Mergers and Acquisitions, Technological Change and Inequality

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Abstract

This paper documents important shifts in occupational composition following merger and acquisition (M&A) activity as well as increases in median wages and wage inequality. We propose M&As 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 M&A event is associated with a 4.2% reduction in establishment routine share intensity and a 3.3% increase in the share of high skill workers at the target as compared to a matched sample of control establishments. These results have important implications on wage inequality: Following an M&A, we observe 9.2% higher hourly wages for the remaining workers in the establishment and an increase in wage polarization as measured by the 90/10 ratio. Our results are generalized at the macro level as we are able to replicate similar patterns industry-wide.

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 firm level mechanisms 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, Zhang, 2017.

depend on the organizational structure within the industry. Specifically, we argue M&As can alter the speed and nature of how and when firms integrate new technology, with important implications on occupational change and wage inequality. Mergers and acquisitions can reduce frictions, such as adjustment costs, thereby lowering the opportunity cost of investing in new technologies and making investments in such technologies more profitable. We discuss three potential mechanisms by which M&As can lead to a reduction in technology adjustment costs: 1) an increase in scale; 2) an increase in efficiency; or 3) lower financial constraints. All three mechanisms predict an increase in investments in automation post-M&A, leading to a lower demand for routine tasks, greater demand for high-skilled labor, higher median wages and greater overall wage inequality.

We use establishment level data from the Occupational Employment Survey (OES), conducted by the Bureau of Labor Statistics (BLS), to identify the effect of M&As on occupational employment and wages. We match horizontal M&A deals that became effective over the 2001-2007 period to the BLS survey and identify M&A impacted treated establishments. We form a control sample matching each treated establishment with similar controls and perform a difference-in-differences (DID) identification strategy. Although causality is a high bar due to the fact that M&As are not randomly assigned, matching mitigates biases that arise from selection based on observable characteristics and the DID estimator deals with unobserved time-invariant group effects and common time, industry, and local trends.

We find that the occupational share of routine intensive jobs is reduced by 4% in treated establishments following M&As, relative to the matched time series change at similar control establishments. These findings are consistent with a prediction of routine-biased technological change, therefore suggesting that M&As induce greater use of labor-saving technology. Routine-intensive occupations have been shown to be over-represented in the middle of the income distribution (Autor and Dorn, 2013). As such, replacement of these workers with technology will tend to increase job polarization. Moreover, technological adoption should not only shift occupational demand away from routine tasks but also increase demand for high skill workers due to the complementarity of skill and technology.

We find that the occupational share of high skill jobs increases by 3.3% in treated establishments following M&As, relative to the matched time series change at similar control establishments.

We explore the implications of these shifts in the employment distribution away from routine occupations and towards more high skill occupations on wages. Median wages should increase following M&As as the relative fraction and productivity of high-skill workers increases. Indeed, we find an 8% increase in the median wage of treated establishments following their acquisition as compared to the matched sample of control establishments. In addition, wages should become increasingly polarized as the labor shares are increasingly represented by both the high- and low-skill tails of the skill distribution. In that regard, we show an increase in wage polarization, as proxied by the standard deviation in wages and the 90^{th} and 10^{th} percentiles log differential of the wage distribution.

In our regressions, we control for time-invariant establishment characteristics by including establishment fixed effects, for time-varying industry characteristics by including interacted industry and year fixed effects, and for time-varying local characteristics by including interacted region and year fixed effects. To further mitigate concerns that selection into treatment might be driving our findings, we define our control group based on a matching analysis where we match treated establishments to controls in terms of industry, year of observation, pre-treatment employment and intensity of routine occupations.

The key impetus of the paper is to show the role of M&As as a mechanism through which labor-saving technology is further utilized by firms, thereby leading to lower employment of routine-intensive occupations. The effects documented in the paper can come from firms pursuing M&As with the express purpose of implementing more labor-saving technology ex-post as well as from a causal channel where firms pursue the M&A for reasons orthogonal to technology and ex-post learn of the benefits to greater technological adoption.

Our findings suggest that M&As act as a catalyst for technology adoption leading to economically important changes in labor demand *within* firms. Considering, however, the large scale of M&A activity, with over 4 $trillion in activity in 2015 alone, it is plausible to expect that the effect of firm reorganizations on labor demand and inequality may be felt economy-wide. Indeed, we provide evidence for routine-biased and skill-biased technological change at M&A impacted industries (or industries-local labor markets) and show patterns of increasing inequality.

To this end, we collect data from Thomson's SDC on M&A activity, starting in 1980. We measure M&A intensity as either the count of horizontal deals in an industry-decade (or as the count of horizontal deals in an industry-local labor market-decade). We then normalize by the count of total horizontal deals in the decade. 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, for each industry we identify the fraction of employment in a given occupation and the share of employees with college education. We also identify the industry wage distribution. To identify the routine-task content of each occupation, we replicate the approach in Autor and Dorn (2013) and measure industry-level routine intensity using employment share of routine occupations in each industry-year. To study the effect of M&A activity in industries contained within a specific local labor market, we follow Autor and Dorn (2013) and map M&A activity first into commuting zones, where commuting zones are designed to approximate local labor markets, then aggregate to the industry level within a given commuting zone.

Consistent with the predictions of routine-biased technological change, we observe a decline in the occupational share of routine intensive jobs within industries (or industry-region pairs) as the intensity of past M&A activity increases. In the time-series, we find that an increase in lagged M&A intensity by 1% is associated with a 2.8% reduction in routine share intensity within a given industry. Consistent with the predictions of skill-biased technological change, we document that high M&A activity is 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 1% is associated with an increase in the share of high-skill employees by 0.9 percentage points within a given industry.

Similar to our establishment level results, we also show that the documented shifts in occupational employment following mergers and acquisitions have implications on wages. We find that high M&A activity within industries is related to higher median 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 wage distribution.

We show these results are robust to a number of tests. First, we control for shocks that are known to trigger M&A waves, as identified in Harford (2005) and Ovtchinnikov (2013) and do not find evidence that results might be driven by such shocks.[2] Second, we exploit the fact there was limited penetration of computers in the 1960s—adoption started in late 1970s and took off in the 1980s and later (Autor, Levy, and Murnane,2003). We show that the relationship between M&As is stronger following 1980, consistent with the fact that the rapid decline in the price of technology which started in the 1980s gave economic incentives to firms to adopt technologies. Third, we construct a similar measure to the M&A activity variable, except for M&A deals that were announced but failed to materialize. We run horseraces between our baseline M&A variable and the equivalent measure based on failed deals. We find no effect of failed M&A deals on our outcome variables, while our baseline effects remain, suggesting that unobservable shocks driving both M&A announcements and changes in labor demand do not seem to be explaining our results.

To understand precisely how M&A activity can act as a catalyst for skill-biased and routine-biased technological change, we explore and show support for three non-mutually exclusive mechanisms. 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. In support of this mechanism, we show that the effect of lagged M&A activity is greater in industries where the median firm size is larger.

[2]Note, 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, 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 adoption at the target. We proxy for financial constraints at the target using average values of credit spreads at the time of deals' announcements.

Our paper builds on several literatures. First, it 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 (2014) 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.

The paper also builds on the 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. However, with the exception of Jaimovich and Siu (2015) and Hershbein and Kahn (2016) which show that technology adoption is accelerated in recessions, when opportunity cost of investing in technology is lower, the existing literature tends to ignore the role of firms in these trends. 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.

II Establishment-level evidence

II.1 Data and summary statistics

We use data from the Occupational Employment Survey (OES), conducted by the Bureau of Labor Statistics (BLS). This data comes from an annual or biannual survey of individual establishments in the US. No establishment is surveyed twice within three years, however, it is common for larger establishments to appear in the data exactly once every three years. The surveyed establishments are selected in a manner to allow for inferences about the US economy as a whole.

In each survey, each included establishment reports the count of all employees in 800 different occupational categories (6-digit SOC codes). Moreover, in later years, the establishment also reports the count of all employees within each wage bin for the 800 unique occupations. Twelve wage bins are identified, with variations in the exact cutoff points for each wage bin changing over time to best reflect changes in wage distributions. We measure wages by taking the occupation-wage bin employment weighted median within each establishment, adjusting to year 2001 constant dollars. Furthermore, for each surveyed establishment, we also observe the county where it is located, EIN, name, legal name (ultimate owner), industry and a time invariant establishment-identifier which we can use to track establishments which have switched owners over time.

We use SDC data to identify and match horizontal M&As which took place between 2001 and 2007 to the BLS data using a two-step procedure. We first match using EIN and the target firm's Compustat provided EIN. However, since firms often report multiple EINs, we also use a name matching procedure to maximize total matches. We start with a fuzzy logic algorithm then hand match all likely candidates. A match is only retained if we observe the target establishment strictly before and after the M&A is completed. Given the difficulties involved in the matching process, we use a sample of publicly listed acquirers and targets for which EINs are more likely to be available. Although our sample does not include a large number of private deals, it includes the largest deals over our sample period with an average transaction value of $3.03 billion, as compared to $0.3 billion for the average deal in that period, and 4,503 employees in the target firm.

We follow Autor and Dorn (2013) to calculate a measure of routine share intensity in our sample.[3] We aggregate total employment of routine intensive occupations (RTI)

[3]Autor and Dorn (2013) define the frequency of "routine" tasks typically performed by employees assigned to a given occupation. Since occupations involve multiple tasks (routine, abstract, manual) at different frequencies, Autor and Dorn (2013) create an indicator which measures the routine task intensity (RTI) by occupation and define an occupation as routine task intensive if in the top employment-weighted third of routine task-intensity. We merge RTI to occupations in OES by SOC codes using crosswalks from David Dorn's website. http://www.ddorn.net/data.htm.

and total employment of all occupations in the sample in a given establishment.[4] Routine share intensity (RSH) of an establishment is defined as the ratio of total employment of routine task intensive occupations over total employment in the establishment. We use a log transformation of one plus the average value of RSH at the firm level to avoid dropping cases where a firm has no high routine occupations. We also use data provided by Autor and Dorn (2013) to define offshorability of a given occupation.[5] To define offshorability for a given establishment, we compute occupational employment weighted average of offshorability.

The OES survey is conducted as a resource to best understand the current occupational demand in the US. Over time, methodology for conducting the survey has changed. This could potentially introduce time series patterns to the data driven by changes in sampling techniques. To ensure that our results are not biased by any such changes, we report changes in employment and wages at target establishments as well as changes in excess employment and wages, where excess wages are defined by using a matched sample. We exclude from the set of possible control establishments, all establishments we know were involved in M&As at this point of time. For each target establishment (treated observation), we find matched establishments which operate in the same 4-digit NAICS and in the same year of the first observation of the establishment in our sample. As with the treated observations, we also require that the matched observation be observed twice within our timeline and require that the year of the second data point is within one year of the treated observation's second data point. We also require that total employment at the control establishment is within 100% of total employment at the treated establishment and that ex-ante RSH is within 0.05 of RSH at the treated establishment. We keep two control establishments for each treated establishment. If more than two control establishments match to the treated establishment, then we keep the two control establishments with the closest value of ex-ante RSH. We allow matched establishments to repeat. In other words, one establishment can be a control observation for multiple treated establishments. With these restrictions, we

[4]As in Autor and Dorn (2013), we drop some occupations, such as military and farming.

[5]We merge those data to OES by SOC codes using crosswalks from David Dorn's website. http://www.ddorn.net/data.htm.

end up with a sample of 116 establishments in the treatment group and 225 in the control group.

Our sample of target establishments covers a wide range of industries. The industry distribution is similar across treated and control samples as by definition we required control establishments to be in the same industry as the treated. Table 1 reports summary statistics for our sample establishments. The average establishment in our sample employs 135 employees, out of which 59 are performing routine occupations and 19 are performing high-skill occupations, it has a routine (high-skill) share intensity of 45% (7.5%), pays on average \$14.5 per hour and has a standard deviation of wages equal to 8.5. Both treated and control establishments are larger than the median establishment in the US as larger establishments are more likely to be surveyed twice and to enter thus in our sample. We also require our treated and control establishments to have no significant differences pre-treatment in terms of their routine share intensity due to the finding by Autor and Dorn (2013) that greater occupational changes due to technology tend to occur when routine share intensity is ex-ante higher.

II.2 Methodology

To identify the effect of M&As on labor outcomes at the establishment level, we estimate the following difference-in-differences specification at the establishment-year level:

$$\mathrm{y}_{i,t} = \alpha_t + \alpha_i + \gamma \cdot \mathrm{Post}_t \cdot \mathrm{M\&A}_i + \beta \cdot X_{i,t} + \epsilon_{i,t} \tag{1}$$

where i denotes establishments and t denotes years. $Post_t$ is an indicator set equal to one for years following M&As—zero otherwise. $M\&A_i$ is an indicator equal to one for establishments where M&As take place (treated) and zero for the matched set of control establishments.[6] $X_{i,t}$ is the vector of establishment-level control variables (offshorability);

[6]Note the terms $Post_t$ and $M\&A_i$ are absorbed by the fixed effects in the specification, and thus, not reported.

controlling for offshorability alleviates concerns that changes in establishments offshoring potential could affect both the probability of M&As and our measured outcomes. α_i is an establishment fixed effect, which controls for establishment characteristics that do not vary over our sample period; and α_t is a year fixed effect, which absorbs aggregate shocks affecting all states. In all specifications, we report robust standard errors clustered at the establishment level.

II.3 Results

We begin by examining how the share of routine intensive workers, RSH, changes following an M&A, as compared to a matched group of control establishments. Table 2 presents the results. Column 1 shows that M&As are associated with a 4% average decrease in routine share intensity of the establishment which is statistically significant at the 5% level. 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] Columns 3, 4 and 5 repeat the estimation controlling for interacted (4-digit NAICS) industry and year fixed effects, interacted state and year fixed effects, and for (9 Census) regions times year fixed effects, respectively, to control for industry shocks as well as local economic shocks that might be contemporaneous with the timing of the merger. Column 5 instead controls for both interacted industry times year and region times year fixed effects. Across specifications, the coefficients are similar in terms of magnitudes and statistical significance suggesting that industry or local shocks are not driving our findings.

The results in Table 2 indicate that M&As act as a catalyst for technology adoption documented to replace workers performing repetitive, routine tasks (Autor, Levy, and Murnane, 2003; Autor and Dorn, 2013). These workers are assumed to be disproportionately

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

represented in the middle of the income distribution, predicting an increase in wage polarization. At the same time, technological adoption should also increase demand for high skill workers as new technology disproportionally increases productivity of high skill employees. Consistent with this argument, we find an increase in the share of high-skill employees in treated establishments following the M&A as compared to the group of control establishments. Table 3 repeats the specifications in Table 2 and shows a 2.4%-4.6% increase in the share of high-skill employees. The coefficients are also statistically significant at the 5% level after controlling for local economic shocks in columns 3-5.

Consistent with the notion that an increase in demand should increase wages at the right tail of the wage distribution, in Table 4, we find a significant 8% increase in establishments' median wages following M&As compared to a matched set of control firms, as compared to pre-M&A years. These results are robust, and if anything stronger, to controlling for industry and local economic shocks (columns 2-5).[8]

To further document polarization within M&A establishments, we examine the effect of M&As on the standard deviation of wages, as in Barth, Bryson, Davis, and Freeman (2015). In Table 5, Panel A, we find positive, although weak statistical evidence, that M&As increase standard deviation of wages in establishments with M&As. However, the effect is stronger, both statistically and economically, after we more carefully control for industry and local shocks: we find a 1.4 percentage points increase in standard deviation of wages, or a 16% increase relative to the sample mean in column 5—statistically significant at the 5% level. To measure the effect of M&As on within establishment inequality, we alternatively consider the 90/10 log wage differential within establishments with M&As as compared to otherwise equivalent establishments without M&As. In Table 5, Panel B, we show an economically large increase of 11% in the 90/10 wage differential, an increase that is also statistically significant in specifications controlling for year fixed effects (column 1) or industry and region time-varying changes (column 5).

[8]We find similar results if we consider establishment average wages instead.

III Industry-level evidence

So far, our results suggest that M&As are associated with occupational changes that result in changes in labor demand and increases in wage inequality within firms. The fact that these results are estimated using a small sample of publicly-listed M&As raises the question as to whether the observed patterns are unique to this sample. On the contrary, if our intuition is correct, we should observe the same changes taking place on aggregate affecting occupational and wage outcomes within M&A impacted industries. To answer this question and examine whether our channel is relevant at the macro level, we next turn to examining whether the same labor market changes occur at the industry level. In the Appendix, we repeat the analysis at the industry-local labor market level instead, where labor markets are proxied by commuting zones.

IV Data

In this section, we review the multiple databases used to create our industry 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).

IV.1 M&A data

We use Thomson's SDC as our primary source for 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.[9]

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

Our primary measure of M&A activity is the count of horizontal deals in a given decade, for a given industry, 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 4-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 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 six years of each decade, and where we consider transaction values instead of counts, when non-missing. In the Appendix, we repeat our analysis at the industry-commuting zone level. We group deals into commuting zones using the target's headquarters geographic location.

In a later section, we alternatively measure M&A activity using delistings, flagged as M&A related. The benefit of this measure is that it allows us to go back further in time to explore earlier decades where computers had limited penetration. However, the data does not allow us to identify horizontal mergers exclusively and is limited to acquisitions of public target firms.

IV.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).[10,11] 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.

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

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

We map NAICS industries from SDC to IPUMs industries, using the cross-walk provided by IPUMs, as detailed in Appendix A1. We have 132 industries and more than 300 occupations in each Census-year.[12] 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 industry-commuting zone-Census year in the Appendix) by computing employment weighted averages. We define all variables used in our analysis, in more detail, in Appendix A2.

[12] For our industry-commuting zone sample in the Appendix, 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. We drop industry-commuting zones with 0 M&A activity over the sample period. In our industry-commuting zone sample, we have 12,029 industry-commuting zone combinations and more than 300 occupations in each Census-year.

IV.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 frequencies, 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.[13] 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 in terms of their routine intensity and construct the share of these routine intensive occupations by industry-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

[13]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 qualitatively similar.

confirmed in Panel B, which shows the average routine intensity for each occupation across 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 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 occupations' offshorability to capture the possibility that M&A activity is concentrated in industries 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 industry-commuting zone which are merged to our sample using the available occupation codes. The industry-year offshorability level is equal to the average offshorability score of employment in each industry-year.

IV.4 Summary statistics

Table 6 reports summary statistics of several key variables used in the analysis. We report the mean value across all industries for a given year along with the standard deviation in brackets. On average, a given industry reflects between 0.46-0.65% of the overall merger activity. Similar to Autor and Dorn (2013), we document that around one third of all occupations are routine-intensive. We find that over 5% of workers in our average industry had a graduate degree in 1980, which we define as five or more years of post-secondary education. This fraction increases over time and is about 8% in 2010. The average hourly wage is \$20.34 in 1980. Moreover, we show an increase in the standard deviation of wages within a given industry.

V Results

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 change, 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.

V.1 M&A and occupational changes

We start by examining the effect of M&A activity on changes in routine employment shares and the share of skilled workers within a given industry. We estimate the following regression:

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

where t indexes years and i indexes industries. $X_{i,t}$ controls for average offshorability of tasks, time-varying at the industry level. *Merger intensity* is our proxy of M&A activity as defined above and log-transformed.[14] 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. y measures the fraction of routine or skilled based occupations within a given industry over a decade, namely 1980-1990, 1990-2000, 2000-2010. Standard errors are clustered at the industry level to take into account correlation in industries over time.

Columns 1-2, Table 7 examine routine share intensity as our outcome variable. All

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

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, and industry fixed effects to control for time-invariant industry characteristics. We also 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. Similar to our firm-level analysis, we report a positive correlation between the percent of offshorable jobs, measured contemporaneously to RSH, and the change in routine share intensity.

An increase in M&A intensity by 1% is associated with a 2.8% decrease in routine intensity share in the industry. In column 2, we address the possibility that our results may be capturing mean-reversion, namely high M&A industries adjust back to an industry-specific routine-intensity equilibrium level. To address this concern, we interact the value of the dependent variable 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 that depend on industry 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.[15]

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. To round our argument, in columns 3-4, Table 7 we look at the share of high-skill workers within a given industry, following mergers and acquisitions. We proxy for high-skill employees as the share of employees with graduate education, namely employees

[15]In the Appendix, we show our results are robust to several specifications: Table A2 shows results are robust to defining routine and non-routine occupations each Census year as opposed to using the 1980 Census as in Table 2; Table A3 shows results are robust to redefining M&A activity using only mergers observed in the first six years of the preceding decade, allowing 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; Table A4 presents results using a measure of merger intensity calculated based on M&A transaction values instead of counts.

with 5 or more years of post-high school education.[16] Column 3 includes year and industry fixed effects and column 4 further controls 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 relative share of high-skill workers within a given industry. The results are economically important: an increase in M&A intensity by 1% is associated with an increase in the share of highly-educated employees by nearly 1 percentage point within industries (column 3)

Overall, these findings are consistent with the argument in Autor, Levy, and Murnane (2003) that industries 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.[17]

V.2 M&A and wages

Similar to our firm level evidence, these results show that M&A activity is followed by a decrease in routine-intensive labor and a simultaneous increase in the share of high-skilled workers in a given industry. Next, we repeat our firm level analysis at the aggregate level to test whether these occupational changes have important implications for wages.

First, we explore predictions related to hourly wages in columns 1-2, Table 8. We use the log of the industry median hourly wage as the dependent variable and find an increase in the median wage in affected industries. 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 jobs as indicated in the previous two tables.[18]

[16]In Appendix Table A5, we alternatively consider the fraction of workers with college education, defined as 4 or more years of post-secondary education. Our results are qualitatively robust to using this alternative measure of skill.

[17]In Appendix, Table A7, we confirm our results also hold at the industry-local level.

[18]In unreported results, we repeat the specifications in columns 1-2 Table 8 using annual or full-

To test the effect of wages on wage polarization following M&A activity, we follow our firm level analysis and start by examining the standard deviation of wages repeating the same specifications as in columns 3-4. Within industries, an increase in M&A activity by 1% increases wage disparity by 2.1% (column 3). We provide further evidence that M&As contribute to wage polarization by examining wage percentiles at the top-end (90^{th} percentile), bottom-end (10^{th} percentile) and the ratio of the two in columns 5-7, Table 8.[19] Wages are log-transformed and all regressions include year fixed effects and industry fixed effects. Consistent with earlier findings, 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, the effect at the 90/10 wage differential provides somewhat weaker evidence.[20]

In Table 9, we exploit our sample heterogeneity following Autor and Dorn (2013), who argue that the treatment effect of technology adoption on the share of routine intensive jobs should be magnified when the share of such workers is high in the first place. Following their intuition, we look within the distribution of wages to test whether wage inequality increases more in cases where the initial share of routine intensive jobs was higher in the prior decade. We present results using the 90/10, 90/50, and 75/25 log wage differentials, respectively, as the dependent variable. The coefficient of interest is the interaction term between lagged M&A activity and industry routine share intensity in the previous decade. The coefficient is positive and statistically significant consistent with the intuition that larger changes in

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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 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.

[19]The IPUMs is top coded in the top percentiles by state-year, however, there is no evidence that this top coding impacts our estimation of the wages at the 90^{th} percentile.

[20]In Appendix, Table A8, we provide stronger evidence of wage polarization in M&A impacted industry-local labor markets. The sharper effect we capture in industries locally, as compared to the overall industry, may be interpreted in light of the lower labor mobility in more "fragmented" local labor markets which should compress wages of low skill workers more but, at the same time, should imply greater wage increases for scarce talent.

wage inequality following M&A activity should be seen in industries characterized a priori by high intensity of routine tasks, namely tasks easily substitutable by technology.

Overall, the increase in median 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. These results also confirm that our within firm evidence are not unique to our firm level sample, but they have industry wide implications for labor outcomes and inequality.

V.3 Evidence against alternative interpretations

In this section, we discuss alternative explanations that could partially explain our findings. We also show our results are robust to a number of tests that suggest that industry shocks, rather than M&As, should not be driving these findings.

V.3.1 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 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.3.2 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.3.3 Technological and 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 10.

The dummy variable, industry shock, takes the value of one if the relevant industry experienced a technology shock during the previous decade. The dummy variable, deregulation shock, takes the value of one if the relevant industry experienced a regulatory shock during the previous decade. Controlling for these shocks in our baseline regressions does not significantly change our coefficients of interest in terms of significance or economic magnitudes. Moreover, the shocks themselves are only weakly correlated with two of our outcome variables, routine share intensity and average wages, but, interestingly, the effect of the shock goes in the opposite direction of the prediction of either routine-biased or skill-biased technological change.

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

V.3.4 Time series results

According to the wage inequality literature, the observed polarization of job opportunities coincides with the rapid decline in the price of technology that started principally in the 1980s. Using this observation as our starting point, we perform an additional analysis that examines whether the effect of M&A activity on labor market outcomes matches the pattern documented in the labor economics literature. According to our hypothesis, M&A activity should have a more pronounced effect on occupational changes and wage inequality starting in 1980s. If, instead, the effect is driven by omitted variables which are correlated with M&As, then the effect should be more even over time.

To test this hypothesis, and in the absence of complete M&A data from SDC platinum prior to 1980, we proxy for M&A activity by looking at the count of stock delistings associated with M&A events over the 1950-2010 period using CRSP. Similarly to our baseline analysis, we define our key variable as the number of delistings in a given industry-decade normalized by the total number of delistings during the decade. Although this measure is noisier by construction, it is positively and significantly correlated with our baseline M&A measure over the time period for which they are both available (pairwise correlation is 0.76). Overall, we have 76 industries over 7 decades.

We interact our newly defined M&A variable with a dummy that takes a value of one for the decades following 1980, and 0 prior to that. We control for year and industry fixed effects in all specifications. Table 11 reports the results. We observe a negative effect of M&A activity on routine share intensity following 1980s, which is significant at the 10% level. On the contrary, there seems to be no significance prior to the 1980s. Similarly, we observe positive and mostly significant interaction coefficients for our measures of high-skill workers, mean wages, and wage inequality, while the M&A effect in the early decades of 1950s-1970s is, if anything, negative. These results further address concerns that common shocks correlated with M&A activity and labor market outcomes can explain our findings.

V.4 Failed M&A deals

In a further attempt to address concerns that common shocks explain both M&A activity and the observed labor market outcomes, we consider the effect of "failed" M&A activity on the outcome variables of interest. To construct our measure of "failed" M&A activity, we identify all deals in SDC platinum that were announced but were eventually withdrawn. From this sample, we exclude deals that were cancelled but the target firms got eventually acquired by a different firm (23% of the observations). Similar to our primary M&A measure, we define a new M&A measure based on cancelled deals defined as the number of cancelled deals in a given industry decade normalized by the number of cancelled deals in the decade. We predict the results reported throughout the paper are driven by completed M&As. In contrast, assuming withdrawn deals are motivated by possible omitted variables correlated with M&A activity but where, importantly, these deals are not consummated and thereby do not result in economies of scale, reduced financial constraints or the transfer of best practices, we should observe no significant effect on key outcome variables.

Table 12 presents horseraces between our baseline M&A measure and the measure of "failed" M&As on our main variables of interest. We find that the effect of our M&A activity variable is similar in magnitude to our baseline specifications and, in most cases, statistically significant. On the contrary, the "failed" M&A activity measure is never statistically significant, is much smaller in magnitude, and has often the opposite sign to our predictions. These results provide an additional piece of evidence against concerns that common shocks can explain our findings, as such shocks should be driving all M&A deals, irrespective of whether they materialized or not.

VI 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. We use the industry, instead of the establishment-year sample, to make general inferences from our findings.

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.[21]

The results are reported in Table 13, Panel A. We repeat the regressions looking separately at routine share intensity, share of high-skilled 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 most 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 targets 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

[21]We match 4-digit NAICS industry codes in Compustat to our sample industries using the crosswalk detailed in Appendix A1.

is higher than the sample median.[22] 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 technology adoption by facilitating the transfer of 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 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 significantly more pronounced in industries with greater variation in employee productivity for all our outcome variables with the exception of routine intensity where the results are insignificant.

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 high-skilled workers, and wage inequality when one of these mechanisms is more likely to be important.

VII 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,

[22]Since all regressions in Table 13 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.

improved efficiency, or lower financial constraints. Automation should in turn lead to occupational and wage changes consistent with changes predicted by skill-biased and routine-biased technological change. We find that M&As within establishments are followed by a reduction in the share of routine share intensive occupations. 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 occupational distributions are also mirrored in the wage data: we observe an increase in the median wages and, most importantly, in overall wage inequality within establishments. We are able to generalize those findings at the macro level, where we find that industries impacted by high M&A activity exhibit similar changes in labor outcomes and wages as those identified within firms.

Our results do not require that M&As happen in the absence of technology shocks. On the contrary, as suggested by Harford (2005), merger waves might be triggered by the appearance of new technologies; however, our results suggest that M&As are a necessary condition for the observed changes in labor markets as they act as a catalyst for rapid adoption of these technologies. Our results are also unique to the sample of employed workers. As such, they 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 firm or industry.

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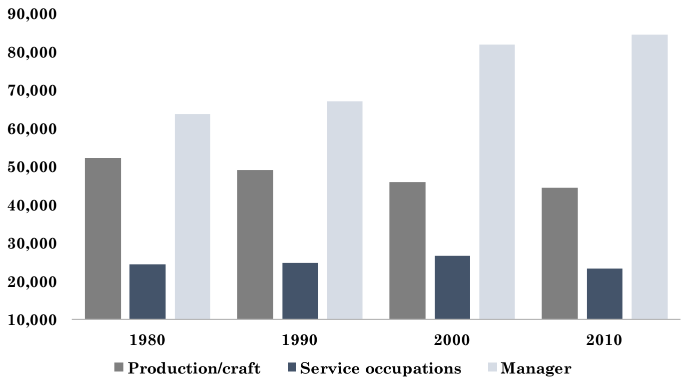
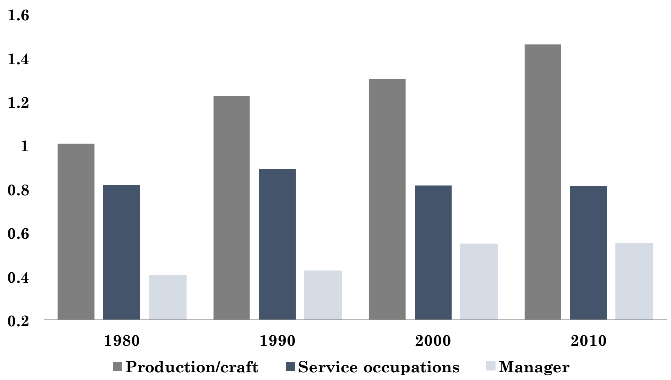
Figure 1

(a) Mean Annual Wage by Occupation and Year



(b) Mean Routine Intensity by Occupation and Year



(c) Mean Employment Share by Occupation and Year

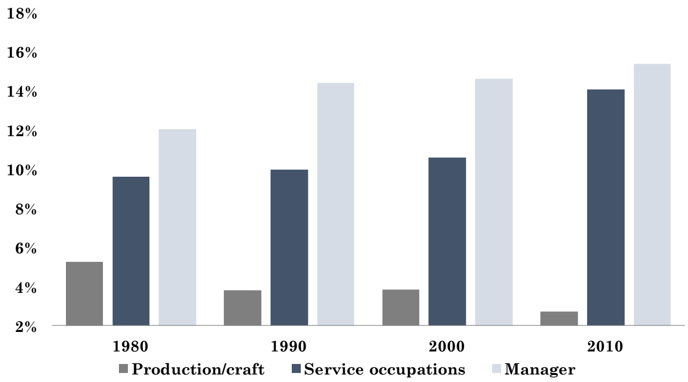


Table 1: Summary statistics of establishment-level variables

This table reports the mean and standard deviation of key variables from the Occupational Employment Statistics (OES) survey conducted by Bureau of Labor Statistics. Each observation is measured at the establishment-level. All variable definitions are provided in Appendix A2.

				Before M&A					
	All Establishments			Establishments without M&A			Establishments with M&A		
	N	Mean	Std. Dev.	N	Mean	Std. Dev.	N	Mean	Std. Dev.
Routine employment	341	59.80	142.8	225	36.82	73.15	116	104.4	216.4
High-skill employment	341	18.91	83.90	225	13.21	67.14	116	11.05	47.97
Total employment	341	135.3	301.1	225	85.76	173.1	116	231.3	442.3
Routine employment share (RSH)	341	0.452	0.314	225	0.452	0.313	116	0.452	0.316
High-skill employment share	341	0.076	0.161	225	0.071	0.158	116	0.070	0.177
Offshorability	341	0.418	0.680	225	0.426	0.696	116	0.402	0.650
Median hourly wage ($)	341	14.50	6.878	225	14.06	6.388	116	15.36	7.698
Wages_90th/10th(logged)	341	0.950	0.446	225	0.958	0.466	116	0.935	0.406
Standard deviation of hourly income	335	8.481	5.038	220	8.345	5.096	115	8.740	4.937

Table 2: Effects of M&A on establishment RSH

This table presents estimates of routine employment share changes at establishments of M&A targets as compared to control establishments. The dependent variable is the logarithm of routine share intensity (RSH) defined at the establishment-level. The sample consists of establishments of firms targeted in M&As between 2001 and 2007 and those of matched control establishments. All variables are defined in Appendix A2. Robust standard errors are clustered at the establishment-level. *** indicates $p < 0.01$, ** indicates $p < 0.05$, and * indicates $p < 0.1$.

	(1)	(2)	(3)	(4)	(5)
	lg(RSH)	lg(RSH)	lg(RSH)	lg(RSH)	lg(RSH)
$Post_t \cdot M\&A_i$	-0.041	-0.033	-0.049	-0.048	-0.042
	(0.018)**	(0.017)*	(0.025)*	(0.019)**	(0.020)**
Offshorability	0.114	0.104	0.113	0.119	0.108
	(0.022)***	(0.024)***	(0.025)***	(0.021)***	(0.024)***
Year FE	Yes				
Establishment FE	Yes	Yes	Yes	Yes	Yes
Industry*Year FE		Yes			Yes
State*Year FE			Yes		
Region*Year FE				Yes	Yes
Observations	682	636	546	670	626
R-squared	0.87	0.92	0.91	0.90	0.93

Table 3: Effects of M&A on establishment high-skill employment

This table presents estimates of high-skill employment share changes at establishments of M&A targets as compared to control establishments. The dependent variable is the share of high-skill employment defined at the establishment-level. The sample consists of establishments of firms targeted in M&As between 2001 and 2007 and those of matched control establishments. All variables are defined in Appendix A2. Robust standard errors are clustered at the establishment-level. *** indicates $p < 0.01$, ** indicates $p < 0.05$, and * indicates $p < 0.1$.

	(1)	(2)	(3)	(4)	(5)
	High-skill share	High-skill share	High-skill share	High-skill share	High-skill share
$Post_t \cdot M\&A_i$	0.024	0.021	0.046	0.034	0.034
	(0.015)	(0.014)	(0.021)**	(0.015)**	(0.014)**
Offshorability	0.055	0.047	0.073	0.058	0.047
	(0.022)**	(0.018)***	(0.031)**	(0.022)***	(0.019)**
Year FE	Yes				
Establishment FE	Yes	Yes	Yes	Yes	Yes
Industry*Year FE		Yes			Yes
State*Year FE			Yes		
Region*Year FE				Yes	Yes
Observations	682	636	546	670	626
R-squared	0.88	0.92	0.91	0.89	0.93

Table 4: Effects of M&A on establishment median wages

This table presents estimates of median wage changes at establishments of M&A targets as compared to control establishments. The dependent variable is the log-transformed median hourly wage at the establishment-level. The sample consists of establishments of firms targeted in M&As between 2001 and 2007 and those of matched control establishments. All variables are defined in Appendix A2. Robust standard errors are clustered at the establishment-level. *** indicates $p < 0.01$, ** indicates $p < 0.05$, and * indicates $p < 0.1$.

	(1)	(2)	(3)	(4)	(5)
	lgWages	lgWages	lgWages	lgWages	lgWages
$Post_t \cdot M\&A_i$	0.081	0.071	0.083	0.100	0.092
	(0.036)**	(0.037)*	(0.047)*	(0.035)***	(0.039)**
Offshorability	0.017	-0.002	0.001	0.012	-0.013
	(0.040)	(0.047)	(0.047)	(0.038)	(0.044)
Year FE	Yes				
Establishment FE	Yes	Yes	Yes	Yes	Yes
Industry*Year FE		Yes			Yes
State*Year FE			Yes		
Region*Year FE				Yes	Yes
Observations	682	636	546	670	626
R-squared	0.87	0.92	0.92	0.90	0.93

Table 5: Effects of M&A on establishment wage dispersion

This table presents estimates of standard deviation of hourly wage changes at establishments of M&A targets as compared to control establishments in Panel A, and estimates of wage percentile ratio changes at establishments of M&A targets as compared to control establishments in Panel B. In Panel A, the dependent variable is the log-transformed standard deviation of hourly wages at the establishment-level. In Panel B, the dependent variable is the log-transformed ratio of the 90^{th} percentile of wages to the 10^{th} percentile of wages at the establishment-level. The sample consists of establishments of firms targeted in M&As between 2001 and 2007 and those of matched control establishments. All variables are defined in Appendix A2. Robust standard errors are clustered at the establishment-level. *** indicates $p < 0.01$, ** indicates $p < 0.05$, and * indicates $p < 0.1$.

Panel A					
	(1)	(2)	(3)	(4)	(5)
	lg_StdWages	lg_StdWages	lg_StdWages	lg_StdWages	lg_StdWages
$Post_t \cdot M\&A_i$	0.886	0.920	1.059	0.982	1.400
	(0.545)	(0.584)	(0.941)	(0.581)*	(0.667)**
Offshorability	0.731	0.872	0.997	1.076*	0.859
	(0.607)	(0.693)	(0.900)	(0.602)	(0.787)
Year FE	Yes				
Establishment FE	Yes	Yes	Yes	Yes	Yes
Industry*Year FE		Yes			Yes
State*Year FE			Yes		
Region*Year FE				Yes	Yes
Observations	664	616	532	654	606
R-squared	0.81	0.86	0.86	0.83	0.87

Panel B					
	(1)	(2)	(3)	(4)	(5)
	Wages_90th/10th	Wages_90th/10th	Wages_90th/10th	Wages_90th/10th	Wages_90th/10th
$Post_t \cdot M\&A_i$	0.105	0.127	0.132	0.129	0.159
	(0.049)**	(0.049)**	(0.071)*	(0.050)***	(0.053)***
Offshorability	0.091	0.071	0.161	0.120	0.099
	(0.053)*	(0.054)	(0.071)**	(0.053)**	(0.063)
Year FE	Yes				
Establishment FE	Yes	Yes	Yes	Yes	Yes
Industry*Year FE		Yes			Yes
State*Year FE			Yes		
Region*Year FE				Yes	Yes
Observations	682	636	546	670	626
R-squared	0.77	0.84	0.85	0.81	0.86

Table 6: Summary statistics of industry 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. Each observation is an industry-year, measured once per decade, with the exception of merger intensity, which is measured over years t-10 to t-1. All variable definitions are provided in Appendix A2.

	1980	1990	2000	2010
Merger intensity_ind (%)		0.46%	0.54%	0.65%
		[.0075]	[.0087]	[.0132]
Routine employment share (RSH) (%)	34.75%	32.75%	33.28%	33.82%
	[.164]	[.1562]	[.1548]	[.161]
Offshorability	0.12	0.12	0.13	0.16
	[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]
Hourly wage 90th/10th percentile ratio ($)	1.31	1.37	1.40	1.50
	[.2131]	[.147]	[.1705]	[.2009]
Median hourly income ($)	17.85	17.61	18.18	18.55
	[4.4235]	[4.4258]	[[4.5684]]	[5.5824]
Standard deviation of hourly income	13.6387	15.682	20.2701	18.3593
	[2.4344]	[3.7138]	[5.121]	[5.8441]

Table 7: Past merger activity and employment share

The dependent variable in columns 1 and 2 is lg(RSH), the log-transformed share of routine employment. The dependent variable in columns 3-4 is the percent of employees with graduate degrees (5+ years of post-secondary education). 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)
	lg(RSH)	lg(RSH)	Share(%)	Share(%)
Merger Intensity_ind	-2.820	-2.691	0.975	0.682
	(0.866)***	(0.833)***	(0.241)***	(0.246)***
Offshorability	0.365	0.392	0.012	0.016
	(0.313)	(0.300)	(0.023)	(0.021)
Year FE	Yes		Yes	
Industry FE	Yes	Yes	Yes	Yes
Year FE*dependent80		Yes		Yes
Observations	396	396	396	396
R-squared	0.96	0.96	0.97	0.97

Table 8: Past merger activity and wages

The dependent variable in columns 1 and 2 is lgWages, the median hourly wage (log-transformed). The dependent variable in columns 3 and 4 is lgStdWages, the log-transformed standard deviation of hourly wage. The dependent variables in columns 5-7 are the 90^{th} percentile of wages (log transformed), the 10^{th} percentile of wages (log transformed), and the ratio of the 90^{th} percentile of wages to the 10^{th} percentile of wages respectively. 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)
	lgWages	lgWages	lgStdWages	lgStdWages	lgWages90th	lgWages10th	Wages90th/10th
Merger Intensity_ind	3.152	3.046	2.124	1.457	2.516	2.285	0.231
	(0.836)***	(0.808)***	(1.237)*	(1.313)	(1.184)**	(0.449)***	(1.222)
Offshorability	-0.053	-0.052	0.007	0.005	0.033	-0.052	0.085
	(0.074)	(0.074)	(0.152)	(0.136)	(0.092)	(0.068)	(0.074)
Year FE	Yes		Yes		Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE*dependent80		Yes		Yes			
Observations	396	396	396	396	396	396	396
R-squared	0.97	0.97	0.88	0.93	0.94	0.97	0.88

Table 9: The relation between past merger activity, past routine share intensity and wage dispersion

The dependent variable in columns 1 is the log of the ratio of the 90^{th} percentile of the wage distribution to the 10^{th} percentile of the wage distribution, using hourly wages. The dependent variable in columns 2 is the log of the ratio of the 90^{th} percentile of the wage distribution to the 50^{th} percentile of the wage distribution, using hourly wages. The dependent variable in columns 3 is the log of the ratio of the 75^{th} percentile of the wage distribution to the 25^{th} percentile of the wage distribution, using hourly wages. 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)
	Wages90th/10th	Wages90th/50th	Wages75th/25th
Merger Intensity_ind	7.145	3.258	3.393
	(4.117)*	(2.506)	(2.340)
Merger Intensity_ind×lg(RSH)_t-1	4.876	2.627	2.402
	(2.394)**	(1.475)*	(1.351)*
lg(RSH)_t-1	-0.132	-0.039	-0.059
	(0.057)**	(0.038)	(0.041)
Offshorability	0.089	0.090	0.064
	(0.083)	(0.058)	(0.055)
Year FE	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes
Observations	396	396	396
R-squared	0.89	0.90	0.86

Table 10: Robustness: Technological and regulatory shocks

The dependent variable in column 1 is lg(RSH). The dependent variable in column 2 is the share (%) of workers with graduate degrees (5+ 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 $p < 0.1$.

	(1)	(2)	(3)	(4)
	lg(RSH)	Share (%)	lgWages	lg_StdWages
Merger Intensity_ind	-2.805	0.978	3.105	2.031
	(0.876)***	(0.243)***	(0.813)***	(1.184)*
Offshorability	0.347	0.014	-0.005	0.012
	(0.316)	(0.023)	(0.08)	(0.155)
Industry shock	-0.019	0.002	-0.007	-0.012
	(0.019)	(0.003)	(0.0094)	(0.0181)
Deregulation shock	0.077	-0.003	-0.014	-0.086
	(0.044)*	(0.013)	(0.029)	(0.0638)
Year FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Observations	396	396	396	396

Table 11: Robustness: Time-series results

The dependent variable in column 1 is lg(RSH). The dependent variable in column 2 is the share (%) of workers with graduate degrees (5+ 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 1950 and ends in 2010 with one observation per decade for each industry. *Merger intensity_ind* is constructed using companies' delisting data from CRSP. 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)
	lg(RSH)	Share (%)	lgWages	lg_StdWages
Merger Intensity_ind	-0.237	-0.180	-0.340	-0.802
	(1.345)	(0.182)	(0.596)	(0.717)
Offshorability	0.230**	0.006	0. 005	0.074
	(0.0972)	(0.00667)	(0.0418)	(0.0511)
Merger Intensity_ind*Post1980	-5.081*	1.011*	3.045	3.683*
	(2.789)	(0.552)	(2.011)	(2.203)
Post1980	0.267***	0.0450***	0.474***	0.865***
	(0.0671)	(0.00641)	(0.0280)	(0.0376)
Year FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Observations	532	532	532	532
R-squared	0.85	0.94	0.91	0.90

Table 12: Robustness: Failed M&A deals

The dependent variable in column 1 is lg(RSH). The dependent variable in column 2 is the share (%) of workers with graduate degrees (5+ 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. Merger Intensity_W_ind is the M&A meaasure based on withdrawn deals. 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)
	lg(RSH)	Share (%)	lgWages	lg_StdWages
Merger Intensity_ind	-2.755	1.030	3.659	1.799
	(0.943)***	(0.270)***	(0.943)***	(1.322)
Merger Intensity_W_ind	-0.080	-0.068	-0.632	0.404
	(0.766)	(0.159)	(0.532)	(0.596)
Offshorability	0.364	0.012	-0.059	0.011
	(0.316)	(0.0225)	(0.073)	(0.154)
Year FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Observations	396	396	396	396
R-squared	0.956	0.965	0.965	0.884

Table 13: 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 graduate degrees (5+ 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	-2.698	0.900	3.046	1.713
	(0.699) ***	(0.200)***	(0.696)***	(0.903)*
Merger Intensity_ind * Median industry firm size high	-2.639	0.637	2.321	3.157
	(1.278)**	(0.208)***	(0.781)***	(1.240)**
Median industry firm size high	0.00893	-0.00059	0.0069	-0.0107
	(0.0377)	(0.00551)	(0.0177)	(0.0325)
Offshorability	0.283	0.0054	-0.110	-0.0202
	(0.372)	(0.0279)	(0.0756)	(0.188)
Year FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Observations	346	346	346	346
R-squared	0.962	0.97	0.97	0.89

Panel B				
	(1)	(2)	(3)	(4)
	lg(RSH)	Share (%)	lgWages	lg_StdWages
Merger Intensity_ind	-2.101	0.390	1.525	-0.786
	(2.079)	(0.205)*	(0.836)*	(1.512)
Merger Intensity_ind * Credit_spread high	-0.749	0.628	1.736	3.083
	(1.780)	(0.222)***	(0.750)**	(1.308)**
Credit_spread high	0.0089	0.00022	-0.0036	-0.0161
	(0.0237)	(0.00330)	(0.0119)	(0.0215)
Offshorability	0.368	0.0108	-0.058	-0.0035
	(0.315)	(0.0221)	(0.073)	(0.151)
Year FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Observations	396	396	396	396
R-squared	0.96	0.97	0.96	0.89

Panel C				
	(1)	(2)	(3)	(4)
	lg(RSH)	Share (%)	lgWages	lg_StdWages
Merger Intensity_ind	-2.157	-0.061	0.014	-3.985
	(3.671)	(0.475)	(1.689)	(2.211)*
Merger Intensity_ind * Acquirer industry profitability variance	-0.0074	0.0090	0.0285	0.0525
	(0.0296)	(0.00416)**	(0.0138)**	(0.0177)***
Acquirer industry profitability variance	1.73e-05	0.00011	0.0002	0.00034
	(0.000254)	(5.57e-05)**	(0.00019)	(0.000290)
Offshorability	0.39	0.0193	-0.090	-0.0151
	(0.266)	(0.0207)	(0.0996)	(0.161)
Year FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Observations	302	302	302	302
R-squared	0.97	0.97	0.97	0.90

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.[23] 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

[23] 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.[24] 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.[25] 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$\times$labor supply weight$\times$the probability that a resident of PUMA j lives in CZONE k in Census year t.[26]

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

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

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

Appendix A2. Variable Definitions

OES Dataset for Establishment-level Analysis

$M\&A_i$ is an indicator equal to one if the establishment belongs to a firm acquired in an M&A and zero otherwise.

$Post_t$ is an indicator equal to one in the period following the M&A and zero otherwise.

Routine employment share (RSH) measures the employment share of routine occupations in an establishment. It is defined as the total employment of routine occupations in establishment i and year t divided by the total employment in the same establishment-year. We define occupations as routine following Autor and Dorn (2013) and merge their data to OES data by SOC codes. The routine occupation data are available at: http://economics.mit.edu/faculty/dautor/data/autor-dorn-p.

Median hourly wage is the median hourly wage in each establishment and year. OES data reports twelve hourly wage bins for each occupation and employment in each wage bin-occupation. We take the average of the lower and upper bounds of each wage bin to proxy for hourly wage of workers in that wage bin. Then we take employment-weighted median of hourly wages of all workers in the establishment as a proxy of establishment-level hourly wages.

Standard deviation of hourly wage is the employment-weighted standard deviation of hourly wages in each establishment and year.

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

High-skill workers labor share (Share %) is defined as the employment share of high skill workers in each establishment and year. Following Hecker (2005), high skill occupations include the following occupational groups and detailed occupations: computer and mathematical scientists, Standard Occupational Classification (SOC) 15-0000; engineers, SOC 17-2000; drafters, engineering, and mapping technicians, SOC 17-3000; life scientists, SOC 19-1000; physical scientists, SOC 19-2000; life, physical, and social science technicians, SOC 19-4000; computer and information systems managers, SOC 11-3020; engineering managers, SOC 11-9040; and natural sciences managers, SOC 11-9120. See more details at https://labor.ny.gov/stats/cap/hightech.pdf

Offshorability captures the degree to which the tasks performed by occupations in an establishment 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 OES data using SOC occupation codes.

IPUMs Dataset for Industry-level and Industry-Commuting Zone-level Analysis

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 (4-digit NAICS) industry-decade normalized by all horizontal deals in the decade. In our baseline, this variable is constructed using merger and acquisition data from SDC platinum. In Table 11, this variable is constructed using companies' delisting data from CRSP.

Merger intensity_ind_cz captures the intensity of M&A activities in an industry-commuting zone-decade. It is the logarithm of one plus the count of horizontal deals in a given (4-digit NAICS) industry-commuting zone-decade normalized by all horizontal deals in the decade. This variable is constructed using merger and acquisition data from SDC platinum.

Merger intensity_V_ind captures the intensity of M&A activities in an industry-decade. It is the logarithm of one plus the total transaction values of horizontal deals in a given

(4-digit NAICS) industry-decade normalized by total transaction values of all horizontal deals in the decade.

Merger intensity_V_ind_cz captures the intensity of M&A activities in an industry-commuting zone-decade. It is the logarithm of one plus the total transaction values of horizontal deals in a given (4-digit NAICS) industry-commuting zone-decade normalized by total transaction values of all horizontal deals in the decade.

Merger intensity_W_ind captures the intensity of withdrawn M&A activity in an industry-decade. It is the logarithm of one plus the count of failed horizontal deals in a given (4-digit NAICS) industry-decade normalized by of all failed horizontal deals in the decade.

Routine employment share (RSH) measures the employment share of routine occupations in an industry-year or an industry-commuting zone-year. It is defined as the total employment of routine occupation in industry (industry-commuting zone) j and year t divided by the total employment in the same industry-year (industry-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

High-skill workers labor share (Share %) is defined as the employment share of high skill workers in each industry (industry-commuting zone) and year. Those are workers with graduate degrees (5+ years of post-secondary education).

Offshorability captures the degree to which the tasks performed by an industry (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.

Median hourly wage is the median hourly wage in each industry (industry-commuting zone) and year. It is employment-weighted median of hourly wages of workers in that industry (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 (industry-commuting zone) and year.

lg_Wage90th is the logarithm of the hourly wage at 90th percentile of the industry (industry-commuting zone) hourly wage distribution.

lg_Wage10th is the logarithm of the hourly wage at 10th percentile of the industry (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 (industry-commuting zone) hourly wage distribution (log-transformed).

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.

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

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

Post1980 equals to 1 for decades after 1980.

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)

Table A2: Robustness: Alternative definition of employment share

The dependent variable in column 1 is Δlg(RSH). The dependent variable in columns 2-3 is lg(RSH). We define routine occupations to be the set of occupations that are in the top employment-weighted third of routine task-intensity every Census year. All variables are defined at the industry-level. 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)
	Δlg(RSH)	lg(RSH)	lg(RSH)
Merger Intensity_ind	-1.539	-2.586	-2.521
	(0.504)***	(1.216)**	(1.195)**
Offshorability	0.0012	0.668	0.677
	(0.0328)	(0.119)***	(0.114)***
Year FE	Yes	Yes	
Industry FE		Yes	Yes
Year FE*dependent80			Yes
Observations	396	396	396
R-squared	0.01	0.95	0.95

Table A3: Robustness: Defining M&A counts using first six years of each decade

The dependent variable in column 1 is lg(RSH). The dependent variable in column 2 is the percent of employees with graduate degrees (5+ 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 variables are defined at the industry-level. M&A intensity is based on M&A counts over the first six years of each decade. 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)
	lg(RSH)	Share(%)	lgWages	lg_StdWages
Merger Intensity_ind	-3.943	1.169	3.760	2.510
	(0.989)***	(0.249)***	(0.754)***	(1.115)**
Offshorability	0.370	0.0108	-0.0582	0.00407
	(0.310)	(0.0232)	(0.0742)	(0.153)
Year FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Observations	396	396	396	396
R-squared	0.96	0.97	0.97	0.88

Table A4: Robustness: Defining M&A intensity using transaction values

The dependent variable in column 1 is lg(RSH). The dependent variable in column 2 is the percent of employees with graduate degrees (5+ 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 variables are defined at the industry-level. M&A intensity is based on M&A transaction values. 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)
	lg(RSH)	Share(%)	lgWages	lg_StdWages
Merger Intensity_V_ind	-0.985	0.369	1.091	1.407
	(0.622)	(0.147)**	(0.606)*	(0.406)**
Offshorability	0.364	0.0127	-0.0523	0.0098
	(0.316)	(0.0223)	(0.0754)	(0.151)
Year FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Observations	396	396	396	396
R-squared	0.96	0.97	0.96	0.88

Table A5: Robustness: Alternative definition of high-skill workers

The dependent variable in column 1 is ΔShare, the change in the percent of employees with college degrees (4+ years of post-secondary) education. The dependent variable in columns 2-3 is share (%), the percent of employees with college degrees (4+ years of post-secondary education). All variables are defined at the industry-level. 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)
	ΔShare	Share(%)	Share(%)
Merger Intensity_ind	0.744	0.988	0.757
	(0.190)***	(0.438)**	(0.486)
Offshorability	0.0261	0.0409	0.0446
	(0.00581)***	(0.0444)	(0.0450)
Year FE	Yes	Yes	
Industry FE		Yes	Yes
Year FE*dependent80			Yes
Observations	396	396	396
R-squared	0.08	0.16	0.97

Table A6: Industry-commuting-zone sample: Summary statistics

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-commuting-zone sample. Each observation is an industry-commuting-zone-year, measured once per decade, with the exception of merger intensity, which is measured over years t-10 to t-1. All variable definitions are provided in Appendix A2.

	1980	1990	2000	2010
Merger Intensity__cz__ind (%)		0.01%	0.01%	0.01%
		[.0004]	[.0003]	[.0004]
Routine employment share (RSH) (%)	39.36%	37.45%	37.75%	38.64%
	[.2288]	[.2201]	[.2174]	[.2915]
Offshorability	0.22	0.21	0.21	0.25
	[0.5054]	[0.507]	[0.5116]	[0.6478]
College workers labor share(%)	16.38%	20.05%	23.87%	28.22%
	[.1487]	[.16]	[.1811]	[.2576]
Graduate workers labor share (%)	6.10%	5.03%	6.41%	7.89%
	[.09]	[.0777]	[.0898]	[.1405]
Hourly wage at 90 percentile ($)	32.16	33.14	36.51	38.29
	[11.264]	[12.6052]	[16.4058]	[23.9007]
Hourly wage at 10 percentile ($)	9.46	9.13	9.61	11.26
	[3.7998]	[3.36]	[3.3949]	[7.3175]
Hourly wage 90th/10th percentile ratio ($)	1.44	1.46	1.53	1.31
	[.4219]	[.3851]	[.4263]	[.6586]
Median hourly income ($)	17.31	17.04	17.96	19.58
	[5.4893]	[5.3196]	[[6.2594]]	[10.1262]
Standard deviation of hourly income	11.9466	12.9870	16.7542	14.2704
	[6.1721]	[7.0918]	[10.5449]	[11.252]

Table A7: Industry-commuting-zone sample: Past merger activity and employment share

The dependent variable in columns 1 and 2 is lg(RSH), the log-transformed share of routine employment. The dependent variable in columns 3-4 is the percent of employees with graduate degrees (5+ years of post-secondary education). The timeline starts in 1980 and ends in 2010 with one observation per decade for each industry-commuting-zone. All variables are defined in Appendix A2. Robust standard errors are double clustered at the industry and commuting-zone-level. *** indicates $p < 0.01$, ** indicates $p < 0.05$, and * indicates $p < 0.1$.

	(1)	(2)	(3)	(4)
	lg(RSH)	lg(RSH)	Share(%)	Share(%)
Merger Intensity_cz_ind	-2.982	-2.737	5.729	5.058
	(1.407)**	(1.405)*	(1.709)***	(1.663)***
Offshorability	0.097	0.094	0.027	0.023
	(0.0109)***	(0.0106)***	(0.008)***	(0.007)***
Year FE × Industry FE	Yes	Yes	Yes	Yes
Year FE × CZone FE	Yes	Yes	Yes	Yes
Year FE × dependent80		Yes		Yes
Observations	35,757	35,757	35,757	35,757
R-squared	0.91	0.91	0.90	0.91

Table A8: Industry-commuting-zone sample: Past merger activity and wages

The dependent variable in columns 1 and 2 is lgWages, the median hourly wage (log-transformed). The dependent variable in columns 3 and 4 is lgStdWages, the log-transformed standard deviation of hourly wage. The dependent variables in columns 5-7 are the 90^{th} percentile of wages (log transformed), the 10^{th} percentile of wages (log transformed), and the ratio of the 90^{th} percentile of wages to the 10^{th} percentile of wages respectively. The timeline starts in 1980 and ends in 2010 with one observation per decade for each industry-commuting-zone. All variables are defined in Appendix A2. Robust standard errors are double clustered at the industry and commuting-zone-level. *** indicates $p < 0.01$, ** indicates $p < 0.05$, and * indicates $p < 0.1$.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	lgWages	lgWages	lgStdWages	lgStdWages	lgWages90th	lgWages10th	Wages90th/10th
Merger Intensity_cz_ind	17.75	16.43	15.53	14.95	25.18	15.58	9.60
	(3.658)***	(3.226)***	(2.526)***	(2.533)***	(2.247)***	(2.743)***	(2.126)***
Offshorability	0.023	0.027	0.0938	0.0881	0.074	0.027	0.047
	(0.01)**	(0.009)***	(0.0264)***	(0.0256)***	(0.026)***	(0.016)*	(0.022)**
Year FE *Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE × CZone FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE × dependent80		Yes		Yes			Yes
Observations	35,757	35,757	34,944	34,722	35,757	35,757	35,757
R-squared	0.84	0.86	0.62	0.63	0.74	0.78	0.52