Mergers and Acquisitions, Technological Change and Inequality

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Abstract

This paper documents important shifts in the occupational composition of industries following high merger and acquisition (M&A) activity as well as accompanying increases in mean wages and wage inequality. We propose mergers and acquisitions act as a catalyst for skill-biased and routine-biased technological change. We argue that due to an increase in scale, improved efficiency or lower financial constraints, M&As facilitate technology adoption and automation, disproportionately increasing the productivity of high-skill workers and enabling the displacement of occupations involved in routine-tasks, typically mid-income occupations. An increase in M&A intensity of 10% is associated with a 24% (27%) reduction in industry (local labor market) routine share intensity and an eight (sixteen) percentage point increase in the share of high skill workers. These results have important implications on wage inequality: An increase in M&A activity by 10% is associated with a 24% (43%) increase in the mean industry (local labor market) hourly wage and an 20% (48%) increase in industry (local labor market) wage polarization. Our results are robust to several robustness tests which further support the notion that firm reorganizations through M&As are a first-order driving force of job polarization and inequality.

Keywords: mergers, technological change, inequality.

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I Introduction

Rapid technological adoption has been documented to be a key driving force of increasing wage inequality in the United States and other developed countries. Machines enable firms to automate routine tasks replacing middle-skill workers involved disproportionately in such tasks (Autor, Levy, and Murnane, 2003; Acemoglu and Autor, 2011; Autor and Dorn, 2013) and increasing the productivity of high-skilled labor (Katz and Autor, 1999). More recently, the literature has expanded to consider the role of firms and industry structure in impacting these trends.[1] One important conclusion from this new literature is that inequality in the United States is primarily driven by differences between firms, suggesting that firm reorganizations over time play a role in driving inequality (Song et al., 2016, Barth et al., 2016). In this paper, we explore the drivers of technological adoption through the lens of firm reorganization and show evidence that mergers and acquisitions (M&As) act as a catalyst for technological change and rising inequality.

Machines have been changing the nature of work for centuries. Consider, for example, automatic teller machines (ATMs). As ATMs began being deployed by banks, this reduced the need for employees to perform the same tasks of taking deposits and dispensing cash. The adoption of this new technology did not lead to dramatic changes in gross banking employment but did change the types of skills needed (Bessen 2015). There was a decrease in the relative demand for junior bank tellers, a middle-skilled occupation substitutable for the new technology, as compared to employment in other occupations within the industry. This new technology also improved banks' profitability, leading to an increase in the number of branches, thereby increasing relative demand for the higher- and lower-skilled occupations at the bank. Interestingly, ATMs were not uniformly adopted. From a customer's perspective, the value of an ATM increased, the more ATMs at a given bank, thereby benefiting larger banks relatively more (Saloner and Shepard, 1995).

As suggested by the previous example, the speed by which technology is adopted can

[1] See for example Barth et al., 2016; Hershbein and Kahn, 2016; Jaimovich and Siu, 2016; Mueller, Ouimet, and Simintzi, 2016; Song at al., 2016.

depend on the organizational structure within the industry. As such, we argue M&As may alter the speed and nature of how and when firms integrate new technology, with important implications on occupational change and wage inequality. Our argument is that mergers and acquisitions can reduce frictions such as adjustment costs, thereby lowering the opportunity cost of investing in new technologies, and make investment in such technologies more profitable. A reduction of technology adjustment costs is possible due to 1) an increase in scale; 2) an increase in efficiency; and 3) lower financial constraints.

All three mechanisms predict a pattern where investments in automation increase post-M&A, leading to a lower demand for routine tasks, greater demand for high-skilled labor, higher mean wages and greater overall wage inequality. Considering the large scale of M&A activity, with over 4 $trillion in activity in 2015 alone, it is plausible to expect M&A activity may be an economically important catalyst of routine-biased and skill-biased technological change. We provide evidence this is indeed the case performing two types of independent analyses: first, we define M&A activity at the industry level and document a pattern of *within-industry* polarization and inequality; second, we define M&A activity at the local level and show patterns of increasing inequality in local labor markets impacted by high M&A activity.

To test our hypotheses, we collect data from Thomson's SDC on M&A activity, starting in 1980. We measure M&A intensity as the count of horizontal deals in an industry-decade or as the count of horizontal deals in a local labor market-decade, normalized by the count of total horizontal deals in the decade. We focus on horizontal deals as these are the type of deals where we can more naturally argue that our proposed mechanisms directly apply. Data on occupational employment is collected from the Integrated Public Use Microdata Service (IPUMS). Using the 5% extract from Census years 1980, 1990, 2000 and the American Community Survey (ACS) for 2010, we identify the fraction of employment in a given occupation and the share of employees with college education within each industry as well as industry wage distributions. To identify the routine-task content of each occupation, we replicate the approach in Autor and Dorn (2013) and construct time-varying shares of routine intensity using an employment-weighted mean to aggregate at the industry-level. To study the effect of M&A activity in local labor markets we follow Autor and Dorn (2013) and map M&A activity into community zones (approximately local labor markets).

Consistent with the view of routine-biased technological change, we observe a decline in the occupational share of routine intensive jobs within industries and affected locations as the intensity of past M&A activity increases. In the time-series, we find that an increase in lagged M&A intensity by 10% is associated with a 24% reduction in routine share intensity within a given industry and a 27% reduction within a given local labor market.

Consistent with the view of skill-biased technological change, we document that high M&A activity is also accompanied with a relative increase in the demand for high-skill workers. We show that the share of workers with college education increases with past M&A intensity. In the time-series, an increase in M&A activity by 10% is associated with an increase in employees with college education by 8 percentage points within a given industry and by 16 percentage points within a given local labor market.

The documented shifts in occupational employment following mergers and acquisitions have implications on wages. Mean wages should increase following significant M&A activity as the relative fraction and productivity of high-skill workers increases. Second, wages should become increasingly polarized and unequal as the labor shares are increasingly represented by both the high- and low-skill tails of the skill distribution. Indeed, we find that high M&A activity within industries or within local labor markets is related to higher mean and standard deviation of wages and to higher upper-tail wage disparity as shown by a comparison between the 90^{th} and 10^{th} percentiles of the industry or local wage distributions.

To understand precisely how M&A activity can act as a catalyst for skill-biased and routine-biased technological change, we consider three non-mutually exclusive mechanisms. We show empirical support for all three. First, the increased scale associated with M&As can reduce the fixed costs of investing in new technology. For example, if an investment in computer software can more efficiently perform a specific function in accounting, then it can displace one worker in a small firm but possibly several workers in a larger firm.

Indeed, we show that the effect of lagged M&A activity is greater in industries where the median firm size is larger.

Second, M&As often target underperforming firms leading to ex-post efficiency gains (Maksimovic and Phillips, 2001). A higher productivity acquirer may transplant best practices, including how best to integrate computers and automation to the target. We do not take a stand as to whether utilization of greater automation at the target would have been ex-ante efficient, or if it is the skill and experience of the acquirer which is necessary to achieve these gains. However, there is one agency-based explanation of ex-ante under-utilization of technology at the target. It may be that the target firm manager was reluctant to adopt valuable technology that would replace employees due to the high non-pecuniary costs associated with firing employees. The manager of the acquiring firm may feel less loyalty to employees at the target and more willing to implement value maximizing automation. To test this, we consider M&A activity in industries where acquirers are most likely to be importing best practices. We exploit median industry standard deviation of employee productivity at the start of the decade to determine industries where it is more likely that more efficient acquirers merge with less productive targets. Consistent with best practices, we show stronger treatment effects in industries where median standard deviation of industry productivity is higher.

Third, M&As may resolve financial constraints at the target firm (Erel, Jang, and Weisbach, 2015). This may induce automation if financially constrained targets were unable to finance the initial fixed costs necessary to invest in new technologies. We also find evidence consistent with this channel: We show that treatment effects are higher within industries when financing constraints are most likely to be impeding technology adaption at the target. We proxy financial constraints at the target considering average values of credit spreads at the time of deals' announcements.

We perform several tests that support a causal interpretation. First, to support the view that our results are not driven by industry or technology shocks, we turn to our industry analysis and directly control for shocks that are known to trigger M&A waves, as identified in Harford (2005) and Ovtchinnikov (2013). The "shock" variable is negatively correlated with our main outcome variables and significant in 3 out of the 4 specifications. However, when this variable is included as a control together with M&A intensity, it does not change our coefficient of interest in a meaningful way. We are not arguing that M&A activity takes place in the absence of industry shocks. Instead, we conjecture that these shocks in the absence of M&A activity cannot explain our findings.

Second, we perform an IV analysis where we instrument for merger activity in a given industry with merger activity in upstream or downstream industries. We argue that merger waves can propagate via customer-supplier industry links as downstream/upstream industries react to changes in their customers/suppliers concentration, consistent with evidence in Ahern and Harford (2014) and that merger waves in upstream/downstream industries are quasi-exogenous to changes in labor demand in the own industry. Such concentration in upstream/downstream industries may lead to higher bargaining power for suppliers/customers which have been shown in the literature to impact firms' decisions (Hennessy and Livdan, 2009). Our instrumented results are consistent with the OLS findings.

Third, we can further support a causal interpretation by employing exogenous law changes at the state level that increase labor market rigidities in respective labor markets, thereby affecting firms' ability to fire or hire workers. For this purpose, we employ the good faith exception wrongful discharge laws, shown by prior work to have significant effects on firm employment outcomes (Autor, Donohue III, and Schwab, 2006). Consistent with our hypothesized channel, we find weaker treatment effects in states where such laws apply.

Our paper builds on several literatures. First, it builds on the important literature on skill-biased technological change (Katz and Autor 1999; Goldin and Katz 2008, 2009; Acemoglu and Autor 2011) and routine-biased technological change (Autor, Levy, and Murnane 2003; Autor and Dorn, 2013; Goos, Manning, and Salomons, 2014). Rapid technological progress is viewed as the primary cause of the pattern of increasing income inequality in US labor markets. More recently, Jaimovich and Siu (2015) and Hershbein and Kahn (2016) show that technology adoption is accelerated in recessions, when opportunity cost of investing in technology is lower. We contribute to the literature by showing that M&A activity acts as catalyst for job polarization leading to occupational shifts and wage trends which assimilate the aggregate patterns.

The paper also contributes to the finance literature on mergers and employment outcomes. This literature argues that human capital considerations are important determinants of M&As. Ouimet and Zarutskie (2015) show that acquiring and retaining target firms' skilled employees is an important motive for acquisitions. Tate and Yang (2015) show that human capital complementarities between industries is an important driver of diversifying acquisitions. Dessaint, Gobulov, and Volpin (2015) and John, Knyazeva, and Knyazeva (2015) find that labor restructuring (in the form of layoffs) is a primary source of synergies and value creation in corporate takeovers. Agrawal and Tambe (2016) show that IT investment following LBOs changes the career path of workers employed at the target firm, while Olsson and Tåg (2016) provide evidence of the job polarization process in leverage buyout private equity deals in Sweden. This paper adds to this literature documenting that M&A activity is associated with occupational shifts and increasing wage disparity in impacted sectors which imply value enhancing outcomes of M&As.

II Data

In this section, we review the multiple databases used to create our sample. We combine databases from three key sources to form our estimation sample: Thompson's SDC; IPUMs; and datasets on routine intensity and offshorability of occupations from Autor and Dorn (2013).

II.1 M&A data

We use Thomson's SDC to identify mergers and acquisitions. SDC provides information on the date the deal was announced and the date it became effective. The data also include the industry affiliation of the target and the acquirer, the location of the target and acquirer headquarters and, for some observations, the transaction value. We use all completed M&As, announced between 1980 and 2010, of a US target and US acquirer, for which we can confirm the acquirer completed a purchase of a majority stake.[2]

Our primary measure of M&A activity is the count of horizontal deals in a given decade, for a given industry or commuting zone, normalized by all horizontal deals in the decade. We define a horizontal deal when the target and the acquirer share a primary NAICS code at the 6-digit level. We normalize by all deals in the decade to control for changes in the scope of coverage of SDC over time. This variable is log transformed (adding one to account for industries or commuting zones with no mergers) to address skewness. In robustness tests, we consider variants of this measure, where we define M&A counts based on the first half of each decade, and where we consider transaction values instead of counts, when non-missing. We group deals into industries or commuting zones using the target industry or geographic location.

II.2 IPUMs

Data on occupational employment is collected from the Integrated Public Use Microdata Service (IPUMs) 5 percent extract for 1980, 1990, 2000 and the 2010 American Community Survey (ACS).[3,4] IPUMs provides detailed surveys of the American population drawn from federal censuses and the American Community Surveys. IPUMs was created to facilitate time series analysis and, as such, has unique industry (IND1990) and occupational identifiers (OCC1990), which are defined as to minimize changes in industry and occupation definitions over time. We use the crosswalk defined by Autor and Dorn (2013), which is a slightly modified version of occupational identifiers (OCC1990) provided by IPUMs, to ensure time-consistent occupation categories.

For our industry sample, we map NAICS industries from SDC to IPUMs industries, using the cross-walk provided by IPUMs, as detailed in Appendix A1. In our industry

[2]Our sample begins in 1980 due to availability of M&A activity in SDC.

[3]ACS is the continuation of the decennial Census surveys post-2000.

[4]For more information, see Ruggles, Genadek, Goeken, Grover, and Sobek (2015).

sample, we have 132 industries and more than 300 occupations in each Census-year. For our commuting zone sample, we map city names from SDC using a fuzzy match to commuting zone codes using crosswalks provided by the Missouri Census Data Center as detailed in Appendix A1. In our commuting zone sample, we have 722 industries and more than 300 occupations in each Census-year.

Our IPUMs sample consists of individuals who are between 18 and 64 years old and who were employed in the prior survey. We apply the same sample criteria as in Autor and Dorn (2013) and drop military and farming occupations, residents of institutional group quarters (e.g., prisons) and unpaid family workers. We follow Autor and Dorn (2013) and calculate a labor supply weight equal to the number of weeks worked times the usual number of hours per week. Each individual is weighted by their employment weight which is equal to the Census sampling weight times the labor supply weight.

IPUMs also provides data on yearly wage and salary income (*incwage*), from which we exclude self-employed workers and observations with missing wages, weeks, or hours worked. We define hourly wages as yearly wages and salary divided by the product of weeks worked (*wkswork*) and usual weekly hours (*uhrswork*). We also define full-time weekly wages as the product of hourly wages and usual weekly hours based on workers who worked for at least 40 weeks per year and 35 hours per week. Wages are inflated to year 2009 using the Consumer Price Index of all urban consumers in order to be comparable to those of the 2010 ACS (which collects earnings in the previous year). IPUMs also provides data on workers' education allowing us to define workers with college education (at least 4 years of post-secondary education) or with graduate education (at least 5 years of post-secondary education). We aggregate all variables at the industry-Census year or commuting zone-Census year by computing employment weighted averages. We define all variables used in our analysis, in more detail, in Appendix A2.

II.3 Data on routine employment share and offshorability

We use data provided by Autor and Dorn (2013) to define the frequency of "routine" tasks typically performed by employees assigned to a given occupation. Given occupations involve multiple tasks (routine, abstract, manual) at different levels of intensity, Autor and Dorn (2013) create an indicator which measures the routine task intensity (RTI) by occupation and define certain occupations as routine task intensive if in the top employment-weighted third of routine task-intensity in 1980.[5] Occupations that score highly in the routine task intensity indicator include: Secretaries and stenographers, bank tellers, bookkeepers and accounting and auditing clerks, upholsterers, pharmacists. Such occupations are assumed to be more easily automated. As shown in Autor, Levy, and Murnane (2003), a number of these high routine intensity occupations are in the middle of the skill distribution. Occupations that are considered non-routine, according to the indicator, involve high-skill occupations, such as computer systems analysts and computer scientists; electrical engineers; physicians, and low-skill occupations, such as railroad conductors and yardmasters; taxi cab drivers and chauffeurs; and bus drivers.

We merge these data with IPUMs using the occupation crosswalks detailed above. Following these steps, we can characterize occupations in a given industry-year (commuting zone-year) in terms of their routine intensity and construct the share of these routine intensive occupations by industry-year (commuting zone-year).

To illustrate the data, we focus on three specific representative occupational groups in Figure 1: managers, production/craft, and service occupations. As proxied by wages, Panel A, shows that managers are the most high-skilled occupations, production/craft are in the middle, and service occupations are lower-skilled. Moreover, production/craft, employees in the middle of the wage distribution, are performing a relatively higher share of routine tasks in contrast to the high skill (e.g., managers) or low-skill workers (e.g., services). This is confirmed in Panel B, which shows the average routine intensity for each occupation across

[5]We replicate our results defining occupations as routine task intensive if they are in the top employment-weighted third of routine task-intensity every Census year. Results are similar.

time. Finally, panel C confirms the "displacement" of the middle-skill routine occupations, as argued by Autor, Levy, and Murnane (2003). We observe an increase in relative demand for occupations in the left (service occupations) and the right (managers) tail of the skill distribution and a sharp decline in the fraction of workers employed in occupations that have a high concentration of routine tasks (production/craft).

After categorizing occupations based on their routine intensity, we calculate for each industry-year and each commuting zone-year in our sample a measure of routine employment share, RSH, which will be used in our analysis. Appendix Table A1 provides some examples of our sample industries with high and low routine employment shares. Industries with a high share of routine intensive occupations include accounting and legal services. On the other hand, industries with a low share of routine intensive occupations include taxicab services and vending machines operators.

We also collect data on industries' offshorability to capture the possibility that M&A activity is concentrated in industries or commuting zones with high offshoring potential. We use data provided by Autor and Dorn (2013) to measure the offshoring potential of job tasks in a given industry or commuting zone which are merged to our sample using the available occupation codes. The industry-year (commuting zone-year) offshorability level is equal to the average offshorability score of employment in each industry-year (commuting zone-year).

II.4 Summary statistics

Table 1 reports summary statistics of several key variables used in the analysis of the industry sample (Panel A) and the commuting zone sample (Panel B). We report the mean value across all industries or commuting zones for a given year along with the standard deviation in brackets. We observe that our measure of normalized merger intensity is relatively evenly distributed across the industries and commuting zones. The average industry has about 0.50-0.70% of the overall merger activity in the given decade. The average commuting zone has about 0.13-0.14% of the overall merger activity in the given decade.

Similar to Autor and Dorn (2013), we document that about one third of all occupations are routine-intensive. We observe there is greater variation in offshorability within the industry sample, with some industries having a very high offshorability score. This leads to a higher mean score for the industry sample, as compared to the commuting zone sample. We find that over 16% of workers in our average industry and labor market has a college degree in 1980, which we define as four or more years of post-secondary education. This fraction increases over time and is 25-28% in 2010. The average hourly wage is \$20.34 in 1980 for the industry sample and \$18.19 for the commuting zone sample. Moreover, we show a steady increase in the standard deviation of wages within a given industry and local labor market over time.

III Results

In the following section, we present the main results in the paper. We evaluate the role of M&As as a catalyst for skill-biased technological change and routine-biased technological change. To examine whether M&As lead to changes consistent with routine-biased technological change, we evaluate how shares of routine intensive occupations evolve following M&A activity. To document evidence consistent with skill-biased technology changes, we look at the relation between M&A activity and subsequent changes to the share of high-skill employees. Moreover, we explore the wage implications of such technology adoption following M&As.

III.1 M&A and occupational changes

We start by examining the effect of M&A activity on changes in routine employment shares within a given industry in columns 1-3 and within a given commuting zone in columns 4-6. We estimate the following panel regression:

$$\Delta log(rsh)_{i,(t-10,t)} = \alpha_t + \gamma \cdot \log(\text{merger intensity})_{i,(t-10,t-1)} + \beta \cdot X_{i,t} + \epsilon_{i,(t-10,t)} \qquad (1)$$

where t indexes years and i indexes either industries or commuting zones. $X_{i,t}$ controls for average offshorability of tasks, time-varying at the industry or commuting zone level. *Merger intensity* is our proxy of M&A activity as defined above and log-transformed.[6] The IPUMs data is only available every 10 years for the period between 1980 and 2000. As such, M&A activity is measured over three decades in our sample: 1980-1989; 1990-1999; and, 2000-2009. $\Delta log(rsh)$ measures the change in the fraction of routine-based occupations within a given industry or commuting zone over a decade, namely 1980-1990, 1990-2000, 2000-2010. Standard errors are clustered at the industry or commuting zone level to take into account correlation in industries or commuting zones over time.

Columns 1 and 4 of Table 2, present the results. All regressions include time fixed effects to control for differences in computer costs, and hence uses, as well as other macro-level trends in occupational shares. We control for the offshorability of tasks within an industry. Blinder and Krueger (2013) estimate that 25% of US jobs are offshorable and an increasing exposure to foreign competition from low-wage countries has led to large changes in domestic local labor markets and worker outcomes. We report a positive correlation between the percent of offshorable jobs, measured contemporaneously to RSH, and the change in routine share intensity. This finding is consistent with Goos, Manning and Salomons (2014) which finds a positive correlation of 0.46 between routine employment shares and offshorability, suggesting a relationship between the characteristics that make a job offshorable and that lead it to be classified as routine-based.[7]

We find that industries and commuting zones characterized by higher merger intensity over the past decade are associated with a more rapid decline in the share of routine-based occupations. The results are both statistically and economically significant. An increase in M&A intensity by 10% is associated with a 15% greater increase in the speed of change in the share of routine intensive occupations for a given industry (column 1) and a 19% greater increase for a given commuting zone (column 3). In the remaining columns of Table

[6] All variables are also defined in Appendix A2.

[7] In our data, we also confirm a positive univariate correlation between RSH and offshorability.

2, we turn to a time-series estimation. We consider the following specification:

$$\log(\mathrm{rsh})_{i,t} = \alpha_t + \alpha_i + \gamma \cdot \log(\text{merger intensity})_{i,(t-10,t-1)} + \beta \cdot X_{i,t} + \epsilon_{i,t} \tag{2}$$

where t indexes years and i indexes industries or commuting zones. All variables are defined as in Equation (1). Standard errors are clustered at the industry or commuting zone level to take into account correlation in industries or commuting zones over time.

Columns 2 and 5 of Table 2, confirm that our intuition also holds in the time-series. An increase in M&A intensity by 10% is associated with a 24% (27%) decrease in routine intensity share in the industry (commuting zone). In columns 3 and 6, we address the possibility that our results may be capturing mean-reversion, namely high M&A industries (commuting zones) adjusting back to an industry-specific (commuting zone-specific) routine-intensity equilibrium level. To address this concern, we interact the value of the dependent variable for each industry defined in 1980 (the start of the sample) with a full set of time dummies. This test allows us to flexibly control for mean-reversion and for differential trends across industries (commuting zones) that depend on industry (commuting zone) characteristics (e.g., based on industries' labor supplies). The results are similar, indicating that mean-reversion or differential trends based on start-of-the-sample routine intensity are not driving the results.

In unreported results, we consider a first-difference specification where we take the first differences of both the merger intensity and routine share intensity. This specification also addresses concerns of mean-reversion and is a test on the strict exogeneity assumption necessary for consistency of the fixed-effects estimator (Wooldridge and Jeffrey, 2002) and on the importance of measurement error (Griliches and Hausman 1986). The first-difference estimation yields results similar to the baseline analysis.[8] Results are also similar if we use a measure of merger intensity calculated based on M&A transaction values or redefine M&A

[8] All unreported results mentioned in the text are available upon request from the authors.

activity using only mergers observed in the first half of the preceding decade.[9] Furthermore, results are robust to defining horizontal mergers based on 4-digit NAICS or if we, instead, define routine and non-routine occupations each Census year as opposed to using the 1980 Census as in Table 2.

These results show a pattern where high M&A intensity is associated with a subsequent decline in occupational shares of routine tasks, consistent with our hypothesis. At the same time, this process of automation can also increase relative demand for high-skill employees as technology tends to be complementary to skilled labor, leading to an "upskilling" of affected industries and locations. To round our argument, we look next at the share of high-skill workers within a given industry or commuting zone, following mergers and acquisitions.

We proxy for high-skill employees as the share of employees with college education, namely employees with 4 or more years of post-high school education.[10] As in Table 2, we estimate the effect of M&A activity in industries (columns 1-3) and commuting zones (columns 4-6). All regressions include year fixed effects and standard errors are clustered at the industry or commuting zone level.

Table 3 reports the results. In columns 1 and 4, the dependent variable is the change in the share of workers with a college education within a given industry (column 1) or commuting zone (column 4). Columns 2-3 and 5-6 repeat the estimation in the time-series using the share of workers with a college education as the dependent variable. Columns 2 and 5 include year and industry or commuting zone fixed effects. Columns 3 and 6 further control for time dummies interacted with the value of the dependent variable at the start of the sample. We show that an increase in lagged merger intensity is related to an increase in the change or relative share of college educated workers within a given industry or commuting zone. The results are economically important: an increase in M&A intensity

[9]This allows for a greater time lag between the merger effective date and the year in which occupational shares are measured addressing concerns that occupational changes take time to materialize.

[10]Given the findings in Oreopoulos and Petronijevic (2013) that the college wage premium is specific to having graduated from college, we define college education as a minimum of 4 years.

by 10% is associated with an increase in the share of college-educated employees by 8 percentage points within industries (column 2) and 1.6 percentage points within commuting zones (column 5).[11]

Overall, these findings are consistent with the argument in Autor, Levy, and Murnane (2003) that industries and local labor markets with low routine task intensity employ relatively more high-skill workers. Moreover, these findings are also consistent with Autor and Dorn (2013) who argue the adoption of technology that replaces routine-based labor inputs will lead to an outsized increase in the share of high-skilled employees due to the complementarities between high-skilled employees and technology.

III.2 M&A and wages

So far, our results show that M&A activity is followed by a decrease in routine-intensive labor and a simultaneous increase in the share of college educated workers in a given industry or local labor market. Autor and Dorn (2013) show that routine intensive occupations are over-represented in the middle of the skill distribution. Taken together, these results have important implications for wages suggesting an increasing mean wage and wage disparity in sectors and labor markets with high M&A activity.

We draw data on hourly wages in Table 4. The dependent variable in columns 1 and 4 is the change in the mean hourly wage (log transformed) for a given industry (column 1) and given local labor market (column 4). Both regressions show a positive and statistically significant correlation between lagged M&A activity and the change in the average hourly wages. The results are economically important. An increase in M&A activity by 10% is associated with a change in mean hourly wages in that industry by 13% in the cross-section of industries. It is also associated with an increase of 8% in the cross-section of local labor markets. These results do not necessarily translate into an increase in wages for the same employed workers but, instead, likely reflect a change in the composition of

[11]In unreported results, we alternatively consider the fraction of workers with a graduate education, defined as 5 or more years of post-secondary education. Our results are robust to using this alternative measure of skill.

jobs as indicated in the previous two tables. In columns 2-3 (columns 5-6), we use the log of the industry (commuting zone) average hourly wage as the dependent variable and add industry (commuting zone) fixed effects. In columns 3 and 6 we also add time dummies interacted with the value of the dependent variable at the start of the sample. We find similar results in the time-series.

In unreported results, we repeat the specifications in Table 4 using annual or full-time workers' weekly wages. The results are similar both in terms of statistical significance and economic magnitudes. However, we prefer to focus on hourly wages as wage trends for full-time, full-year weekly workers depicted with our measure of full-time workers' weekly wages may obscure wage developments lower in the wage distribution, where a larger part of the workforce is part-time or part-year (Acemoglu and Autor, 2011). Moreover, measures of annual income may be capturing changes in hours worked and related practices and not in wages.

To test the effect of wages on wage polarization following M&A activity, we look at the standard deviation of wages, as in Barth, Bryson, Davis, and Freeman (2015). Table 5 presents results using hourly wages as our measure of wages. Columns 1 and 4 use the change in standard deviation of industry wages (log transformed) as the dependent variable and shows a positive correlation between lagged M&A activity and wage disparity. An increase of lagged M&A activity by 10% in a sector is correlated with a 12% increase in the change in the standard deviation of wages at the industry level. Alternatively, when we perform our analysis at the local level, we find that a 10% increase in M&A activity in a local labor market is correlated with a 20% increase in the change in the standard deviation of wages in the cross-section. In columns 2-3 and 5-6, we use the log of the standard deviation of industry wages as the dependent variable and include industry fixed effects and controls for differential trends in wage inequality (columns 3 and 6). The positive correlation also holds in the time-series. Within industries, an increase in M&A activity by 10% increases wage disparity by 20% (column 2). Within commuting zones, an increase in M&A activity by 10% increases wage disparity by 49% (column 4). The larger wage dispersion we identify on commuting zones may be explained by the fact that local labor markets are naturally more segmented as compared to more aggregate industry labor markets, and thus characterized by lower outside options for low-skill workers but also greater scarcity of talent.

In Table 6, we provide further evidence that M&As contribute to wage polarization by examining wage percentiles at the top-end (90$^{\text{th}}$ percentile), bottom-end (10$^{\text{th}}$ percentile) and the ratio of the two.[12] Wages are log-transformed and all regressions include year fixed effects and industry fixed effects (columns 1-3) or commuting zone fixed effects (columns 4-6). Consistent with Table 5, we report increases in wage dispersion following higher M&A activity. We report a larger increase in the wages at the top-end as compared to the bottom-end in response to higher M&A activity. However, only when looking at commuting zones does the ratio of the 90$^{\text{th}}$ percentile to the 10$^{\text{th}}$ percentile increase significantly. Again, the sharper effect we capture at the local level, as compared to the industry level, may be interpreted in the light of the lower labor mobility in more "fragmented" local labor markets which should compress wages of low skill wages more but, at the same time, should imply greater wage increases for scarce talent.

Overall, the increase in mean wages and wage inequality following M&A activity suggest that M&A activity acts as a catalyst for wage polarization and skill-biased technological change.

III.3 State laws

The ability of firms to replace employees with technology will depend on laws governing the ability to fire employees. Wrongful discharge laws, set by court precedence, place limits on firm's ability to fire employees.[13] Legal scholars have argued that one of such laws, the good-faith exception, places the greatest restrictions on the ability of firms to fire workers (Kugler and Saint-Paul, 2004). Specifically, this ruling limits the ability of

[12]The IPUMs data does top code wages in the top percentiles by state-year, however, there is no evidence that top coding will impact our estimation of the wages at the 90$^{\text{th}}$ percentile.

[13]See Aalberts and Seidman (1993), Walsh and Schwarz (1996), Miles (2000), Kugler and Saint-Paul (2004), Autor et al. (2006) and Acharya et al. (2012) for discussion of these laws.

firms to fire workers for what the court deems to be "bad" cause and, furthermore, to impose penalties beyond what is required to provide restitution to the injured employee as a deterrent to future wrong-doing by the firm. We, thus, focus on this law and create a dummy variable, "Good-faith exception applies", if a particular legal precedent has been set at a given state-decade, indicating that this exception will apply to termination decisions of employees located in a given state. We predict that the applicability of the good-faith exception will mitigate the effect of M&As on changes to employment and wages.

Table 7 presents the results. We report results using the commuting zone sample since geography is defined in this sample. In all regressions, we control for year fixed effects and state fixed effects to absorb other time-invariant differences across states which may explain the decision to adopt these laws. We, thus, rely on the within-state time series variation in the adoption of these laws for identification. As predicted, when the good-faith exception applies, M&As have a significantly more modest effect on labor market characteristics for three out of four of our measures. These findings support a causal interpretation of our estimates given we identify expected outcomes following exogenous changes (due to regulation) in firms' ability to restructure their workforce.

IV Evidence concerning mechanisms

In this section, we explore potential mechanisms driving the relationship between M&As and skill-biased and routine-biased technological change. We propose three non-mutually exclusive mechanisms: 1) an increase in scale; 2) adoption of best practices; and 3) lower financial constraints. Since for two out of three of the mechanisms, our tests involve using proxies based on Compustat data, we define these measures using industry data and limit our tests to the industry sample.

To the extent that M&A activity increases the count of employees involved in similar routine tasks that can be replaced with a given technological investment, the fixed cost of technology adoption will be reduced, thereby predicting greater ex-post effects on the labor force. As we cannot directly observe employees engaged in similar occupations within a given firm, we use firm size as a proxy for increased scale. Since many of target SDC firms and a significant portion of the acquirer firms are private, and size is unobserved for these firms, we rely on industry medians based on Compustat firms as a proxy for size. Specifically, we create a dummy variable, *Median industry firm size high*, which takes the value of one if the median firm has total assets in that industry-decade greater than the sample median.[14]

The results are reported in Table 8, Panel A. We repeat the regressions looking separately at routine share intensity, share of college workers, and the mean and standard deviation of wages. In all regressions, we include year and industry fixed effects. In industries with larger firms, the impact of M&A activity on labor market outcomes is more pronounced. In fact, in all four specifications the impact in high firm size industries is nearly two times the impact in low firm size industries suggesting economically important effects of this mechanism.

Alternatively, we consider the role of financing constraints. We assume targets are more likely to be financially constrained and acquirers select some target with the specific objective of easing these constraints, as in Erel, Jang, and Weisbach (2015). We assume targets are most likely to be financially constrained when credit spreads are high, as in Officer (2007). We compute credit spreads taking the difference between BAA and the effective federal funds rate at the time of the deal announcement. Then, we define a dummy variable which takes the value of 1 if the average credit spread at a given industry-decade is higher than the sample median.[15] The results are reported in Panel B. As predicted, we find stronger treatment effects when credit spreads are relatively higher at the time of the M&A activity.

Finally, M&As may increase the technology adoption by facilitating the transfer of

[14]We match 6-digit NAICS industry codes in Compustat to our sample industries using the crosswalk detailed in Appendix A1.

[15]Since all regressions in Table 8 include year fixed effects, we are estimating this effect by using variation in the timing of M&A deals for a given industry *within* the decade and variations in the credit spread *within* this same window of time.

best practices from the acquirer to the target. Since the M&As in our sample all involve acquirers and targets from the same industry, we use a measure of the variance of within-industry adoption of best practices as our proxy. Again, we rely on Compustat based industry measures due to the presence of private firms in our sample. Specifically, we measure the standard deviation of profits per employee (log-transformed) at the start of each decade in a given industry. The results are reported in panel C. As predicted, the treatment effect of M&A activity is more pronounced in industries with greater variation in employee productivity for all our measures, except for routine intensity which is not significant.

In sum, these results suggest three specific mechanisms by which M&As can act as a catalyst to skill-biased and routine-biased technological change. We observe a more pronounced relationship between ex-ante M&A activity and routine share intensity, the share of college-educated workers, and wage inequality when one of these mechanisms is more likely to be important.

V Evidence regarding causality

In this section, we discuss and subsequently refute alternative explanations that could partially, but not fully, explain our findings. Thus, we discuss the possibility that cost-cutting, market power, or industry shocks may be driving our findings.

V.1 Cost-cutting by reducing employment and payroll

Shleifer and Summers (1988) argue that M&As can be used to break implicit contracts with employees at the target firm, resulting in a lower ex-post payroll. More recently, Dessaint, Golubov, and Volpin (2015) and John, Knyazeva, and Knyazeva, (2015) show that labor restructuring, in the form of layoffs or wage cuts, is a primary source of synergies for mergers and acquisitions. More broadly, M&As can be motivated to reduce agency costs present at the target firm. For example, a manager may be reluctant to fire employees who are no longer adding value to the firm due to the high social costs associated with such actions. Our results support these earlier findings by also showing evidence of post-M&A labor restructuring. However, our story has unique predictions regarding which type of workers will be replaced (those involved in routine-intensive occupations). Moreover, predictions regarding average wage increases do not directly follow from a simple cost-cutting motivation.

V.2 Market power and the distribution of rents

Another alternative explanation might be that mergers increase market power and capital concentration in industries they affect, thereby creating rents. These rents are more likely to be captured by high skill employees within the firm leading to higher wage disparity. Again, although plausible, this explanation does not fully explain our findings. It is not obvious, for example, how rent extraction would explain the decline in share of routine intensive occupations, namely occupations in the middle of the skill distribution.

V.3 Technological or regulatory shocks

Mergers may be motivated by unexpected changes within the industry. It is possible these same shocks that predict greater adoption of labor-saving technology also predict greater M&A intensity and as such we are capturing two concurrent trends driven by one omitted variable. To address this issue, we include dummy variables for both the technology and regulatory shocks identified in Harford (2005) and Ovtchinnikov (2013) and report the results in Table 9.

The dummy variable, industry shock, takes the value of one if the relevant industry experienced either a technology or regulatory shock during the previous decade. As expected, we find a positive and significant correlation between this shock variable and industry M&A activity, indicating firms respond to shocks by modifying existing firm boundaries. In columns 1-4, we explore the relationship between the shocks and our key labor market outcomes. We find that a shock has a significant effect on the share of college educated workers, average wages and the standard deviation of wages. However, interestingly, the effect of the shock on labor market outcomes is always in the opposite direction of the prediction of either routine-biased or skill-biased technological change. Moreover, once we control for past merger activity in columns 5-8, these significant correlations are reduced and only the relationship between past shocks and the standard deviation of wages remain. Furthermore, in columns 5-8, the reported magnitude of the relationship between past merger activity and labor market outcomes is basically unchanged as compared to the baseline results reported earlier in the paper.

These results show that a set of the most important industry shocks known to be associated with merger waves explains none of our findings. Moreover, besides having an insignificant influence on our coefficient of interest, the industry shock variable cannot directly predict our dependent variable in the same direction as the impact of M&A activity.

V.4 IV evidence

As additional evidence in support of a causal interpretation of our results, we instrument for merger activity in a given industry with merger activity in upstream or downstream industries. There are several reasons to expect that merger activity in one industry may lead to greater merger activity in industries connected via customer supplier networks for reasons that are quasi-exogenous to expected future changes in labor inputs. For example, following consolidation in an upstream industry, firms downstream may decide to merge to counter any change in market power of their suppliers (Galbraith, 1952). Ahern and Harford (2014) provide further support for this argument by documenting a pattern of merger waves propagating via customer-supplier industry links.

Following the approach of Ahern and Harford (2014), we identify customer-supplier relationship using BEA input-output tables. We use the 1997 tables as this represents an approximate mid-point of our sample and the first year where the BEA based their industries on NAICS1997 industries, which facilitates the mapping of the BEA industries into our data. We map BEA industries to NAICS1997 using a crosswalk provided by

BEA.[16] We map NAICS1997 industries to our data, in two steps: first, we map NAICS1997 to NAICS2007, and second, we map NAICS2007 to our sample meta-NAICS industries. We identify connected industries if there is a transfer between industries representing one percent or more of the industries total transfers (including within industry transfers).

We define a merger wave in a given industry if the count of horizontal mergers in that industry exceeds the 90$^{\text{th}}$ percentile of the distribution for that industry, measured from 1980 to 2014. We then create an indicator variable, *Dummy_hor_wave*, which takes the value of one if any connected industry (defined as having a significant supplier or customer linkage) had a merger wave in the preceding ten years.

We present the results Table 10. In the first stage, reported in column 1, we observe that the instrument predict merger waves in connected industries with a Cragg-Donald Wald F statistic is 13.5. In columns 2-6, we repeat previous key regressions using the IV approach. The instrumented results are consistent with earlier findings providing further support to a causal interpretation of the relationship between M&A activity and routine- and skill-biased technological change.[17]

VI Conclusion

We explore the impact of mergers and acquisitions on changes in job polarization and wage inequality. Given the importance of trends in job polarization and wage inequality for workers, firms, and society, understanding their causes and consequences has been at the epicenter of an important literature in economics and finance.

We argue that M&As may accelerate technology adoption due to an increase in scale, improved efficiency, or lower financial constraints. Automation should in turn lead to occu-

[16]The crosswalk can be found here: http://www.bea.gov/industry/io_benchmark.htm

[17]One concern with the above analysis is that merger activity in both upstream and downstream industries may be driven by a common shock, where this shock may also have implications for future labor demand. However, we repeat this analysis including the dummy variable for deregulatory and product-market shocks and find similar evidence.

pational and wage changes consistent with changes predicted by skill-biased and routine-biased technological change. We find that high M&A intensity in a given industry or local labor market is followed by a reduction in the share of routine share intensive occupations in the industry or local labor market. This is often described as "hollowing-out" of the occupational distribution as routine-intensive occupations, those most easily replaced by computers, disproportionately comprise middle-skill occupations. Simultaneously, we also observe an ex-post increase in the demand for high-skill workers following higher M&A activity. This "upskilling" is consistent with the argument that technology is complementary to skilled human capital and, as such, increases demand for high-skill employees. The changes observed in worker occupation and education are also mirrored in the wage data. Following greater M&A activity, we observe an increase in the mean wage and, most importantly, in overall wage inequality.

Our results on wage and wage distributions are unique to the sample of employed workers. As such, our results are consistent with patterns of increasing skill premia and increasing income inequality documented in the macro economy. However, our results do not take into account unemployed or under-employed workers. In particular, while we show an increase in wages following M&A activity, this is only for the employees who remain employed in the industry or local labor market.

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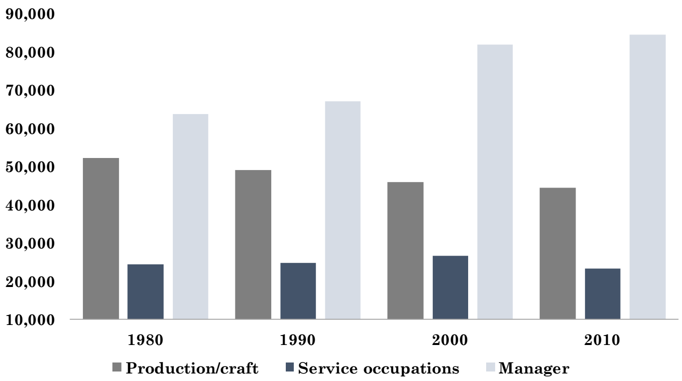
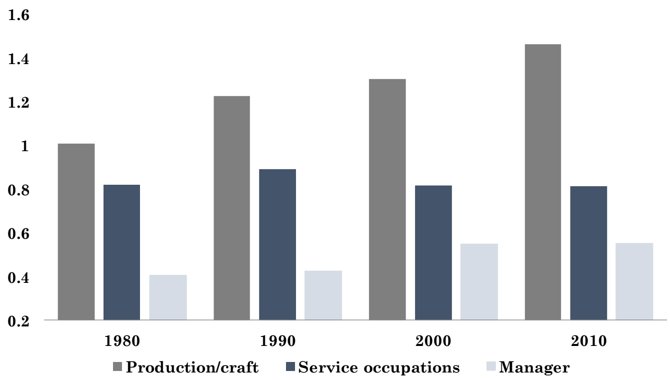
Figure 1

(a) Mean Annual Wage by Occupation and Year



(b) Mean Routine Intensity by Occupation and Year



(c) Mean Employment Share by Occupation and Year

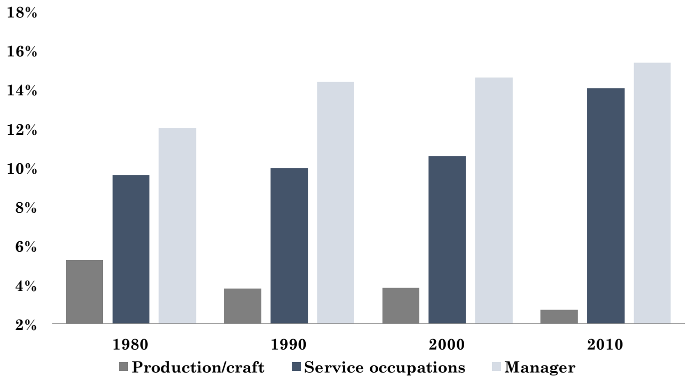


Table 1: Summary Statistics of Merger Intensity and Worker Variables

This table reports the mean and standard deviation of key variables from SDC and IPUMs for the years identified in the column header for the industry sample (Panel A) and the commuting zone sample (Panel B). Each observation is an industry-year (Panel A) or commuting zone-year (Panel B), measured once per decade, with the exception of merger intensity, which is measured over years t-10 to t-1, and Δlg(RSH)which is the change in log RSH from the previous decade. All variable definitions are provided in Appendix A2.

Panel A				
	1980	1990	2000	2010
Merger intensity_ind (%)		0.52%	0.61%	0.66%
		[.0084]	[.01]	[.0143]
Routine employment share (RSH) (%)	34.75%	32.75%	33.28%	33.82%
	[.164]	[.1562]	[.1548]	[.161]
lg(RSH)	-1.1588	-1.2184	-1.2032	-1.196
	[.4584]	[.4582]	[.4672]	[.494]
Δ lg(RSH)		-0.0596	0.0151	0.0072
		[.101]	[.1497]	[.1578]
Offshorability	0.1226	0.1182	0.1291	0.1549
	[0.43]	[0.44]	[0.45]	[0.45]
College workers labor share(%)	16.74%	20.75%	24.39%	28.27%
	[.1247]	[.1387]	[.1561]	[.1717]
Graduate workers labor share (%)	6.72%	5.91%	7.21%	8.62%
	[.0805]	[.0735]	[.0801]	[.0977]
Hourly wage at 90 percentile ($)	33.43	34.37	37.00	39.74
	[6.905]	[7.7239]	[9.5709]	[13.2939]
Hourly wage at 10 percentile ($)	9.13	8.73	9.09	8.74
	[2.2959]	[2.1009]	[2.0871]	[2.2869]
Average hourly income ($)	20.34	20.71	22.35	22.87
	[4.2728]	[4.6082]	[5.3545]	[6.6784]
Standard deviation of hourly income	10.8241	10.9368	11.1045	11.085
	[.2252]	[.243]	[.2679]	[.3194]

Panel B				
	1980	1990	2000	2010
Merger intensity_cz (%)		0.1368%	0.1369%	0.1365%
		[.0048]	[.0047]	[.0052]
Routine employment share (RSH) (%)	0.3059	0.3053	0.3061	0.3063
	[.0378]	[.0289]	[.0263]	[.0338]
lg(RSH)	-1.1922	-1.191	-1.1877	-1.1898
	[.1263]	[.0965]	[.0872]	[.1159]
Δ lg(RSH)		0.0012	0.0033	-0.0022
		[.0712]	[.0554]	[.0905]
Offshorability	-0.0694	-0.0883	-0.1348	-0.1139
	[.097]	[.0945]	[.097]	[.111]
College workers labor share(%)	16.26%	19.25%	22.05%	25.45%
	[.0409]	[.05]	[.0586]	[.0686]
Graduate workers labor share (%)	7.22%	6.36%	7.20%	8.77%
	[.0227]	[.0197]	[.0241]	[.0324]
Hourly wage at 90 percentile ($)	30.88	29.75	30.95	32.48
	[3.544]	[3.7479]	[4.4244]	[5.1933]
Hourly wage at 10 percentile ($)	7.61	6.79	7.43	6.92
	[.7955]	[.9031]	[.7934]	[.7568]
Average hourly income ($)	18.19	17.15	18.33	18.59
	[2.1623]	[2.247]	[2.4993]	[2.5509]
Standard deviation of hourly income	10.729	10.7341	10.8715	10.8817
	[.1112]	[.1321]	[.157]	[.1614]

Table 2: Past Merger Activity and Routine Employment Share

The dependent variable in columns 1 and 4 is Δlg(RSH). The dependent variable in columns 2-3 and 5-6 is lg(RSH). Columns 1-3 use the industry sample; columns 4-6 use the commuting zone sample. The timeline starts in 1980 and ends in 2010 with one observation per decade for each industry (columns 1-3) or commuting zone (columns 4-6). All variables are defined in Appendix A2. Robust standard errors are clustered at the industry-level in columns 1-3 and at the commuting zone-level in columns 4-6. *** indicates $p < 0.01$, ** indicates $p < 0.05$, and * indicates $p < 0.1$.

	(1)	(2)	(3)	(4)	(5)	(6)
	Δlg(RSH)	lg(RSH)	lg(RSH)	Δlg(RSH)	lg(RSH)	lg(RSH)
Merger Intensity_ind	-1.477***	-2.380***	-2.293***			
	(0.422)	(0.834)	(0.795)			
Merger Intensity_cz				-1.894***	-2.695**	-2.199**
				(0.357)	(1.279)	(1.032)
Offshorability	0.0300*	0.364	0.392	0.0716***	0.581***	0.590***
	(0.0170)	(0.313)	(0.300)	(0.0193)	(0.0543)	(0.0544)
Year FE	Yes	Yes		Yes	Yes	
Industry FE		Yes	Yes			
Commuting Zone FE					Yes	Yes
Year FE*lgRSH80			Yes			Yes
Observations	396	396	396	2,166	2,166	2,166
R-squared	0.072	0.956	0.957	0.015	0.819	0.825

Table 3: Past Merger Activity and High-Skill Workers

The dependent variable in columns 1 and 4 is ΔShare, the change in the percent of employees with 4 or more years of college education. The dependent variable in columns 2-3 and 5-6 is share (%), the percent of employees with 4 or more years of college education. Columns 1-3 use the industry sample; columns 4-6 use the commuting zone sample. The timeline starts in 1980 and ends in 2010 with one observation per decade for each industry (columns 1-3) or commuting zone (columns 4-6). All variables are defined in Appendix A2. Robust standard errors are clustered at the industry-level in columns 1-3 and at the commuting zone-level in columns 4-6. *** indicates $p < 0.01$, ** indicates $p < 0.05$, and * indicates $p < 0.1$.

	(1)	(2)	(3)	(4)	(5)	(6)
	ΔShare	Share(%)	Share(%)	ΔShare	Share(%)	Share(%)
Merger Intensity_ind	0.675***	0.771*	0.563			
	(0.171)	(0.430)	(0.479)			
Merger Intensity_cz				0.452***	1.597*	1.197*
				(0.157)	(0.829)	(0.738)
Offshorability	0.0267***	0.0410	0.0448	0.0576***	0.0377*	0.0209
	(0.00581)	(0.0447)	(0.0452)	(0.00584)	(0.0225)	(0.0228)
Year FE	Yes	Yes		Yes	Yes	
Industry FE		Yes	Yes			
Commuting Zone FE					Yes	Yes
Year FE*Share80			Yes			Yes
Observations	396	396	396	2,166	2,166	2,166
R-squared	0.160	0.968	0.969	0.087	0.923	0.924

Table 4: Past Merger Activity and Mean Wages

The dependent variable in columns 1 and 4 is ΔlgWages, the change in mean hourly wage (log-transformed). The dependent variable in columns 2-3 and 5-6 is lgWages, the log-transformed mean hourly wage. Columns 1-3 use the industry sample; columns 4-6 use the commuting zone sample. The timeline starts in 1980 and ends in 2010 with one observation per decade for each industry (columns 1-3) or commuting zone (columns 4-6). All variables are defined in Appendix A2. Robust standard errors are clustered at the industry-level in columns 1-3 and at the commuting zone-level in columns 4-6. *** indicates $p < 0.01$, ** indicates $p < 0.05$, and * indicates $p < 0.1$.

	(1)	(2)	(3)	(4)	(5)	(6)
	ΔlgWages	lgWages	lgWages	ΔlgWages	lgWages	lgWages
Merger Intensity_ind	1.294***	2.363***	2.145***			
	(0.338)	(0.753)	(0.724)			
Merger Intensity_cz				0.799***	4.344***	4.637***
				(0.303)	(1.267)	(1.472)
Offshorability	0.0261**	-0.0225	-0.0304	0.0731***	-0.0263	0.00811
	(0.0124)	(0.0822)	(0.0814)	(0.0132)	(0.0347)	(0.0350)
Year FE	Yes	Yes		Yes	Yes	
Industry FE		Yes	Yes			
Commuting Zone FE					Yes	Yes
Year FE*lgWages80			Yes			Yes
Observations	396	396	396	2,166	2,166	2,166
R-squared	0.177	0.960	0.961	0.449	0.938	0.939

Table 5: Past Merger Activity and Wage Dispersion Using Standard Deviation

The dependent variable in columns 1 and 4 is Δlg_StdWages, the change in the standard deviation in the mean hourly wages (log transformed). The dependent variable in columns 2-3 and 5-6 is lg_StdWages, the standard deviation of log-transformed mean hourly wages. Columns 1-3 use the industry sample; columns 4-6 use the commuting zone sample. The timeline starts in 1980 and ends in 2010 with one observation per decade for each industry (columns 1-3) or commuting zone (columns 4-6). All variables are defined in Appendix A2. Robust standard errors are clustered at the industry-level in columns 1-3 and at the commuting zone-level in columns 4-6. *** indicates $p < 0.01$, ** indicates $p < 0.05$, and * indicates $p < 0.1$.

	(1)	(2)	(3)	(4)	(5)	(6)
	Δlg_StdWages	lg_StdWages	lg_StdWages	Δlg_StdWages	lg_StdWages	lg_StdWages
Merger Intensity_ind	1.239***	2.033**	1.729**			
	(0.451)	(0.850)	(0.838)			
Merger Intensity_cz				2.010***	4.874*	4.461*
				(0.458)	(2.596)	(2.527)
Offshorability	0.0411***	-0.0314	-0.0514	0.0804***	-0.106*	-0.119**
	(0.0139)	(0.129)	(0.125)	(0.0181)	(0.0560)	(0.0557)
Year FE	Yes	Yes		Yes	Yes	
Industry FE		Yes	Yes			
Commuting Zone FE					Yes	Yes
Year FE*lgStdWages80			Yes			Yes
Observations	396	396	396	2,166	2,166	2,166
R-squared	0.426	0.948	0.950	0.350	0.899	0.900

Table 6: Past Merger Activity and Wage Dispersion Using Wage Percentiles

The dependent variable in columns 1 and 4 is the 90th percentile of wages (log transformed). The dependent variable in columns 2 and 5 is the 10th percentile of wages (log transformed). The dependent variable in columns 3 and 6 is the ratio of the 90th percentile of wages to the 10th percentile of wages. Columns 1-3 use the industry sample; columns 4-6 use the commuting zone sample. The timeline starts in 1980 and ends in 2010 with one observation per decade for each industry (columns 1-3) or commuting zone (columns 4-6). All variables are defined in Appendix A2. Robust standard errors are clustered at the industry-level in columns 1-3 and at the commuting zone-level in columns 4-6. *** indicates $p < 0.01$, ** indicates $p < 0.05$, and * indicates $p < 0.1$.

	(1)	(2)	(3)	(4)	(5)	(6)
	lg_Wages90th	lg_Wages10th	Wages_90th/10th	lg_Wages90th	lg_Wages10th	Wages_90th/10th
Merger Intensity_ind	1.948**	1.558***	0.389			
	(0.830)	(0.440)	(0.799)			
Merger Intensity_cz				3.975**	-0.449	8.389*
				(1.943)	(2.683)	(4.494)
Offshorability	0.0274	-0.0523	0.0797	0.0226	0.0162	0.00851
	(0.0756)	(0.0684)	(0.0610)	(0.0381)	(0.0449)	(0.0573)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes			
Commuting Zone FE				Yes	Yes	Yes
Observations	396	396	396	2,166	2,166	2,166
R-squared	0.950	0.972	0.889	0.922	0.846	0.764

Table 7: Past Merger Activity and Routine Share Intensity, High-Skill Workers, Mean Wages and Standard Deviation of Wages: Interactions with Good-faith Exception

The dependent variable in column 1 is lg(RSH). The dependent variable in column 2 is the share (%) of workers with college degrees (4+ years of post-secondary education). The dependent variable in column 3 is log hourly wages. The dependent variable in column 4 is the log of the standard deviation of hourly wages. All regressions use the commuting zone sample. The timeline starts in 1980 and ends in 2010 with one observation per decade for each commuting zone. All variables are defined in Appendix A2. Robust standard errors are clustered at the commuting zone-level. *** indicates $p < 0.01$, ** indicates $p < 0.05$, and * indicates $p < 0.1$.

	(1)	(2)	(3)	(4)
	lg(RSH)	Share (%)	lgWages	lg_StdWages
Merger Intensity_cz	-0.943	3.400***	11.72***	8.523***
	(0.585)	(0.704)	(1.580)	(1.260)
Merger Intensity_cz * good-faith exception applies	-0.846	-2.099**	-6.139***	-4.898**
	(1.308)	(1.052)	(2.317)	(1.933)
Good-faith exception applies	0.00777	0.00131	0.0153	0.0145
	(0.0102)	(0.00446)	(0.0105)	(0.00928)
Offshorability	0.683***	0.259***	0.463***	0.392***
	(0.0264)	(0.0195)	(0.0448)	(0.0351)
Year FE	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes
Observations	2,166	2,166	2,166	2,166
R-squared	0.651	0.616	0.654	0.701

Table 8: Mechanisms: Increase in scale, Increase in efficiency, Lower financial constraints

The dependent variable in column 1 is lg(RSH). The dependent variable in column 2 is the share (%) of workers with college degrees (4+ years of post-secondary education). The dependent variable in column 3 is log hourly wages. The dependent variable in column 4 is the log of the standard deviation of hourly wages. All regressions use the industry sample. The timeline starts in 1980 and ends in 2010 with one observation per decade for each industry. All variables are defined in Appendix A2. Robust standard errors are clustered at the industry-level.*** indicates $p < 0.01$, ** indicates $p < 0.05$, and * indicates $p < 0.1$.

Panel A

	(1)	(2)	(3)	(4)
	lg(RSH)	Share (%)	lgWages	lg_StdWages
Merger Intensity_ind	-2.281***	0.681	2.140***	1.773***
	(0.675)	(0.439)	(0.502)	(0.571)
Merger Intensity_ind * Median industry firm size high	-2.443**	1.134***	2.411***	2.385***
	(1.230)	(0.375)	(0.718)	(0.797)
Median industry firm size high	0.00991	0.00149	0.00706	0.00841
	(0.0381)	(0.00964)	(0.0172)	(0.0221)
Offshorability	0.283	0.0140	-0.0700	-0.0852
	(0.370)	(0.0480)	(0.0899)	(0.150)
Year FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Observations	346	346	346	346
R-squared	0.962	0.971	0.964	0.950

Panel B				
	(1)	(2)	(3)	(4)
	lg(RSH)	Share (%)	lgWages	lg_StdWages
Merger Intensity_ind	-1.611	-0.491	0.892	0.224
	(1.878)	(0.533)	(0.822)	(1.068)
Merger Intensity_ind * Credit_spread high	-0.932	1.500***	1.761**	2.149**
	(1.590)	(0.462)	(0.733)	(0.911)
Credit_spread high	-0.00314	-0.00358	-0.000653	-0.00582
	(0.0281)	(0.00700)	(0.0132)	(0.0176)
Offshorability	0.367	0.0361	-0.0281	-0.0384
	(0.317)	(0.0431)	(0.0809)	(0.127)
Year FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Observations	396	396	396	396
R-squared	0.956	0.970	0.961	0.949

Panel C				
	(1)	(2)	(3)	(4)
	lg(RSH)	Share (%)	lgWages	lg_StdWages
Merger Intensity_ind	1.072	-2.954**	-2.610	-1.798
	(4.887)	(1.241)	(2.767)	(2.197)
Merger Intensity_ind * Acquirer industry profitability variance	-0.809	0.844***	1.013*	0.916*
	(1.006)	(0.271)	(0.609)	(0.483)
Acquirer industry profitability variance	0.00253	-4.43e-05	0.0157	0.0119
	(0.0107)	(0.00374)	(0.00994)	(0.00721)
Offshorability	0.383	0.0308	-0.0756	-0.0714
	(0.284)	(0.0440)	(0.134)	(0.0981)
Year FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Observations	301	301	301	301
R-squared	0.966	0.973	0.952	0.965

Table 9: Robustness: Controlling for Industry Shocks

The dependent variable in columns 1 and 5 is lg(RSH). The dependent variable in columns 2 and 6 is the share (%) of workers with college degrees (4+ years of post-secondary education). The dependent variable in columns 3 and 7 is log hourly wages. The dependent variable in columns 4 and 8 is the log of the standard deviation of hourly wages. All regressions use the industry sample. The timeline starts in 1980 and ends in 2010 with one observation per decade for each industry. All variables are defined in Appendix A2. Robust standard errors are clustered at the industry-level. *** indicates $p < 0.01$, ** indicates $p < 0.05$, and * indicates $p < 0.1$.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	lg(RSH)	Share (%)	lgWages	lg_StdWages	lg(RSH)	Share (%)	lgWages	lg_StdWages
Merger Intensity_ind					-2.405***	0.757*	1.970**	2.301***
					(0.850)	(0.431)	(0.842)	(0.746)
Offshorability	0.262	0.0678	0.0330	0.0174	0.360	0.0386	-0.0419	-0.0328
	(0.250)	(0.0417)	(0.0979)	(0.0649)	(0.315)	(0.0444)	(0.127)	(0.0796)
Industry shock	-0.00765	-0.0200**	-0.0487**	-0.0444***	-0.0129	-0.00736	-0.0328	-0.0323*
	(0.0273)	(0.00890)	(0.0191)	(0.0162)	(0.0343)	(0.0112)	(0.0221)	(0.0178)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	528	528	528	528	396	396	396	396
R-squared	0.944	0.951	0.920	0.926	0.956	0.968	0.948	0.961

Table 10: Robustness: IV Regressions

Column 1 reports the first stage regression with merger intensity as the dependent variable. Columns 2-5 report the 2nd stage results of 2SLS regressions. The dependent variable in column 2 is lg(RSH). The dependent variable in column 3 is the share (%) of workers with college degrees (4+ years of post-secondary education). The dependent variable in column 4 is log hourly wages. The dependent variable in column 5 is the log of the standard deviation of hourly wages. All regressions use the industry sample. The timeline starts in 1980 and ends in 2010 with one observation per decade for each industry. All variables are defined in Appendix A2. Robust standard errors are clustered at the industry-level. *** indicates $p < 0.01$, ** indicates $p < 0.05$, and * indicates $p < 0.1$.

	(1)	(2)	(3)	(4)	(5)
	First Stage	Second Stage			
	Merger Intensity_ind	lg(RSH)	Share (%)	lgWages	lg_StdWages
dummy_hor_wave	0.0051**				
	(0.0025)				
Merger Intensity_ind		-17.11*	5.611*	10.21*	10.45*
		(8.968)	(3.285)	(5.764)	(5.436)
Year FE	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes
Observations	396	396	396	396	396
R-squared		0.924	0.940	0.924	0.930

Appendix A1: Industry & Community Zone mapping between IPUMs and SDC data

Industries

IPUMs was created to facilitate time series analysis and, as such, has unique industry identifiers (IND1990), which offer consistent industry definitions over time. There are 224 unique industries defined in IND1990. IPUMs also provides a different definition of industry, INDNAICS, and a crosswalk between INDNAICS and 2007 NAICS. SDC includes information on the target and acquirer 2007 NAICS. To map IND1990 to 2007 NAICS, we take the following steps.

In the first step, we map the variable INDNAICS from ACS 2008-2014 samples to NAICS 2007 using a crosswalk provided by IPUMs.[18] Unfortunately, about 4% percentage of the unique IND1990 industry classifications are not mapped to an INDNAICS. We drop these IND1990 classifications. We also standardize NAICS codes by limiting all NAICS to 4 digits. This crosswalk provides a one-to-one mapping between INDNAICS and IND1990.

In the second step, we map IND1990/INDNAICS to NAICS 2007. This step is more complicated as one IND1990/INDNAICS may match to more than one NAICS and one NAICS may match to more than one IND1990/INDNAICS. We start by saving all unique combinations of IND1990 and NAICS 2007 codes. To identify only the set of industries for which we can cleanly match between IND1990 and NAICS 2007 and avoid noise associated with ambiguous industry mapping, we consider only cases (after possibly aggregating IND1990 industries to one meta-industry) of industries (or meta-industries) that map to one and only one NAICS 2007, or aggregation of NAICS 2007 codes.

For example, IND1990 industry 0190 maps to NAICS 2213 and to NAICS 2212. NAICS 2213 and NAICS 2212 only map to IND1990 industry 0190. In this case, we combine NAICS 2213 and NAICS 2212 into one meta-industry and identify a clean link between IND1990 industry 0190 and NAICS industry 2213-2212. We follow an iterative approach

[18] The crosswalk is available at the following website: https://usa.ipums.org/usa/volii/indcross03.shtml

to identify all possible such matches. Industries which cannot be assigned to a clean match are dropped.

Upon completion, we have a mapping from IND1990 to INDNAICS to NAICS 2007. It is useful to think of the industry definitions in the paper as meta-industries as they may include more than one unique IND1990 and more than one unique 4-digit NAICS 2007. We have 132 unique meta-industries. Of the 224 unique industries in IND1990, we are able to successfully map 178 industries into our meta-industries or 79.5% of the unique IND1990 industries in IPUMs. Our mapping includes 209 unique 4-digit NAICS 2007.

Commuting zones

We map the city name in SDC to 1990 commuting zones using a fuzzy match and crosswalks provided by the Missouri Census Data Center.[19] All matches with a matching score below 0.8 were dropped. Matches with a matching score between 0.8 and 1 were manually checked. M&A deals in cities that were mapped to multiple commuting zones were dropped from the sample. We map IPUMs data with 1990 commuting zones on Public Use Micro Area (PUMA) using a crosswalk provided on the website of David Dorn.[20] All other steps are similar to the creation of the industry sample, except when aggregating IPUMs data to the commuting zone level, we use a regional employee weighting. For the commuting zone sample, we use a weight calculated as the following: Census sampling weight×labor supply weight×the probability that a resident of PUMA j lives in CZONE k in Census year t.[21]

[19]The crosswalk is available at the following website: http://mcdc.missouri.edu/websas/geocorr90.shtml.

[20]The crosswalk is available at the following website: http://www.ddorn.net/data.htm.

[21]The variable is also available from David Dorn's website.

Appendix A2. Variable Definitions

M&A Variables

Merger intensity_ind captures the intensity of M&A activities in an industry-decade. It is the logarithm of one plus the count of horizontal deals in a given (6-digit NAICS) industry-decade normalized by all horizontal deals in the decade.

Merger intensity_cz captures the intensity of M&A activities in a commuting zone-decade. It is the logarithm of one plus the count of horizontal deals in a given commuting zone-decade normalized by all horizontal deals in the decade.

Good-faith exception applies is an indicator which equals to 1 if the wrongful discharge laws, good-faith exception, apply in a given state-decade (Autor et al. 2006).

Median industry firm size high is an indicator which equals to 1 if the logarithm of firm assets (based on Compustat firms) at the end of each industry-decade is greater than the sample median.

Credit spread high is an indicator which equals to 1 if the credit spread in a given industry-decade is greater than the sample median. Credit spread is the difference between the BAA yield and the effective federal funds rate at the time of the deal announcement. Credit spread data are taken from WRDS.

Acquirer industry profitability variance measures the logarithm of standard deviation of profits per employee (based on Compustat firms) at the start of each decade in a given industry.

Dummy_hor_wave equals to 1 if there were merger waves in connected industries within the decade. We define a merger wave in a given industry if the count of horizontal mergers in that industry exceeds the 90th percentile of the distribution for that industry, measured from 1980 to 2014.

Industry Shock equals to 1 if a given industry experienced either a technology or regulatory shock during the previous decade (Harford, 2005 and Ovtchinnikov, 2013).

Autor and Dorn (2013)

Routine employment share (RSH) measures the employment share of routine occupations in an industry-year or a commuting zone-year. It is defined as the total employment of routine occupation in industry (commuting zone) j and year t divided by the total employment in the same industry-year (commuting zone-year). We define occupations as routine following Autor and Dorn (2013). The data are available at: http://economics.mit.edu/faculty/dautor/data/autor-dorn-p

Offshorability captures the degree to which the tasks performed by an industry (commuting zone) are offshorable. It is defined as the employment-weighted average of occupational offshorability, which is available by Autor and Dorn (2013) at the occupation level and merged to IPUMs data using the available occupation crosswalks.

IPUMs Dataset

College workers labor share (Share %) is defined as the employment share of high skill workers in each industry (commuting zone) and year. College workers are workers who have attained at least 4 years of college education.

Average hourly wage represents an average level of hourly wage in each industry (commuting zone) and year. It is employment-weighted average of hourly wages of workers in that industry (commuting zone). Each worker's hourly wage is calculated as annual income and salary income divided by the product of weeks worked per year and hours worked per week. All wages are inflated to year 2009 following the instruction provided by IPUMs, https://cps.ipums.org/cps/cpi99.shtml.

Standard deviation of hourly wage is the employment-weighted standard deviation of hourly wages in each industry (commuting zone) and year.

lg_ Wage90th is the logarithm of the hourly wage at 90th percentile of the industry (commuting zone) hourly wage distribution.

lg_ Wage10th is the logarithm of the hourly wage at 10th percentile of the industry (commuting zone) hourly wage distribution.

90-percentile hourly wage/10-percentile hourly wage is the ratio of the hourly wage at 90th percentile and the10th percentile of the industry (commuting zone) hourly wage distribution (log-transformed).

Table A1: Industries Ranked by Level of Routine Share Intensity

Panel A of the table ranks the industries with the highest RSH by decade (in descending order). Panel B of the table ranks the industries with the lowest RSH by decade (in ascending order). 4-digit 2007 NAICS are included in parentheses.

1980	1990	2000	2010
Panel A. Industries with highest RSH			
legal services(5411)	legal services(5411)	legal services(5411)	legal services(5411)
veterinary services_miscellaneous personal services_beauty shops_barber shops(5419_8121_8129)	accounting, auditing, and bookkeeping services(5412)	accounting, auditing, and bookkeeping services(5412)	accounting, auditing, and bookkeeping services(5412)
newspaper publishing and printing_printing, publishing, and allied industries, except newspapers(5111_3231)	newspaper publishing and printing_printing, publishing, and allied industries, except newspapers(5111_3231)	grocery stores(4451)	drug stores(4461)
advertising (5418)	metalworking machinery(3335)	liquor stores(4453)	grocery stores(4451)
metalworking machinery (3335)	advertising(5418)	newspaper publishing and printing_printing, publishing, and allied industries, except newspapers(5111_3231)	metalworking machinery(3335)
Panel B. Industries with lowest RSH			
taxicab service (4853)	retail florists (4531)	retail florists(4531)	taxicab service (4853)
logging (1133)	logging (1133)	taxicab service (4853)	nonmetallic mining and quarrying, except fuels(2123)
metal mining (2122)	taxicab service (4853)	logging (1133)	metal mining(2122)
nonmetallic mining and quarrying, except fuels (2123)	metal mining (2122)	metal mining (2122)	shoe stores(4482)
vending machine operators (4542)	miscellaneous vehicle dealers (4412)	auto and home supply stores (4413)	retail florists (4531)