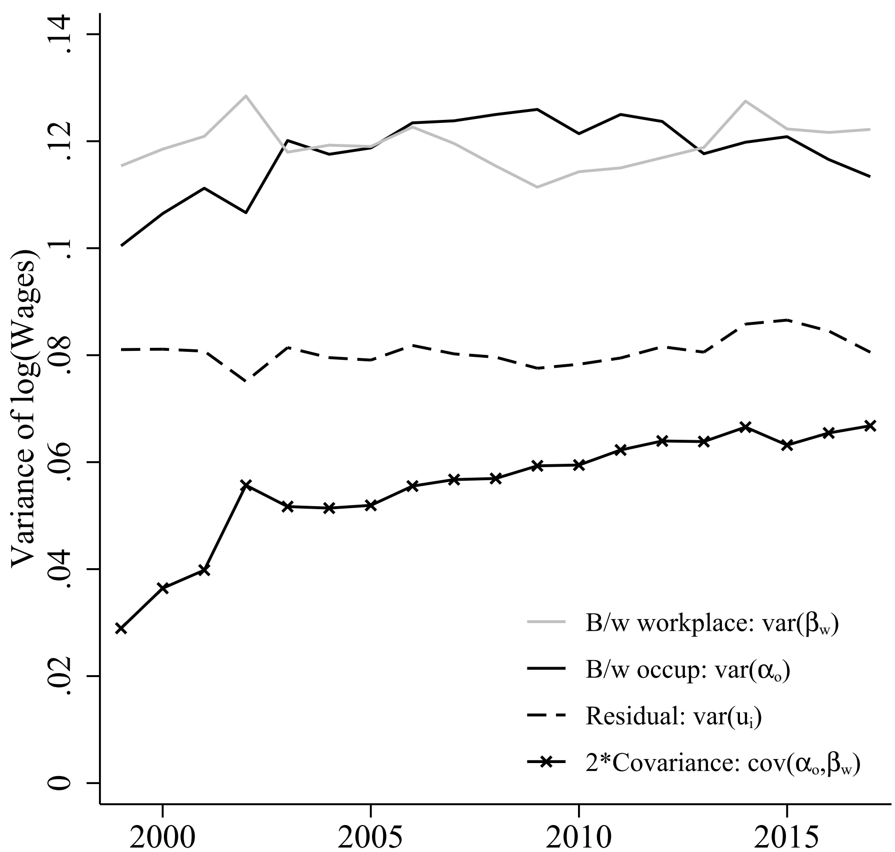
Figure 1: Contrasting Channels of Increased Inequality



Note: This figure contrasts two inequality-increasing changes. We summarize the economy as 4 jobs arrayed by their occupation and workplace premiums. In the top example, inequality increases because of increased inequality in occupation premiums. In the bottom example, inequality in occupation and in workplace premiums stays constant, but consolidation increases overall inequality.

Figure 2: Two-way occupation and workplace decomposition of inequality, 1999-2017.



Data: Occupational Employment Statistics microdata.

Figure 3: Correlation of occupation and workplace fixed effects, 1999-2017.

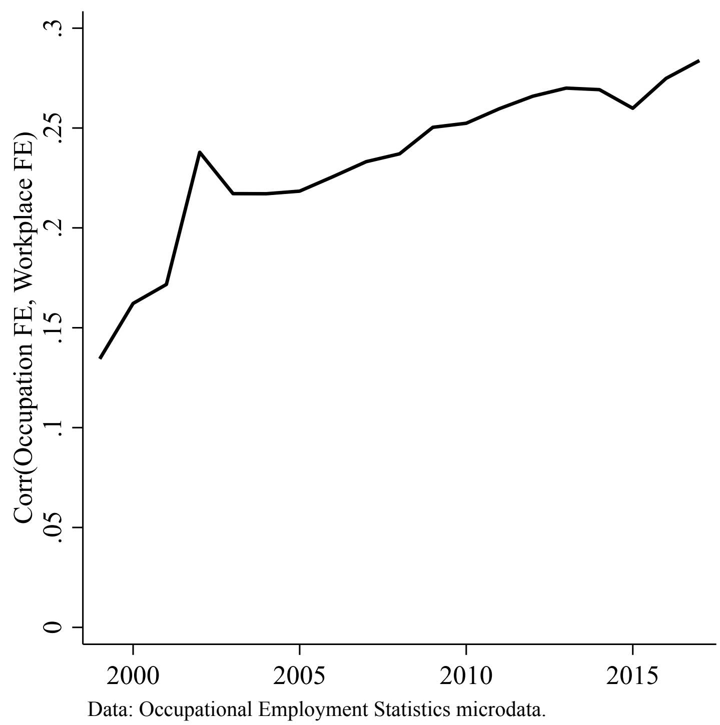
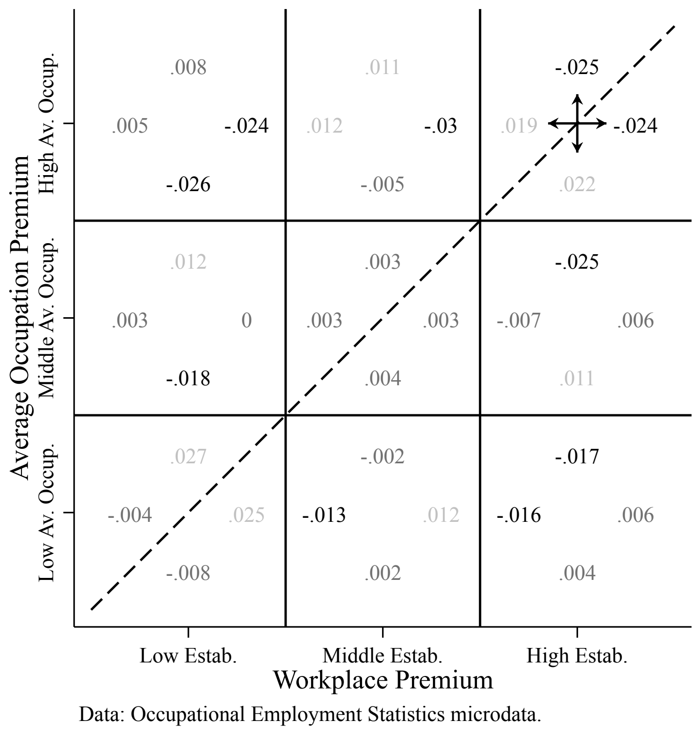


Figure 4: Panel correlation descriptive counterfactuals.

(a) Difference between observed correlation and correlation when increases or decreases in occupation premiums or in workplace premiums are fixed within each cell.



(b) Difference between observed correlation and correlation when workplace growth or decline in employment are fixed within each cell.

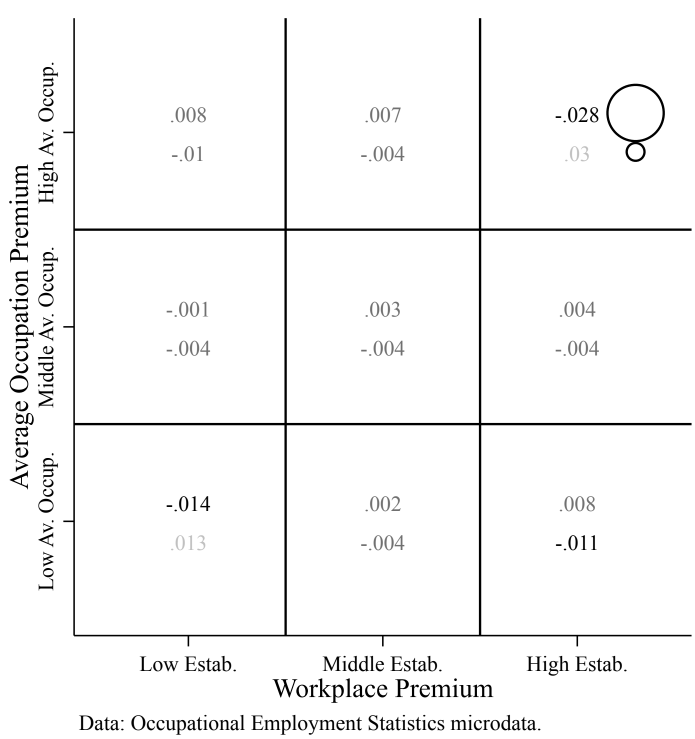


Table 1: Operationalizing channels of consolidation between workplace and occupation premiums

Mechanism	Workplaces Affected	Counterfactual Change	Example
Growth of a polarized service sector			
Expansion of low-paying services	Low workplace premium/low occupation, low workplace/middle occupation, middle workplace/low occupation establishments in retail, food and accommodation and other services	Calculate employment numbers based on starting period number of low-skilled workers for establishments that are increasing their number of nonroutine manual workers	Growth of fast-food restaurants
Expansion of high-paying services	High workplace premium/high occupation, High workplace/middle occupation, middle workplace/high occupation establishments in information, FIRE, professional/technical services and management industries	Calculate employment numbers based on starting period number of managerial and professional workers for establishments that are increasing their number of those workers	Growth of tech companies
Shifting occupations across workplaces			
Outsourcing	High workplace premium/high occupation; high workplace/middle occupation; middle workplace/high occupation; middle workplace/middle occupation	Assign starting period share of nonroutine manual workers to workplaces that decrease their share of those workers and recalculate average occupation FE	Janitors, food service contracted out
	Low workplace premium/low occupation; low workplace/middle occupation; middle workplace/low occupation if in building services, catering, warehousing, trucking or security industries	Assign starting period number of employees	
Focus on core competency	All establishments	Assign starting period average occupation premium if establishment's main occupation has increased its employment share	Law firms hiring more lawyers, fewer administrators
Skill upgrading blue collar jobs	High workplace/low occupation and high workplace/middle occupation in manufacturing, mining, utilities or transportation industries	Assign starting period share of managerial, professional, technical and clerical employees to establishments that are increasing their shares of those occupations and recalculate average occupation FE	Manufacturers upskilling production
Changed sources of workplace pay premiums			
Rent destruction in blue collar jobs	High workplace/low occupation and high workplace/middle occupation establishments in manufacturing, mining, utilities or transportation industries	Assign starting period workplace FE and size to establishments that are shrinking and cutting wages	Deunionization of manufacturing, trucking
Deskilling social sector	Low workplace/high occupation and low workplace/middle occupation in health, social, education and civic	Assign starting period average occupational FE to establishments reducing their occupation FE	Hospitals swapping technicians for doctors
Pay raises in social sector	Low workplace/high occupation and low workplace/middle occupation in health, social, education and civic	Assign starting period workplace FE to establishments increasing workplace FE.	Higher pay for private practice therapists
Top teams	High workplace/high occupation premium establishments in information, FIRE, professional/technical services and management industries	Assign starting period workplace premium to establishments that are increasing workplace and occupational premiums	Hedge funds raising pay

Table 2: Counterfactual correlations

	1999-2005	2012-2018	Share of Change Explained
Observed correlations	0.383	0.487	
All fixed	0.383	0.410	0.75
Growth of a polarized service sector			
Fix expansion of low-paid services	0.383	0.479	0.07
Fix expansion of high-paid services	0.383	0.470	0.17
Shifting occupations across workplaces			
Fix core competency	0.383	0.491	-0.04
Fix outsourcing	0.383	0.485	0.02
Fix skill upgrading to high-paid, low-skill	0.383	0.485	0.02
Changed sources of workplace pay premiums			
Fix wage cuts to high-paid, low-skill	0.383	0.480	0.07
Fix deskilling social servs	0.383	0.475	0.12
Fix increases in social servs	0.383	0.475	0.11
Fix top teams	0.383	0.475	0.11

Note: Estimates based on Occupational Employment Statistics microdata.

A Appendices

A.1 Simulating consolidation-driven inequality

To understand how inequality depends on the correlation between occupation and workplace premiums, consider the simulated jobs charted in Figure A.1. Each job consists of an occupation located at a workplace and its wage is the sum of its underlying occupation and workplace pay premiums. The left side of panel (a) in Figure A.1 shows a lognormal distribution of wages. Inequality increases when this distribution widens. The right side of the panel arrays these same data in a heatplot by occupation and workplace premiums. In panel (a), we set the occupation and workplace premiums to be uncorrelated, so the heatplot is roughly circular. Panel (b) of Figure A.1 shows an increase in inequality due to increased variability of an underlying pay premium. A theory of starker economic segmentation and unequal market power, for example, would predict that the workplace fixed effects increase in variance. Panel (b) illustrates this increased overall inequality by stretching the data along the workplace axis, as variability in workplace premiums increases. Similarly, any theory of rising between-occupation inequality would stretch the wage distribution of jobs, but along the occupation dimension instead of the workplace dimension.

[Figure 5 about here.]

In contrast to the example in panel (b), panel (c) of Figure A.1 shows that inequality can also increase even if the underlying variability of occupation and workplace premiums is unchanged. Although each pay premium continues to contribute the same amount of variability, we increase the correlation between premiums: the same jobs are more likely to receive high workplace premiums and high occupation premiums. The result is an increase in overall wage inequality. The heatplot shows that this change can happen from two directions. consolidated inequality can increase as the on-diagonal components, in which high- or low-workplace premiums match with high- or low-occupation premiums, become increasingly dense. But, consolidation can also increase due to decreased density in off-diagonal, jobs that mismatch high (low) workplace with low (high) occupation premiums.

A.2 OES sampling

The OES combines a semiannual probability sample of private sector establishments and local governments with a census of U.S. Postal Service, federal government executive branch, and state government workplaces. Establishments in the private sector (including both publicly traded and privately held firms) 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 stratified into more than 150,000 cells defined by metropolitan or nonmetropolitan statistical areas and industry. 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 workplaces. The total combined 3-year sample ending in May 2017 comprised approximately 1.2 million establishments with a 72 percent response rate. These respondents accounted for 82 million workers out of 141 million in the United States.

The BLS imputes employment 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. This procedure mechanically increases the share of variance accounted for by the grouping variables used to impute. In our main analysis, following prior inequality research using both the OES and the Current Population Survey (CPS), we exclude observations with imputed data (Spletzer and Handwerker 2014; Mouw and Kalleberg 2010).

The survey covers both full- and part-time workers, but excludes the self-employed, household workers and unpaid family workers. Prior research shows that trends in OES employment by occupation are broadly similar to those observed in the OES (Abraham, Spletzer, and Harper 2010). We weight the data using survey weights calculated by the BLS to account for the OES sampling procedure and for nonresponse. The BLS designs these weights to reflect the inverse probability of selection into a panel, so that a single panel of data, when appropriately weighted, should represent the universe of workplaces in that year with respect to key characteristics.

A.3 Determining midpoints of interval data

In estimating our main model (Equation 1), we face two challenges: first, we only know the interval into which each observation is assigned, and not the actual earnings; and second, the number of occupations and workplaces is very large. If the number of workplaces and occupations were sufficiently small, we could implement a standard interval regression procedure. This relies, however, on inversion of the matrix $\mathbf{X}'\mathbf{X}$ where each row of the design matrix $\mathbf{X}$ is a vector of workplace indicator variables concatenated with a vector of occupation indicator variables. But if there are too many workplaces and occupations – as in our case – we cannot calculate the inverse of $\mathbf{X}'\mathbf{X}$. We wrote an interval regression procedure to handle two high-dimensional fixed effects, but it currently runs too slowly on the large OES data set to be of use.

[Figure 6 about here.]

Alternatively, when predicting a continuous wage variable, we can use the estimate a two-way fixed effects model using procedures developed following the worker-firm fixed effects literature (Abowd, Kramarz, and Margolis 1999). We do this, first, by using the `intmu` variable defined by the BLS. This quantity has been designed by the BLS to reflect the average earnings within an interval for a given state, year, and industry, and is used by the Bureau to estimate average occupational earnings. However, the exact procedure to derive this quantity is not available to us and so we do not rely on it for our main analysis.

In the interest of transparency, we base our main analysis on the lower and upper bounds of each interval, as given on the OES survey form itself and observed by respondents. Figure A.3 shows the interval bounds as they appeared on the OES survey. We then suppose that the wage of every job in a given interval equals the midpoint of that interval's logged lower and upper bounds. We use the federal minimum wage as the lower bound for the bottom interval. We deflate all the interval bounds to 2000 real dollars using the CPI before taking their natural log.

[Figure 7 about here.]

However, the highest interval has no upper bound and therefore no midpoint. Our solution is to fit a Pareto distribution over the top two intervals, separately for each year. This is a standard approach when faced with top-coded income data, such as the CPS (Schmitt 2003). A Pareto-distributed random variable y has two parameters: its minimum y_m and its shape α. The probability that y is greater than some value $t \geq y_m$ is $(\frac{y_m}{t})^\alpha$. In our case, we fit a Pareto distribution to the top two intervals: $[\ln lb_{11}, \ln lb_{12}) \cup [\ln lb_{12}, +\infty)$, where lb_i is the lower bound of the ith interval. For a random variable y following such a distribution, it can be shown that

$$\alpha = \frac{\ln \mathbf{P}\left(y > \ln lb_{12}\right)}{\ln[\ln lb_{11}] - \ln[\ln lb_{12}]},$$

where $\mathbf{P}\left(y > \ln lb_{12}\right)$ is the number of observations in the 12th interval divided by the number of observations in the 11th and 12th intervals. Once we have this parameter α, we can find the conditional expectation of $y \sim Pareto(\ln lb_{11}, \alpha)$ in the top interval:

$$\mathbf{E}\left[y | y > \ln lb_{12}\right] = \frac{\alpha \times \ln lb_{12}}{\alpha - 1}.$$

We assign the value of this conditional expectation to all jobs in the 12th interval. This whole procedure is repeated separately for each year.

The above procedure fits a Pareto distribution to the top two OES intervals. An alternative is to suppose that all earnings, regardless of interval, are distributed according to a single parametric distribution (von Hippel, Hunter, and Drown 2017). We attempt an alternative procedure, fitting a Normal distribution to the log-earnings; note that this implies a log-normal distribution for earnings, which has a great deal of precedent in the study of earnings (Schmitt 2003).

However, this log normal distribution is truncated at the minimum wage. Because of this truncation, the probability that a given observation is in interval i, defined by lower bound lb_i and upper bound ub_i, is

$$\frac{\mathbf{P}\left(\ln lb_i \leq y < \ln ub_i \mid y \sim \mathcal{N}(\mu, \sigma)\right)}{\mathbf{P}(\ln minwage \leq y \mid y \sim \mathcal{N}(\mu, \sigma))},$$

for parameters μ and σ. Taking the natural log and summing over all observations gives the log-likelihood of μ and σ for a given year's distribution across the pay intervals. We use Stata's modified Newton-Raphson algorithm to find the maximum-likelihood estimates for μ and σ for each year. Once the best-fitting truncated normal distribution is found, it is possible to calculate its expectation $\mathbf{E}[y \mid \ln lb_i \leq y < \ln ub_i, y \sim \mathcal{N}(\mu, \sigma)]$ within any given interval $[\ln lb_i, \ln ub_i]$. We then assign this conditional expectation to all observations falling in interval i.

After using these three methods to assign earnings values to each OES interval, we are able to estimate three sets of the two-way variance decomposition. This yields three series for the correlation between workplace and occupation premiums. As Figure A.4 shows, these correlation trends are very similar, suggesting that our main findings on rising workplace-occupation correlation is robust to different strategies for addressing the OES earnings intervals.

[Figure 8 about here.]

Of course, neither the Pareto-midpoint procedure nor the truncated Normal procedure guarantee that we avoid bias. We cannot be sure that the average of log-earnings within an interval equals the midpoints of the logged interval endpoints; nor can we be certain that the underlying continuous log-earnings distribution follows a truncated Normal distribution. However, given that each year's OES sample is very large, that each interval is populated, and that the logged intervals are relatively equal in width, either method should yield acceptably precise estimates of the log-earnings variance (von Hippel, Hunter, and Drown 2017). Indeed, many of the alternative procedures for dealing with earnings intervals were developed with much smaller samples in mind, such as surveys of counties or metropolitan areas (Jargowsky and Wheeler 2018).

A.4 Variance decomposition and wage intervals

Prior research on two-way high-dimensional fixed effects variance decomposition focuses on fully continuous outcome variables (Kline, Saggio, and Sølvsten 2018; Abowd, Kramarz, and Margolis 1999). Because our wage data are intervalled, it is possible that these methods will introduce bias into our decomposition. To assess this possibility, the ideal test would be to compare OES-based decompositions to similar data without the interval filter on wages. Unfortunately, no such data exist on US workers. As an alternative, we obtained linked employer-employee wage data from 16 European countries that include continuous hourly wage information, workplace identifiers and occupation codes. We then imposed an interval filter that approximated that used in our analysis to assess the sensitivity of the variance decomposition to this filtering.

These European data were obtained under a restricted-use data sharing agreement with the European Commission's Eurostat, approved by all participating member countries. We obtained data for 2002, 2006, 2010 and 2014 and excluded all countries that did not share data for all of those years or were missing hourly wage, establishment or occupation information. On each of the remaining 16 countries, we designed an interval filter with a width similar to the OES interval (0.23 log points) and starting at the bottom percentile of the wage distribution for each country (the OES starts at the US Federal minimum wage). We then used these intervals to identify sets of midpoints using the same methods described above: a top code pareto imputation, a truncated normal, and the real interval means. We then estimated the two-way occupation by workplace fixed effects model on all of these midpoints and on the real, continuous logged wage variable.

Figure A.5 shows that across all 17 countries, the interval and non-interval correlation estimates are very similar, in both level and trend. With only a few exceptions, the filtered covariances line up closely enough that they are visually indistinguishable from the non-filtered estimates. Imposing the interval filter does not substantially bias estimates of correlation between fixed effects.

[Figure 9 about here.]

While bias in estimates appears relatively small, there is nonetheless a risk that accuracy changes as a function of the true variance or correlation. Such bias would cast doubt on the trend in correlation rather than the level of correlation. To check this possibility, we compare the correlation estimated using the midpoint-Pareto method to the correlation obtained from the true continuous earnings. Figure A.6 shows that the deviation appears unrelated to both the underlying real variance and the real correlation.

[Figure 10 about here.]

We also compare the industry-region correlation trends identified in the OES to analogous trends estimated using the American Community Survey (ACS), the Current Population Survey Outgoing Rotation Group (CPS ORG)and the Current Population Survey Annual Social and Economic Supplement (ASEC). These publicly available household surveys include no establishment information, so we estimate industry-by-state premiums. Moreover, each survey relies on slightly different wage and earning definitions, industry and occupation categories and top-coding rules. Nonetheless, Figure A.7 shows some remarkable similarities. All sources show a rise in correlation between 1999 and the mid-2010s. The household surveys then show a leveling off or decline in the most recent years, while the OES correlation continues to increase. These results increase our confidence that the overall rise in correlation over time is not due to quirks of the OES sampling or data collection methodology.

[Figure 11 about here.]

A.5 Comparison of OES to other wage inequality data

Prior research has decomposed variance by occupation, workplace and company (Mouw and Kalleberg 2010; Barth, Bryson, Davis, and Freeman 2016; Song, Price, Guvenen, Bloom, and von Wachter 2018). To compare the OES data to these previous studies, we first fit one-way fixed effects models, giving the variance between and within occupation and workplace categories. We re-estimate the model at each year, allowing an occupation's pay premium, for example, to vary over time.

[Figure 12 about here.]

Figure A.8 shows decompositions from 1999 to 2017 for 3-digit occupation and for workplace.[9] In all years, inequality between occupations and between workplaces each explain more than half of total variance in log-earnings. Moreover, increasing inequality between occupations and between workplace each entirely accounts for rising inequality: within-establishment and within-occupation inequality both show little increase.

The trends shown in these one-way decompositions are similar to results from other data. Consistent with our findings, analysis of the Longitudinal Employer-Household Data (LEHD) finds that between-establishment variance accounts for two thirds of the increase in total earnings variance from 1997 to 2007 (Barth, Bryson, Davis, and Freeman 2016, S74) and analysis of Social Security Administration (SSA) data shows that in the period from 1999 to 2013, between-firm variance entirely accounts for the increase in earnings variance (Song, Price, Guvenen, Bloom, and von Wachter 2018). However, residual within-establishment variation account for more than half of total variance

[9]To assess the relative importance of different aggregations of occupations, we conduct a series of decompositions using 2-, 3-, 4-, and 5-digit occupations. Similarly, we produce decompositions at the workplace level and at the 2-, 3-, and 4-digit industry (NAICS) levels. Results show similar trends (starting from different levels) across these different levels of aggregation. In Figure A.9 in appendix A.7, drawing on results from the two-way fixed effects model, we decompose the finer-grained occupation and workplace categories into broad skill groups, industries and their residuals.

in both the LEHD or SSA (Song, Price, Guvenen, Bloom, and von Wachter 2018, 14). We expect that much of this discrepancy in level is due to the LEHD and SSA data relying on quarterly and annual employee earnings, rather than on hourly wages. If more variance in the former measure is uncorrelated with workplace effects (for example, quitting a job partway through the year), then this mechanically reduces the variance explained by workplace indicators.

Likewise, analysis of the CPS confirms that between-occupation inequality is growing as a share of total inequality (Mouw and Kalleberg 2010, 417). This share rises most rapidly between 2000 and 2010 before flattening, in a pattern very similar to that observed with the OES in Figure A.8. But, as with workplace, between-occupation inequality accounts for a larger portion of total inequality in the OES than the CPS (in the CPS it never goes above 45 percent). A BLS study comparing the two data sources attributes this difference to the employer-reported nature of the OES occupation data (Spletzer and Handwerker 2014). This study suggests that employers are less likely than worker respondents to exaggerate the duties and activities associated with a given position. The OES data also include finer-grained occupational categories than the CPS.

A.6 Two-way fixed effects models with occupation, rather than worker

Our approach is similar to the model specified in Abowd, Kramarz, and Margolis (Abowd, Kramarz, and Margolis 1999) (AKM), in which log earnings are the sum of an individual worker fixed effect, a workplace fixed effect, and an error term. However, it differs in two respects. First, our approach allows both sets of fixed effects to vary by year. This lets us trace the changing earnings premiums of particular occupations or workplaces over time. We can do this because, within a given year and after excluding workplaces with only one 3-digit occupation, all occupation and workplace fixed effects can be identified. If, in the following year, an occupation receives a larger pay premium or a given workplace increases its pay, those changes can be distinguished.

Second, our model estimates a more stable set of fixed effects than the AKM model. The AKM model relies on workplace-switching individuals to properly identify the fixed effects. Identification in our model, on the other hand, relies on workplaces that have multiple occupations (and vice-versa), which is much more common: the median workplace contains 8 jobs.[10] The downside of

[10]Recent econometric research suggests that sampling error introduces important biases in the AKM model (Kline, Saggio, and Sølvsten 2018). In our case, the workplaces that employ more distinct occupations, and whose workplace fixed effects can therefore be more precisely estimated, tend to also employ more workers and therefore receive a

our occupation-by-workplace approach is that we cannot distinguish occupational composition from the sorting of workers by education, demographics, ability, or other factors. Part of the premiums attributed to both workplace and occupation are a result of employing workers at different ability, skill and experience levels.

A.7 Testing alternative explanations for rise in inequality

Figure A.9, discussed in more detail in the main text, decomposes the pay premiums and residual estimated in our main model into further detailed categories.

[Figure 13 about here.]

Table A.1 tests the sensitivity of the covariance between occupation and workplace to the addition of controls for observable worker characteristics. We discuss the implications of the results in detail in the main text.

[Table 3 about here.]

A.8 Testing assumptions of the panel analysis

Beyond the main issues discussed in the text, there are several additional assumptions involved in our panel analysis.

The OES was not designed as a panel survey of establishments. However, prior research on the OES finds that the survey is large enough that following repeated observations over time gives a sample that remains generally representative (Dey and Handwerker 2016). Figure A.10 in the appendix compares the industry composition of the main sample and our panel subsample. While the overall distribution is similar, there are differences. High turnover firms in accommodation and food services are underrepresented in the panel sample, while large and low-turnover firms in heavy manufacturing and healthcare are overrepresented. To account for these differences, we multiply the standard OES weights with the inverse of the probability that an establishment in a given industry will appear in the panel, relative to the full sample.

higher weight in calculations of the variance components. This differs from the worker-workplace fixed effect models, where those with the most precisely estimated individual fixed effects are those who switch workplaces the most in the sample's time frame, which could mean they are less representative of the whole labor force.

[Figure 14 about here.]

In our panel analysis we shift our unit of analysis from the job to the establishment. This is necessary, as examining a panel of jobs would exclude variation due to the disappearance or appearance of new occupations in a given establishment. But correlation can also increase due to declining variability in occupation premiums within establishments, even if the correlation between average occupation and workplace premiums is not changing. If this declining within-establishment variability was an important component of rising overall correlation, then the panel analysis would miss this. However, the correlation between workplace premium and the average occupation premium in each workplace also increases steadily (panel (b) of Figure A.11). In fact, the correlation based on average occupation premium actually increases more steeply than the job-level correlation, as within-establishment variance between occupations increases during the period.

Another potential concern about our analysis is that the Pearson correlation, like variance, could be sensitive to outlier observations. To test this possibility, we also considered the change in correlation over time between percentiles of workplace pay premiums and occupation pay premiums. This correlation of percentiles is more similar to a Spearman rank correlation and is less influenced by outliers than the Pearson correlation in the main analysis. Panel (c) in Figure A.11 shows that the correlation between workplace premium percentiles and occupation premium percentiles exhibits similar growth to the Pearson correlation, increasing our confidence that the correlation trend is not dramatically influenced by outlying observations.

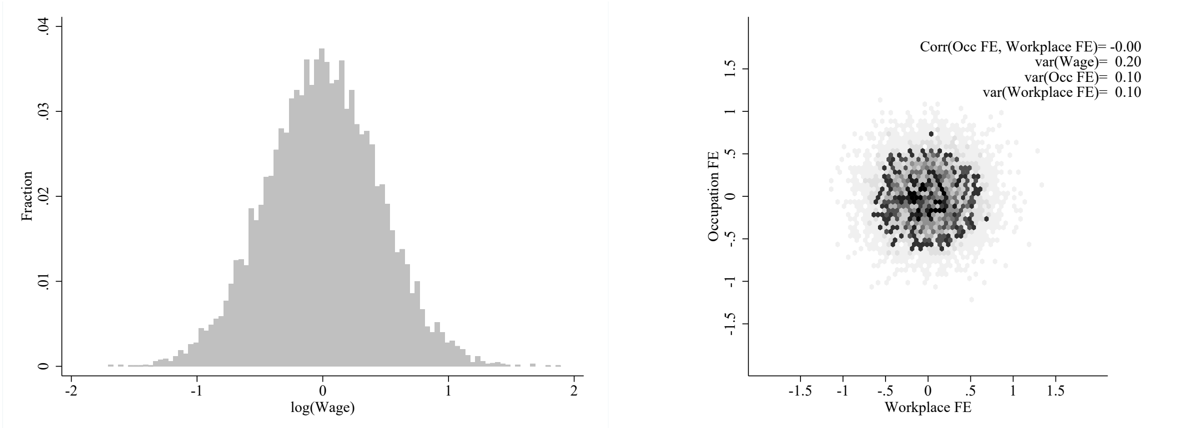
We motivate our panel analysis by arguing that measuring processes of organizational change is crucial for understanding consolidated inequality. But some pathways of change do not require panel information on the starting position of workplaces—specifically, compositional change in industry or skill could drive consolidated inequality. We use the full, cross-sectional sample to test whether the shifting size of skill and industry groups explains the increasing correlation between workplace and occupation pay premiums. We fix the proportions of broad industry and 4-level skill groups to their 1999 starting point. (Lemieux 2006). Panel (c) in Figure A.11 shows that this cross-sectional re-weighting exercise only moderately dampens the increase in correlation. This result is similar in magnitude to our test of shifting composition through the rise of high and low paid services in the panel analysis. The convergence of the cross-sectional and panel analyses provides further evidence that increasing consolidated inequality is not due only to compositional change.

[Figure 15 about here.]

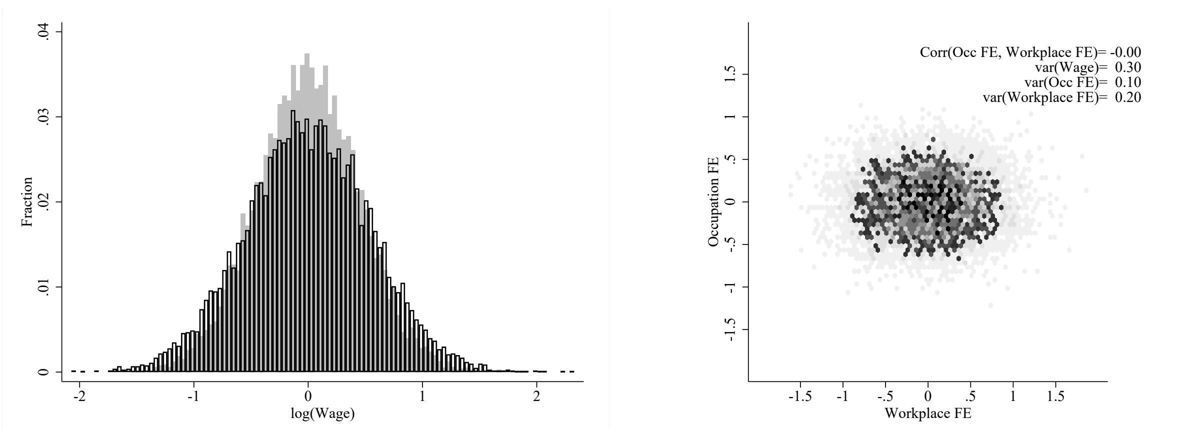
[Table 4 about here.]

Figure A.1: Simulations show how either inequality in pay premiums or in their correlation can drive increased inequality.

(a) Baseline wage inequality, occupation premiums and workplace premiums.



(b) Higher inequality due to greater variation in workplace premiums.



(c) Higher inequality due to greater correlation between premiums.

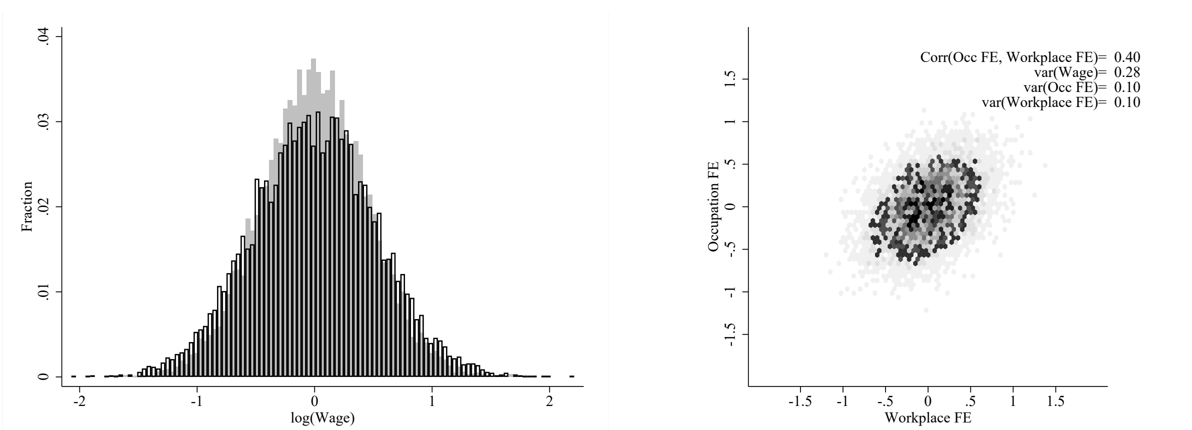


Figure A.2: Detail from OES survey form

7 Please use the following pages to report the employees found in your firm. Please write in each unique occupational title, a short description of duties, the number of employees found in each wage column, and the total employment for each occupation. Refer to the detailed instructions on how to report by occupation and how to determine wages. If additional space is needed to report all of the workers in your establishment, please photocopy this page.

OCCUPATIONAL TITLE AND DESCRIPTION OF DUTIES		NUMBER OF EMPLOYEES IN SELECTED WAGE RANGES (Report Part-time Workers According to an Hourly Rate)												
		A	B	C	D	E	F	G	H	I	J	K	L	T
	Hourly (part-time or full-time)	under $9.25	$9.25 - 11.74	$11.75 - 14.74	$14.75 - 18.74	$18.75 - 23.99	$24.00 - 30.24	$30.25 - 38.49	$38.50 - 48.99	$49.00 - 61.99	$62.00 - 78.74	$78.75 - 99.99	$100.00 and over	Total
	Annual Salary (full-time only)	under $19,240	$19,240 - 24,439	$24,440 - 30,679	$30,680 - 38,999	$39,000 - 49,919	$49,920 - 62,919	$62,920 - 80,079	$80,080 -101,919	$101,920 - 128,959	$128,960 - 163,799	$163,800 - 207,999	$208,000 and over	

EXAMPLE:

	A	B	C	D	E	F	G	H	I	J	K	L	T
Registered Nurses (RN)- *Provide nursing care to sick or injured patients.*						2	4	1					7
	A	B	C	D	E	F	G	H	I	J	K	L	T
	A	B	C	D	E	F	G	H	I	J	K	L	T

Figure A.3: OES interval bounds.

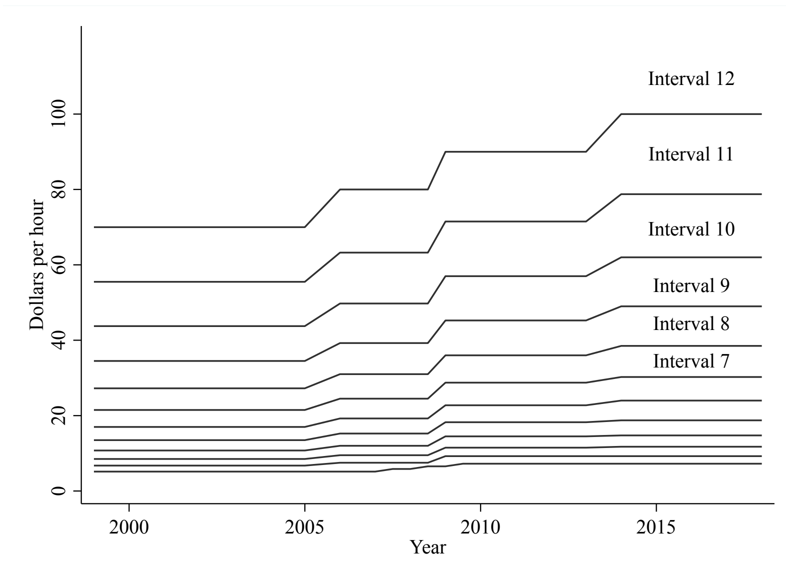
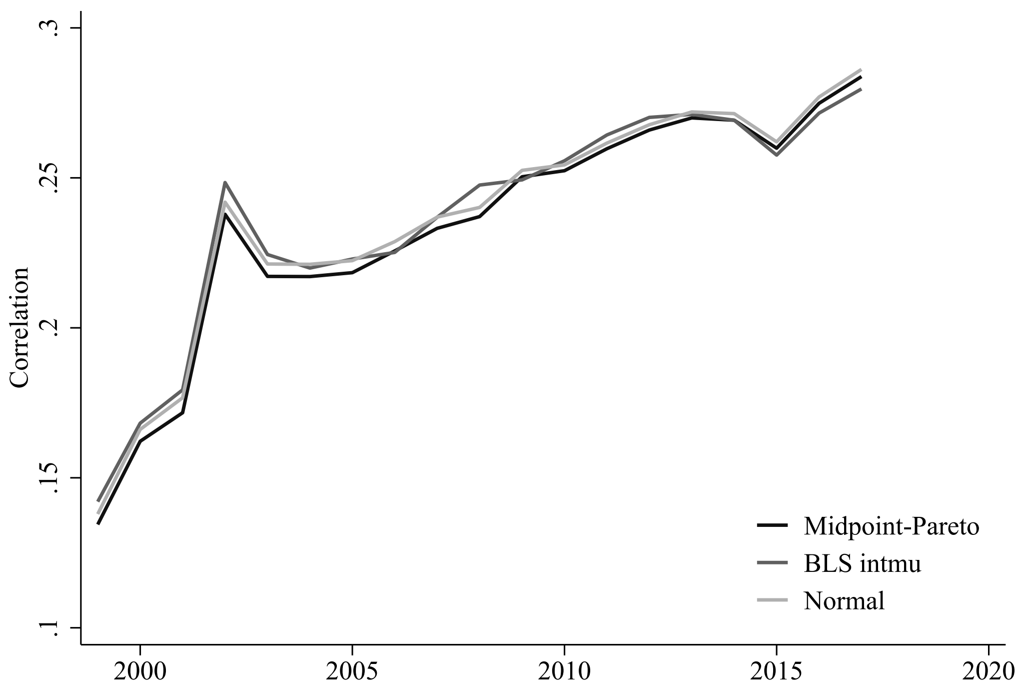
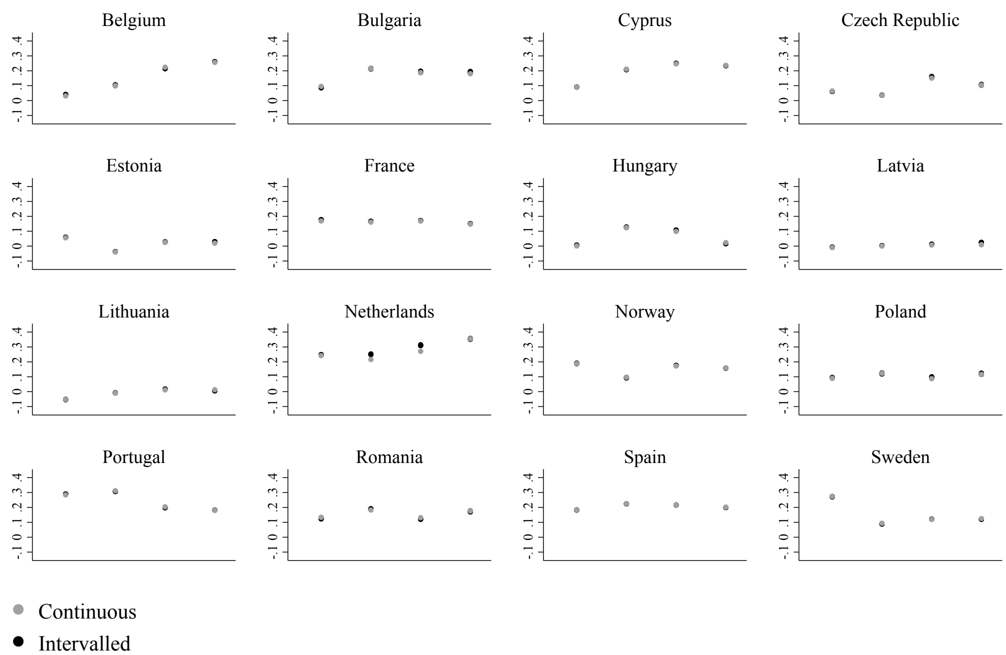


Figure A.4: Comparison of correlation trends derived from three different interval strategies.



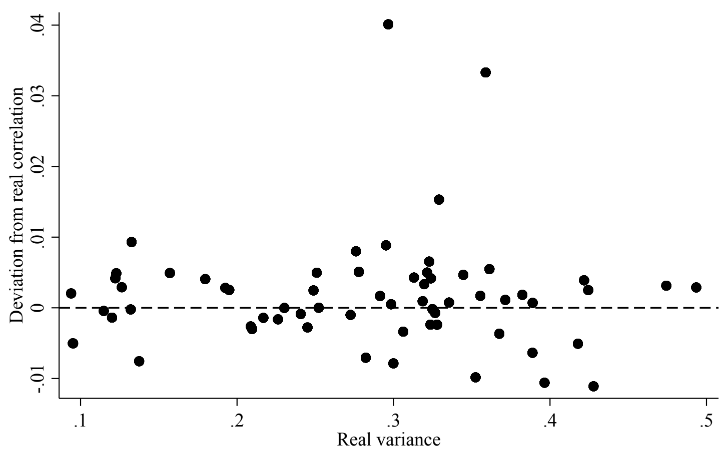
Data from Occupational Employment Statistics. Sample is privately owned workplaces.

Figure A.5: Assessing the impact of interval filtering and midpoint choice on covariance trends in 16 European countries, 2002, 2006, 2010, 2014.



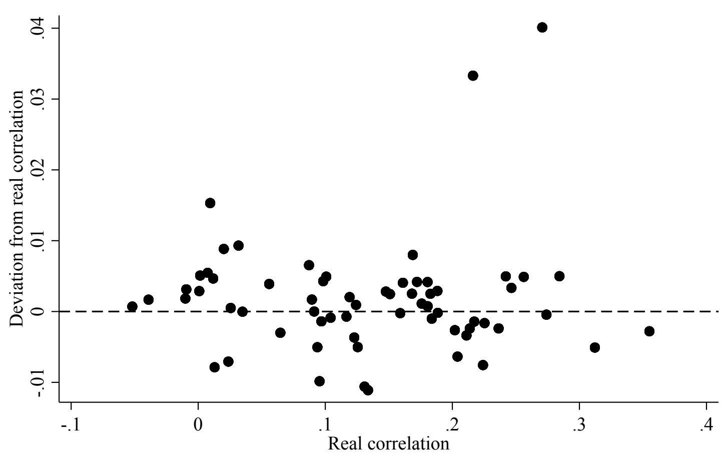
Data are from Structure of Earnings Survey. Black points are based on interval filtered data (using midpoint selection strategies outlined in the text). X-axis is years 2002, 2006, 2010 and 2014. Y-axis is correlation between workplace and occupation fixed effects estimated in a two-way model. Underlying occupations are 2-digit ESCO.

Figure A.6: Correlation trends in alternative data sources



Data are from Structure of Earnings Survey. X-axis is real variance in wages. Y-axis is the difference between the real correlation and the correlation estimated on intervalled data with midpoints identified using a pareto distribution. Underlying occupations are 2-digit ESCO.

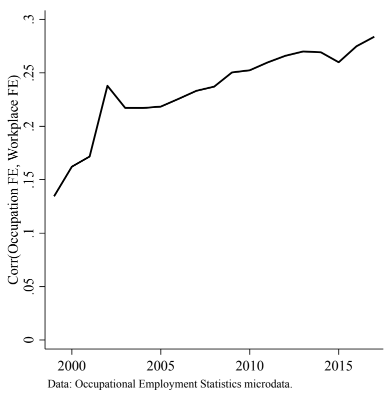
(a) Deviation of correlation estimate by true variance.



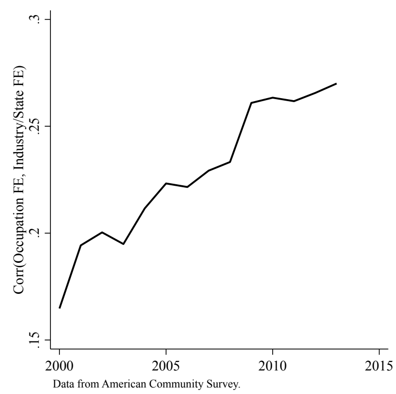
Data are from Structure of Earnings Survey. X-axis is real correlation between workplace and occupation fixed effects estimated in a two-way model. Y-axis is the difference between the real correlation and the correlation estimated on intervalled data with midpoints identified using a pareto distribution. Underlying occupations are 2-digit ESCO.

(b) Deviation of correlation estimate by true correlation.

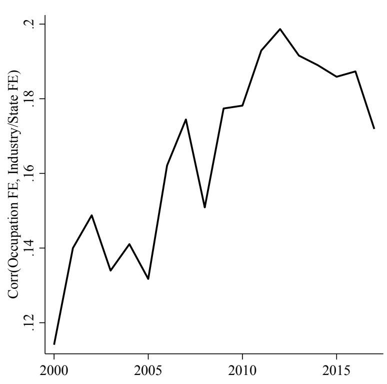
Figure A.7: Correlation trends in alternative data sources



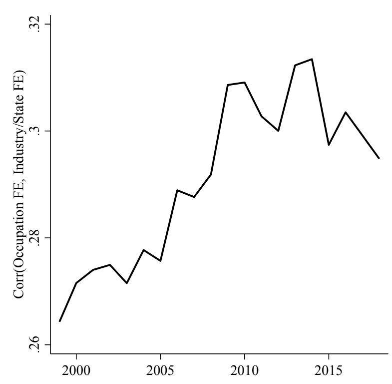
(a) OES



(b) ACS



(c) CPS-ASEC



(d) CPS-ORG

Figure A.8: Rising inequality between occupations and between workplaces, 1999-2017.

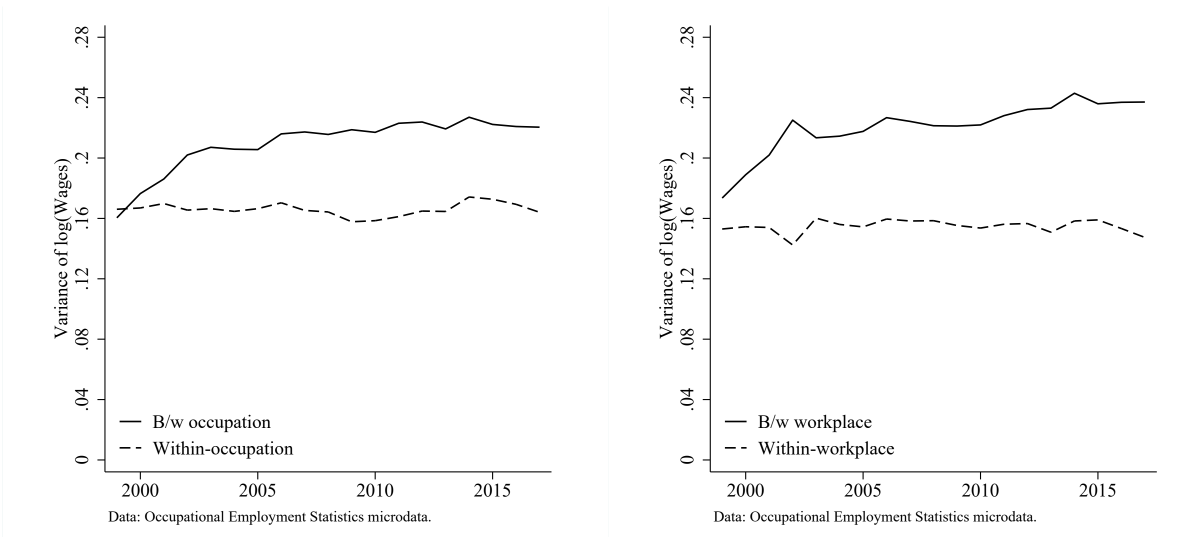
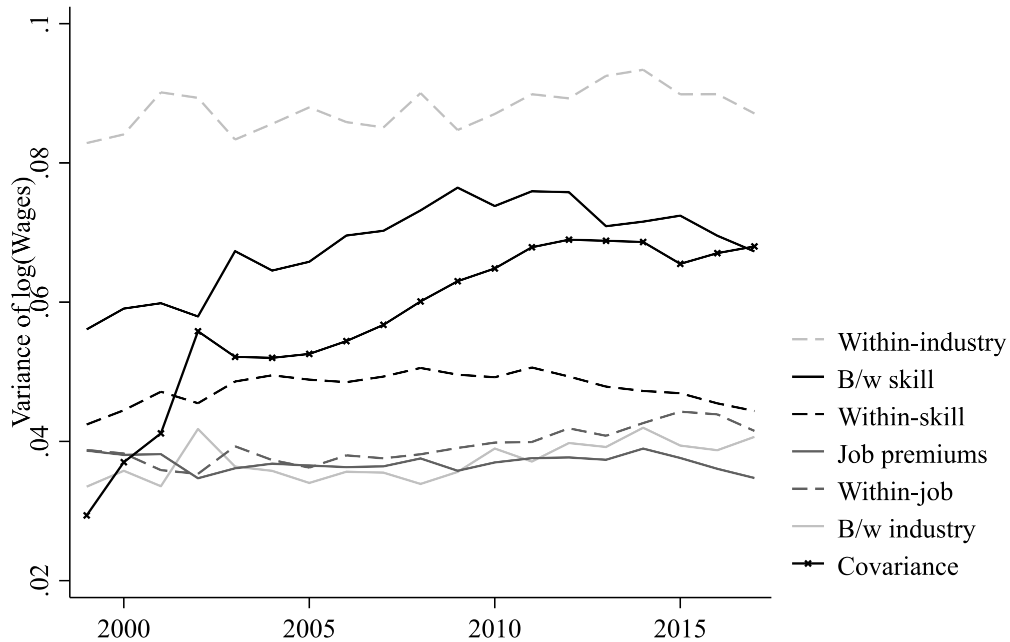


Figure A.9: Detailed decomposition of inequality, 1999-2017.



Note: Data are from OES. Industry is 2-digit NAICS codes. Skill is 4 broad occupation-based skill groups: nonroutine cognitive, routine cognitive, routine manual and nonroutine manual.

Figure A.10: Industry composition of panel and non-panel OES.

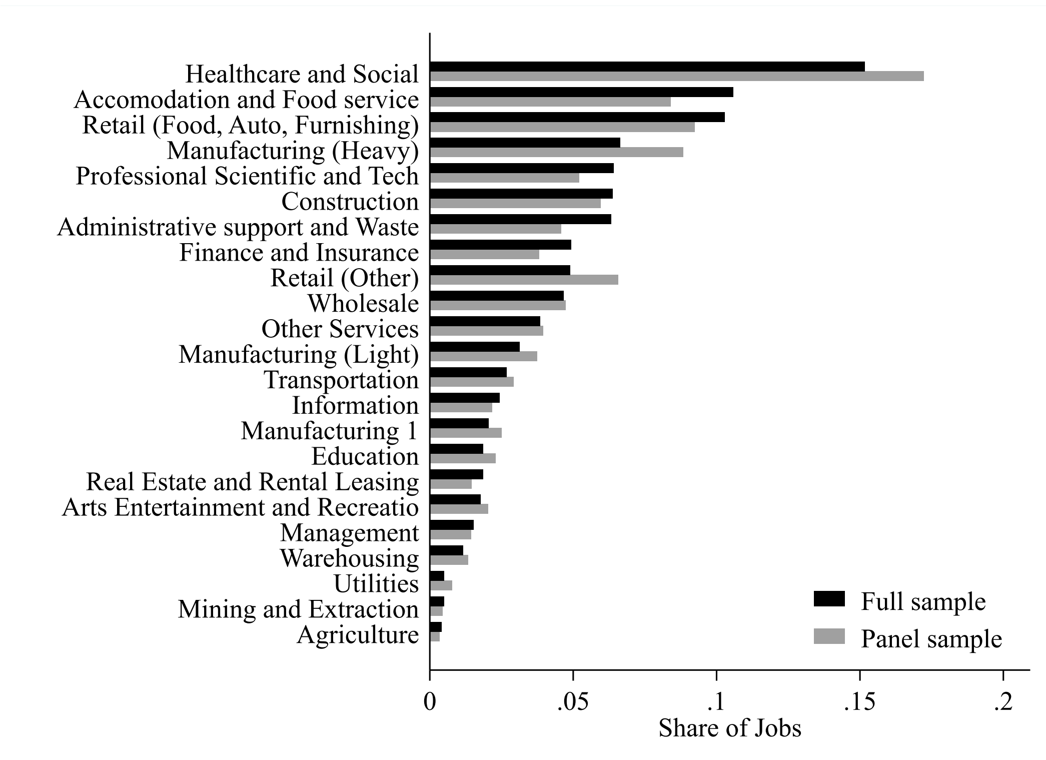
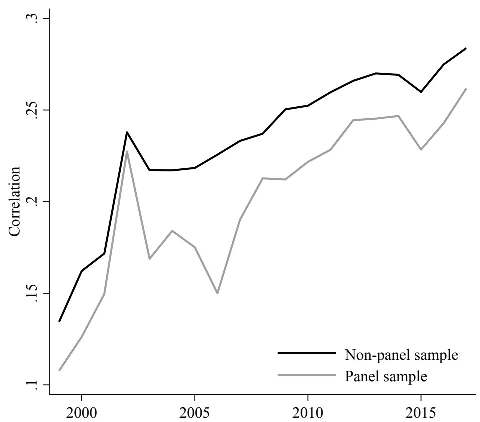
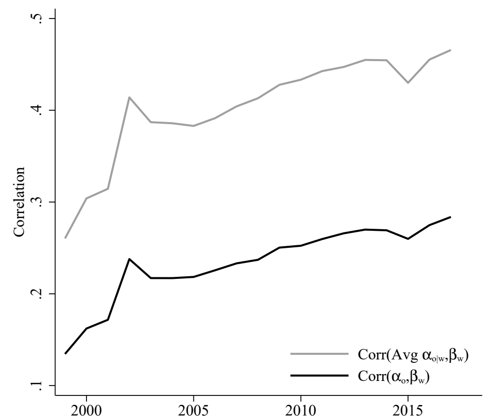


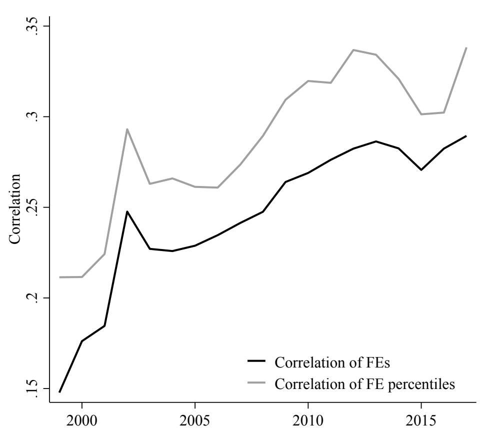
Figure A.11: Rising correlation is not due to industry composition change, firm entry and exit or rising within-workplace occupation variability



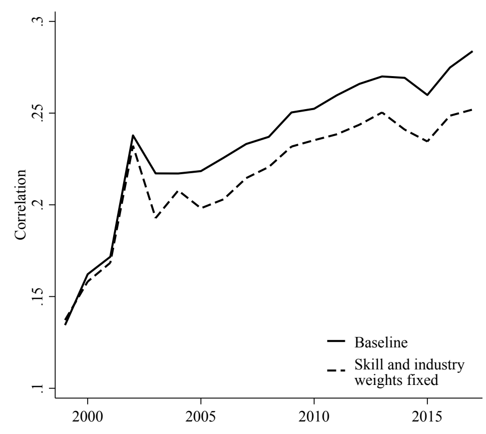
(a) Correlation among stayer establishments



(b) Correlation with FEs averaged within-workplace.



(c) Correlation between percentiles of FES



(d) Correlation with industry and skill weights fixed at 1999.

Table A.1: Sensitivity of covariance trends to controls

	Baseline			Controls					
	$Cov(\alpha_{o,t}, \beta_{w,t})$			$Cov(\alpha_{o,t}, \beta_{w,t})$			$Cov(\gamma_{o,t}, \beta_{w,t})$		
	2002	2014	δ_b	2002	2014	δ_c	δ_d	$\delta_b - \delta_c$	$\delta_b - (\delta_c + \delta_d)$
Sweden	0.01	0.01	-0.009	0.01	0.00	-0.010	-0.000	0.001	0.001
Estonia	0.01	0.00	-0.008	0.01	0.00	-0.007	0.003	-0.001	-0.004
France	0.02	0.02	-0.005	0.02	0.01	-0.004	-0.002	-0.001	0.002
Poland	0.02	0.03	-0.003	0.01	0.02	-0.001	-0.002	-0.001	0.001
Spain	0.03	0.02	-0.002	0.02	0.02	-0.001	-0.003	-0.000	0.002
Norway	0.01	0.01	-0.002	0.01	0.01	-0.003	-0.002	0.001	0.003
Romania	0.04	0.04	-0.001	0.03	0.03	-0.002	-0.005	0.001	0.006
Portugal	0.05	0.04	-0.001	0.04	0.02	-0.008	0.007	0.007	-0.001
Latvia	-0.00	0.00	0.004	-0.00	-0.00	0.002	0.002	0.001	-0.000
Slovakia	0.01	0.01	0.005	0.00	0.00	0.004	-0.001	0.001	0.002
Netherl.	0.03	0.04	0.008	0.01	0.02	0.004	-0.001	0.004	0.005
Czech Rep	0.01	0.02	0.014	0.01	0.01	0.011	-0.000	0.003	0.003
Belgium	0.00	0.02	0.014	0.00	0.01	0.007	0.002	0.007	0.005
Bulgaria	0.02	0.04	0.018	0.02	0.03	0.016	-0.004	0.002	0.007
Lithuania	-0.02	0.00	0.018	-0.02	-0.00	0.016	0.001	0.002	0.001
Hungary	0.00	0.00	0.019	-0.00	-0.00	0.011	0.007	0.008	0.001
Cyprus	0.02	0.05	0.034	0.01	0.04	0.031	0.005	0.004	-0.001

Note: European data is Structure of Earnings Survey. Covariance is the covariance*2 of occupation ($\alpha_{o,t}$) and workplace ($\beta_{w,t}$) premiums drawn from a two-way fixed effects model, as described in the text. Controls ($\gamma_{o,t}$) are education (less than high school, some college, college); age (6 categories); and sex.

Table A.2: Determinants of social sector deskilling

	(1)	(2)	(3)
Starting occupation FE	0.44***	0.44***	0.39***
	(0.02)	(0.02)	(0.02)
Starting workplace FE	0.44***	0.44***	0.46***
	(0.02)	(0.02)	(0.02)
ln(Employees)	-0.06***	-0.06***	-0.05***
	(0.00)	(0.00)	(0.00)
ln(Employees) growth		0.03***	0.03***
		(0.01)	(0.01)
Firm FE change		0.05***	0.04***
		(0.02)	(0.02)
CZ high workpl./high occ. increase occ. FE			-0.25**
			(0.07)
CZ high workpl./high occ. increase workpl. FE			-0.10
			(0.07)
CZ high workpl./high occ. increase size			-0.42***
			(0.05)
Constant	0.60***	0.60***	0.61***
	(0.02)	(0.02)	(0.02)
R2	0.12	0.12	0.13
Observations	13570	13570	13570

Data is Occupational Employment Statistics. Sample is establishments that start in high occupation FE and low workplace FE cell and in health, social, education and civic/ foundations sectors. Dependent variable is dummy variable indicating average occupation FE declined from first period to second period. CZ predictors are averages at the commuting zone level. Standard errors are clustered at the commuting zone level.

* $p < .05$; ** $p < .01$; *** $p < .001$ (two-tailed tests)