Mergers and Acquisitions, Technological Change and Inequality

Finance Working Paper N° 485/2016

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Wenting Ma
University of Massachusetts Amherst

Paige Ouimet
University of North Carolina at Chapel Hill

Elena Simintzi
University of North Carolina and CEPR

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Abstract

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Keywords: M&A, Occupational Change, Technological Change, Wage Inequality

JEL Classifications: G34, J24, J31, O33

Wenting Ma*
Assistant Professor of Management
Isenberg School of Management, University of Massachusetts Amherst
121 Presidents Dr., 310D
Amherst, MA, 01002, United States
phone: + 1 704 840 2500
e-mail: wma7@isenberg.umass.edu

Paige Ouimet
Associate Professor of Finance
University of North Carolina at Chapel Hill, Kenan-Flagler Business School
McColl 4209
Chapel Hill, NC 27599-3490, United States
phone: +1 919 962 9148
e-mail: paige_ouimet@unc.edu

Elena Simintzi
Associate Professor in Finance
University of North Carolina, Kenan-Flagler Business School
McColl 4112, CB 3490
Chapel Hill, NC 27599-3490, United States
phone: +1 919 962 8992
e-mail: elena_simintzi@kenan-flagler.unc.edu

*Corresponding Author

Mergers and Acquisitions, Technological Change, and Inequality*

Wenting Ma† Paige Ouimet‡ Elena Simintzi§

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Abstract

Mergers and acquisitions (M&As) are an important mechanism through which technology is adopted by firms. We document patterns of labor reallocation and wage changes following M&As, consistent with the adoption of technology. Specifically, we show target establishments invest more in technology, become less routine task intensive, employ a greater share of high-technology workers, and pay more unequal wages. We document evidence for three non-mutually exclusive mechanisms underlying this effect: differences in the ability to integrate technology efficiently; financial constraints, and agency conflicts. Moreover, the within-establishment patterns generalize to the industry-level, confirming the external validity of our findings.

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†University of Massachusetts at Amherst. Email: wentingma@umass.edu.

‡University of North Carolina at Chapel Hill. Email: paige_ouimet@unc.edu.

§University of North Carolina at Chapel Hill and CEPR. Email: elena_simintzi@kenan-flagler.unc.edu.

1 Introduction

Several studies on mergers and acquisitions (M&As) have documented important labor reallocation effects, both in terms of employment (Kaplan, 1989; McGuckin and Nguyen, 2001; Dessaint, Golubov and Volpin, 2015; John, Knyazeva and Knyazeva, 2015) and wages (Rosett, 1990; Pontiff, Shleifer and Weisbach, 1990; Babenko, Du and Tserlukevich, 2020; He and le Maire, 2021). These changes are possible because new owners can break implicit contracts with employees associated with wage and employment expectations (Shleifer and Summers, 1988) and because acquirers may be motivated to target firms with over-employment, subsequently raising shareholder value through post-merger layoffs (Shleifer and Vishny, 1988). This paper documents a novel channel through which labor reallocation takes place: Following successful M&As, target firms, on average, adopt more technology, and this greater reliance on technology has implications for target employees. M&As facilitate technology adoption, both by alleviating frictions that discourage firms from adopting available technologies and by potentially increasing the cost-effectiveness of technology adoption.

We derive predictions of the ex-post M&A effects of higher technology adoption on target firm employment and wages based on two well-documented facts. First, technology tends to replace workers performing routine tasks, those that are repetitive in nature. Second, technology is complementary to high-skill employees, increasing their productivity and thus demand for their labor. These changes in labor market composition have a counterpart in wages, with income inequality rising as routine-intensive occupations, which are overrepresented in the middle of the income distribution, are more likely to be displaced and high-skill occupations achieve greater productivity as a result of technology adoption.[1]

To provide evidence of changes in employment and wage distributions following M&As, we use data provided by the Occupational Employment and Wage Statistics program (OEWS), administered by the Bureau of Labor Statistics (BLS). This unique source of data for U.S. establishments contains detailed information on occupational employment and wages. We focus on 5,014 target establishments associated with 1,740 horizontal M&A events covered by the OEWS spanning 2001-2017. We form a control sample of matched establishments in terms of industry, year of observation in the survey, and pre-treatment establishment size.

We find that target establishments become less routine task intensive post M&A, compared to the matched non-M&A establishments. The decline in routine task intensity, by 3.4% relative to the mean for the average treated establishment post-M&A, is economically important. This finding is consistent with technological adoption disproportionately displacing workers performing routine, easily codifiable tasks, a process often referred to as "routine-biased technological change."

We also find that target establishments employ a larger share of high-technology workers following M&As, consistent with the fact that technology is complementary to high-skill employment, a process often referred to as "skill-biased technological change." The occupational share of high-technology jobs increases, on average, by 16% relative to the mean, which can be explained by technology changing the nature of jobs in the firm,

[1]See, for example, Katz and Autor, 1999; Goldin and Katz, 2008, 2009; Acemoglu and Autor, 2011; Autor, Levy, and Murnane, 2003; Autor and Dorn, 2013; and Goos, Manning, and Salomons, 2014.

favoring workers whose skills are complementary to technology. This shift toward high-technology workers is driven by higher levels of employment at engineering-related occupations in target establishments post M&A.

The fact that the typical M&A establishment becomes less routine intensive and employs more high-technology workers parallels changes observed in the economy as a whole over the past four decades which have been attributed to the rising use of automation. These economy-wide occupational changes, including a reduction in the growth of mid-skill employment and an increase in the demand for high-skill employees, have been linked to rising wage inequality. To this end, we also examine whether similar patterns are observed in establishment wages following post-M&A labor reallocation.

We find that mean wages increase following M&As, likely driven by a greater relative demand for high-technology employment. On average, we find a 1.3% increase in the mean wage at treated establishments post M&A, as compared to matched control establishments. Most importantly, we find M&As are associated with more unequal pay, consistent with the observed occupational shift away from routine occupations, typically mid-skill, and toward high-technology occupations, typically high-skill. In economic terms, the standard deviation in wages increases by 4% for the average target establishment, relative to a similar control establishment. Likewise, the wage ratio between the 90^{th} and 10^{th} percentiles increases by 2.9% for treated establishments, relative to controls.

Although the occupational changes we document in target establishments post M&A mirror the aggregate labor market trends attributed to technology, we also directly validate the technology channel. Using establishment-level data on information technology (IT) investment from the Ci Technology Database (CiTDB), we show that investment in

IT increases at target establishments compared to control establishments. Specifically, we find a relative increase of 6% in IT budgets at treated establishments post M&A.

We explore three non-mutually exclusive mechanisms to explain why M&As encourage greater technology adoption. First, some acquiring firms may be able to implement technology more efficiently, due to the presence of complementary assets or institutional knowledge (Gort, 1969). To the extent that the resources of tech-savvy acquirers alleviate frictions to the adoption of technology, we would expect to see relatively greater ex-post changes following deals made by these acquirers. We proxy for tech-savvy acquirers with acquirer ex-ante IT spending and explore cross-sectional patterns. Indeed, we find greater automation at the target, as proxied by investment in IT, when the acquirer had higher ex-ante IT spending.

The second potential mechanism involves financial constraints at the target. Given technology is typically associated with higher fixed but lower operating costs, as compared to employing labor to complete the same tasks, financially constrained targets may be unable to invest in all cost-effective technology. To the extent that the M&A resolves these constraints, we should then expect investment in technology to increase. Indeed, when proxying for financially constrained targets using firm size, we document greater increases in IT following M&As at financially constrained targets.

Finally, M&As may alleviate frictions to adopting cost-effective technology due to agency conflicts. For example, entrenched managers may be reluctant to adopt cost-effective technology if doing so would displace employees and, thus, require the manager to fire workers (Bertrand and Mullainathan, 2003). We identify M&A deals likely to address agency frictions at the target using unsolicited bids, and find greater increases in

IT following an unsolicited deal in support for an agency channel.

Irrespective of whether M&As were explicitly motivated with the objective to adopt labor-saving technology or whether ex-post technology adoption was orthogonal to the drivers of M&As, it is important to rule out the possibility that an omitted variable, such as industry or technology shocks (Harford, 2005), may lead to both M&As and changes in labor demand. We present several results that argue against such an interpretation.

First, in our baseline analysis, we use a matched sample of establishments to control for trends at similar firms. In our specifications, we control for time-invariant establishment characteristics by including establishment fixed effects, time-varying industry characteristics by including interacted industry and year fixed effects, and time-varying local characteristics by including interacted state and year fixed effects. Second, we document no significant pre-treatment trends prior to the M&A, providing support for the validity of a parallel trends assumption.

Third, we consider a sample of M&As that were cancelled due to reasons exogenous to labor demand. Specifically, we look at deals that were cancelled either because of regulatory intervention or due to the bidder being acquired by a third party following the acquisition announcement. In these cases, any omitted variable correlated with our sample of completed M&A deals should also be present in these deals, and, if the omitted variable drives our results, we should find similar effects in this sample. We follow the same matching procedure used for our baseline analysis and create a control sample of matched establishments. We repeat our analysis using the set of the cancelled M&A targets ('pseudo-treated') and the matched set of non-M&A establishments (controls). We cannot replicate the same pattern of results in our baseline analysis; if anything, the estimated coefficients are either zero or show the opposite sign.

Fourth, we present estimations *within* establishments, alleviating concerns that time-varying differences between treated and control establishments drive our findings. This analysis allows us to control for interacted establishment and year fixed effects absorbing any time-varying shocks at the establishment level that may be correlated with changes in establishment labor demand. To this end, we examine whether there are differential effects on employment shares and wages of a given occupational subgroup within a given establishment-year following the M&A, relative to the control group. Consistent with technology adoption disproportionately displacing employees performing routine tasks, we find a relatively greater reduction in demand for those employees performing routine tasks within the establishment (in terms of both employment and wages), relative to their peers in non-routine occupations. Consistent with the notion that technology is complementary to high-skill workers, we observe a relatively greater increase in employment of high-technology workers along with higher wage gains, relative to their peers in non-high-technology occupations.

Finally, we provide external validity to our findings by showing that the labor market changes we identify at M&A targets can be generalized at the industry level. We present industry-wide correlations, using data from the Integrated Public Use Microdata Service (IPUMS), that replicate the same patterns as in our establishment-level analysis: routine task intensity decreases within industries when past M&A activity increases, and, at the same time, industries become more high-skill intensive. Moreover, these shifts in the nature of occupations following M&As have implications for industry inequality. We find that high M&A activity within industries is related to higher average wages and higher wage disparity.

Our paper contributes to the finance literature on the labor outcomes of M&As. Shleifer and Summers (1988) argue that a new owner can break implicit contracts with employees associated with wage and employment expectations and thereby transfer worker surplus to shareholders. Shleifer and Vishny (1988) argue that acquirers may be motivated to target firms with over-employment, subsequently raising shareholder value with post-merger layoffs. The literature finds that M&As are generally followed by labor restructuring in terms of layoffs (Kaplan, 1989; Dessaint, Golubov and Volpin, 2015; John, Knyazeva and Knyazeva, 2015; Lagaras, 2021) or declines in employee compensation (Rosett, 1990; Pontiff, Shleifer and Weisbach, 1990; Babenko, Du and Tserlukevich, 2020; He and le Maire, 2021). One exception is McGuckin and Nguyen (2001), who document a modest mean post-merger employment decline. We contribute to this literature by shedding light on the mechanism through which labor restructuring takes place following M&As. We show that technology adoption post M&A is associated with job and wage losses in specific occupations—those occupations substitutable by technology—and gains in others—those occupations that experience productivity increases as a result of technology. As such, our results suggest that M&A labor market outcomes are more nuanced and depend on whether employee skills are compatible with the production processes of the new firms created post M&A.

We also build on the literature that argues that human capital considerations are important determinants of M&As. Ouimet and Zarutskie (2020) show that some firms use takeover markets to acquire the workforce at the target. Tate and Yang (2016) show that diversifying acquisitions occur more frequently among industry pairs with higher human capital transferability. Beaumont, Hebert and Lyonnet (2021) show that firms enter a new sector via acquisitions when their current workforce does not have the skills required in the sector of entry. Our paper delves into the heterogeneity of employment outcomes post-M&A and provides refined predictions on employment and wage effects of M&As on target establishments.

Finally, our paper builds on the growing literature that examines the drivers of inequality within firms. Song et al. (2019) and Mueller, Ouimet and Simintzi (2017) study the role of firm heterogeneity for trends in aggregate income inequality. Huneeus, et al. (2019) show that business groups exhibit higher earnings inequality than stand-alone firms. Bloom, Ohlmacher, Tello-Trillo and Wallskog (2021) find lower levels of inequality for better managed and higher performing firms. We instead show that firm inequality increases following M&As and argue that this is consistent with M&As encouraging technology adoption.

The remainder of the paper is organized as follows. Section 2 summarizes the data and describes our methodology. Section 3 presents the baseline establishment-level results on labor outcomes, and discusses our identification tests and potential mechanisms. Section 4 provides industry-level evidence. Section 5 concludes.

2 Data and methodology

2.1 Data

Occupational Employment and Wage Statistics Data

We use confidential micro-data from the Occupational Employment and Wage Statistics program (OEWS), conducted by the Bureau of Labor Statistics (BLS). This data come from a semiannual survey of individual establishments in the U.S. Each establishment is surveyed at most once every three years. Moreover, 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 optimal inferences about the U.S. economy as a whole. Aggregated versions of these data are released publicly and used to measure national occupational employment.[2]

For each establishment-year, we observe employment in 800 different occupational categories (represented by 6-digit SOC codes).[3] Within each of these occupations in a given establishment-year, we observe the count of employment for 12 separate wage bins. The cutoff points for the wage bins change over time to reflect changing income distributions. Furthermore, for each surveyed establishment, we observe its location (by county), EIN, name, legal name (ultimate owner), industry and a time-invariant establishment identifier which we can use to track establishments that have switched owners over time.

To construct the sample, we identify horizontal M&A deals, namely M&As where the target and acquirer operate in the same four-digit NAICS industry, using Securities Data Company (SDC) Platinum. We match these M&A deals to establishments in the OEWS survey over the 2001-2017 period.[4] We start in 2001 as the identifier which we need to link OEWS establishments over time is unavailable in earlier years. For each matched establishment, we require it is surveyed in the OEWS at least once before and once after

[2] See more details at `https://www.bls.gov/oes/tables.htm`.

[3] Following Autor and Dorn (2013), we drop military and farming occupations.

[4] In the internet appendix, we document the detailed steps for matching M&A deals from SDC to the OEWS.

the M&A. We identify a total of 1,740 horizontal M&A deals in the OEWS survey covering 5,014 establishments during our sample time period.

Control establishments are sampled from the set of establishments in OEWS but which were not involved in M&As. For each target establishment, we match using the pre-M&A observation. Specifically, we find a control establishment that: i) operates in the same four-digit NAICS industry as the target establishment; ii) appears in the OEWS survey the same year as the target establishment, iii) is sampled again within one year of the target establishment's post-M&A observation, iv) is the nearest best match in terms of size to the target, as measured by number of employees.[5]

To measure occupational changes at the establishment, we start with defining routine task intensity at the occupational level following Autor and Dorn (2013). Since occupations involve multiple tasks (routine, abstract, and manual) at different average frequencies, Autor and Dorn (2013) create an index which measures the routine task intensity by occupation that increases in the importance of the routine inputs and decreases in the importance of the abstract and manual inputs of a given occupation.[6] We then compute the occupation employment-weighted average of routine task intensity for a given establishment-year. We define high-technology employment following Hecker (2005). High-technology occupations include scientists, technicians and managers in computer and information systems, engineering, mathematics, and natural sciences. We then com-

[5]We allow matched control establishments to repeat.

[6]Following Autor and Dorn (2013), routine task intensity for occupation occ is defined as $RTI_{occ} = lnR_{occ,1980} - lnA_{occ,1980} - lnM_{occ,1980}$, where $R_{occ,1980}$, $A_{occ,1980}$ and $M_{occ,1980}$ are the routine, abstract, and manual inputs, respectively, by occupation, indexed by occ, in 1980. RTI_{occ} can range from -2.41 to 6.42 across the different occupations. The average (median) occupation has a score of 1.24 (0.87). We merge RTI_{occ} to occupations in the OEWS data by SOC codes using crosswalks from David Dorn's website: http://www.ddorn.net/data.htm.

pute the share of high-technology employment, normalized by total employment, at the establishment-year level.

To measure establishment wages and inequality, we start with calculating real wages at each establishment-occupation-year. Specifically, we observe employment in 12 hourly wage bins for each establishment-occupation-year. We take the average of the upper and lower bounds of the wage bin as the nominal wage for each occupation-establishment-year and adjust for inflation to real wages in 2001 dollars. The establishment wage is measured as the employment-weighted mean of occupational wages. The within-establishment inequality is measured by the employment-weighted standard deviation of occupational wages.[7]

Lastly, we measure offshorability following Autor and Dorn (2013) at the occupational level. We then compute an employment-weighted average of occupation offshorability at the establishment-year level. All variables used in our analysis are defined in the Appendix.

Table 1, Panel A, reports summary statistics for our sample establishments in the OEWS data. The average establishment in our sample employs 139 employees. As described earlier, the OEWS survey over-samples larger establishments. This limits our ability to reach conclusions about the smallest of establishments but ensures that our results are based on a sample of economically important entities. The average establishment has a routine task intensity of 1.6. On average, 6% of employees are in high-technology occupations. Our sample firms have an average real wage of \$16.92 per hour. This is

[7] In the internet appendix, we show results are robust when within-establishment inequality is measured by ratios of wages at standard percentiles, such as the ratio of the 90^{th} to 10^{th} percentiles.

comparable to the mean hourly U.S. wage in 2001 of \$16.4.[8] Finally, we report an average standard deviation of hourly wages equal to 8.8. In columns 4-9, Table 1, we compare the mean values of the outcome and control variables for treated and matched control establishments in the pre-treatment period. The *p*-values corresponding to the differences between these means (accounting for clustering at the firm-level) are reported in column 10. We find no significant differences between control and treated establishments across characteristics.

Technology Investment Data

To measure investments specific to technology, we use the Ci Technology Database (CiTDB), a proprietary database that provides information on computers and telecommunication technologies at establishments across the U.S. These data are used by the sales and marketing teams at large U.S. IT firms, thereby assuring high data quality, as clients would be quick to detect errors during sales calls. CiTDB generates their data using annual surveys of establishments.

To construct the technology investment sample, we take the following steps. For each treated establishment, we measure the pre-M&A period beginning two years before the M&A effective date and extend the sample through two years after the M&A effective date. We use a name-matching algorithm to match target firm names from SDC to CiTDB and include all establishments in CiTDB linked to the target and observed for this five-year timeline around the M&A event. To create the control sample, we start with the set of establishments observed for a five-year window and are not identified as a target firm during our sample period. We require control firms to match on (four-digit NAICS)

[8]See https://www.bls.gov/oes/bulletin_2001.pdf for more information.

industry, pre-treatment year and type of establishment.[9] To identify one unique control establishment out of the set of possible control establishments (all matched by industry, year, and type), we select the closest match in terms of employment in the pre-M&A year. We end up with a sample of 7,014 unique establishments (treated and control) covering 209 (four-digit NAICS) industries and all states. Our sample timeline is 2010-2015, the years for which IT spending measures are available to us.[10]

Table 1, Panel B, reports summary statistics for our sample establishments in the CiTDB data. The average establishment in our sample has 56 employees, spends $291 thousand in total and $8906 per employee on IT. In columns 4-10, we compare the mean values of the outcome and control variables for treated and control establishments in the pre-M&A period. The *p*-values corresponding to the differences between these means (accounting for clustering at the firm-level) are reported in the last column. We find no significant differences between control and treated establishments across these variables.

2.2 Methodology

To identify the effect of M&As on firm outcomes, we estimate the following OLS specification at the establishment-year level:

$$\mathrm{y}_{i,t} = \alpha_t + \alpha_i + \gamma_1 \cdot \mathrm{Post}_t + \gamma_2 \cdot \mathrm{Post}_t \cdot \mathrm{M\&A}_i + \beta \cdot X_{i,t} + \epsilon_{i,t} \tag{1}$$

where i denotes establishments and t denotes years. $Post_t$ is an indicator set equal to one for years following M&As and zero otherwise. $M\&A_i$ is an indicator equal to one for es-

[9] CiTDB identifies four different types of establishments: branch, headquarters, stand-alone and ultimate headquarters. The majority of our matched establishments are branches (80%) and our results are robust to limiting the sample to just branches.

[10] To maximize sample size, given the differences in time period and the fact that both samples are surveys, we do not merge CiTDB and OEWS data.

tablishments targeted by M&As (treated) and zero for the matched set of control establishments.[11] $X_{i,t}$ controls for changes in establishment offshoring potential ($Offshorability$) that could affect both the probability of M&As and labor outcomes. α_i is an establishment fixed effect which controls for establishment characteristics that do not vary over our sample period; α_t is a year fixed effect, which absorbs aggregate shocks affecting all establishments. We further control for interacted industry and year fixed effects ($\alpha_j \times \alpha_t$) to absorb time-varying industry shocks, and interacted state and year fixed effects ($\alpha_s \times \alpha_t$) to absorb time-varying local shocks. In all specifications, we cluster standard errors at the firm level.

3 Results

3.1 Occupational composition

We first investigate changes in routine task intensity (RTI) of the target, given the well-documented fact in the labor economics literature that technology adoption tends to replace tasks that are routine and highly repetitive in nature (e.g., Autor, Levy and Murnane, 2003; Autor and Dorn, 2013).[12] We thus examine changes in the occupational composition of target establishments compared to a group of similar establishments which did not experience an M&A using the OEWS data. Columns 1-4 of Table 2 present the results.

[11] $M\&A_i$ is absorbed by the establishment fixed effects.

[12] We have no explicit prediction regarding changes in total employment as it is possible that a greater reliance on automation ex-post may lead to an increase in employment in non-routine jobs, offsetting the job losses in routine jobs.

Column 1 shows that M&As are associated with a reduction in RTI at treated establishments compared to the matched control sample, in a specification with establishment and year fixed effects. This result is statistically significant at the 1% level and economically important with RTI declining by 5.5% relative to the mean. In column 2, we control for the potential of establishments to offshore their production—which may also be associated with lower demand for routine jobs— and continue to find a 4% decrease in routine task intensity relative to the mean, significant at the 1% level. Note that we report a positive correlation between the percent of offshorable jobs and the change in routine task intensity. This is consistent with the fact that more offshorable tasks tend to be also more routine intensive.[13] We next repeat the estimation additionally controlling for (four-digit NAICS) industry-year fixed effects (column 3) and both industry-year and state-year fixed effects (column 4) to control for industry and local economic shocks, respectively, that might be contemporaneous with the timing of the M&A. The estimated coefficients remain similar in terms of magnitude and statistical significance suggesting that industry or local shocks are not driving our findings.

We next examine whether M&As increase the share of employment in the target establishment that is complementary to technology. Technology complements skilled human capital (Krueger, 1993; Autor, Katz, and Krueger, 1998), disproportionately increasing demand for high-skill employees. Columns 5-8 of Table 2 repeat the specifications in columns 1-4, respectively, considering the share of high-technology employees as the dependent variable. In column 1, we find a 49 basis point increase in the share of high-

[13]Goos, Manning and Salomons (2014) report a correlation of 0.46. In our data, we also confirm a positive univariate correlation between routine task intensity and offshorability equal to 0.54 and significant at the 1% level.

technology employees in treated establishments compared to control establishments, which corresponds to an 8.2% increase relative to the mean. The magnitude increases after controlling for offshorability (column 2), and for industry and local economic shocks (columns 3 and 4). In column 4, we find that M&As result in a 96 basis point increase in the share of high-technology employment, or a 16% increase relative to the mean.

To more clearly evaluate whether the shift in the target's occupational composition towards high-skill employment is driven by an increase in employment in high-technology occupations, rather than a disproportionate reduction in employment of non-high-technology occupations, we examine the effect of M&As on targets' level of high-technology employment. We report the results in Internet Appendix Table IA1. In column 1, we find a positive but insignificant increase in the overall level of high-technology employment. However, we find an increase in the level of employment in engineering occupations when we decompose high-technology employment into its three main groups: "computer science and math", "engineering" and "life and physical sciences".[14] Among the three groups, engineering occupations are specifically associated with implementing technology at a firm while computer science and math occupations are associated with developing novel technology. Consistent with our intuition, we observe a statistically significant increase in the level of employment in engineering occupations.

[14] "Computer science and math" includes computer and mathematical scientists, SOC 15–0000 and computer and information systems managers, SOC 11–3020. "Engineering" includes engineers, SOC 17–2000; engineering managers, SOC 11–9040; drafters, engineering, and mapping technicians, SOC 17–3000. "Life and physical sciences" includes life scientists, SOC 19–1000; physical scientists, SOC 19–2000; life, physical, social science technicians, SOC 19–4000; and natural sciences managers, SOC 11–9120.

3.2 Wage inequality

These occupational changes at the target have implications for wages. The lower demand for workers performing routine—and thus lower skill— tasks and higher demand for high-skill employees should shift mean wages higher and increase wage inequality within establishments. In columns 1-4 of Table 3, we thus examine the effect of M&As on average hourly wages of target establishments, relative to the control sample of matched establishments. By focusing on hourly wages, we avoid concerns that changes in hours worked around the M&A event could be affecting our results. In column 1, we find a 1.66% increase in treated establishments' average hourly wage compared to the control sample, statistically significant at the 5% level. The estimated coefficients remain significant both statistically and economically across specifications, after controlling for offshorability, interacted industry-year and state-year fixed effects.

In columns 5-8, Table 3, we provide evidence that M&As increase wage inequality within establishments. We measure wage inequality using the establishment standard deviation of wages, as in Barth, Bryson, Davis and Freeman (2016). Column 5 shows a 4.5% increase in the standard deviation of wages at target establishments compared to matched control establishments, significant at the 1% level. The coefficient remains similar in terms of magnitude and significance across all specifications we consider. In Internet Appendix, Table IA2, we alternatively consider the logarithm of $90^{\text{th}}/10^{\text{th}}$ (Panel A), $75^{\text{th}}/25^{\text{th}}$ (Panel B), and $90^{\text{th}}/50^{\text{th}}$ (Panel C) percentile ratios of establishment hourly wages.[15] In columns 1, Panel A, we find a 3.2% increase in top-bottom within-establishment inequality com-

[15] Note that given we are measuring inequality at the establishment level and inferring wages from wage bin midpoints, standard deviation is a more robust measure of inequality.

pared to controls, significant at the 1% level. We find similar effects across specifications and across the three definitions of inequality we consider.

Both the shift in the nature of tasks performed at the establishment and within-establishment wage inequality are consistent with the notion that labor restructuring following M&As reflects changes in production processes involving the adoption of labor-saving technologies. These results suggest a more nuanced impact of M&As on workers compared to earlier work that focuses on total employment changes. Our results suggest that post-M&A changes involve a complex restructuring of the labor force that benefits more skilled occupations that accompany technology investments.

3.3 Robustness tests

A key concern for our analysis is that an omitted variable, such as an industry or technology shock, may be driving both M&A activity and the associated labor changes we document in the data. This concern is mitigated by the fact that we use a matched sample of observationally similar establishments and that we absorb variation in industry and local conditions by controlling for time-varying industry and state fixed effects. We perform additional tests below to provide further evidence consistent with a causal interpretation.

First, we present evidence that both treated and control establishments follow parallel trends prior to the M&A event. To do so, we create separate dummy variables for observations before and after the M&A event for the sub-sample of establishments which are sampled at least six times within our sample period, 2001-2017, in the OEWS. $Post_{+1}$ is the observation observed right after the M&A event for treated observations. $Post_{+2}$

and $Post_{+3}$ are the latter two observations following M&As. Pre_{-2} and Pre_{-3} are the two preceding observations.[16,17] We augment our baseline specification by interacting these variables with $M\&A_i$.

We report the results in Table 4. In column 1, we find no statistically different trends in RTI prior to the M&A events, while RTI declines significantly the first year following the M&A and remains negative and significant for all post-M&A observations. This indicates a persistent negative effect given that each observation post-M&A is separated by at least three years. Similarly, in column 2, we find that the share of high-technology employment is not statistically different for the years prior to the M&A, while it increases in the first post-M&A year we observe and remains positive throughout the post period. In column 3, the dynamics on establishment mean wages are noisier, showing a negative and significant effect in the earliest observation prior to the M&A, and a positive and significant effect starting in the first observation post M&A. Although parallel trends do not seem to hold for wages, the pre-treatment trends we document are the opposite of the predicted M&A effects. In column 4, we find no significant differences in establishment wage inequality prior to the M&A, while standard deviation of wages increases following the M&A.

We next provide further evidence against an omitted variable interpretation of our findings by providing *within*-establishment estimates. For each establishment-year, we use two observations—where one observation is estimated just on non-routine employees

[16] Each establishment in the OEWS is surveyed at most once within three years, so the observations in $Post_{+1}$, $Post_{+2}$ and $Post_{+3}$ are separated by at least three years. Similarly, the observations in Pre_{-2} and Pre_{-3} are separated by at least three years.

[17] Given the regressions include establishment fixed effects, we must exclude one observation. We omit the observation right before or at the M&A event from the estimation, whichever is covered by the survey.

and the other on routine employees, or where one observation is estimated just on high-technology employees and the other on non-high-technology employees. Importantly, since our estimation relies on variation within-establishment in this specification, we now include establishment-year fixed effects, thereby absorbing any time-varying changes at the establishment level that could be driving our results.

In columns 1-2, Table 5, we focus on the effect of M&As on employment and wages of routine occupations, while controlling for changes in non-routine occupations at the same establishment-year. We define *Routine* to take a value of one for occupations which are in the top employment-weighted third of routine task intensity, as defined in Autor and Dorn (2013), and zero otherwise. We then interact *Routine* with $Post_t \cdot M\&A_i$ and estimate the effect of the M&A on the employment share of routine occupations compared to non-routine occupations, within establishments. We show a greater reduction in routine (as opposed to non-routine) employment share in treated establishments post-M&A, as compared to control establishments.

These results suggest lower demand specifically for tasks substitutable by technology in M&A targets—a prediction unique to our technology adoption hypothesis—which is estimated after fully controlling for any contemporaneous shocks at the establishment-year level that could be driving changes in employment. In economic terms, we estimate a decline of 2.9% in the share of routine workers, relative to the share of non-routine workers—a decline which is statistically significant at the 5% level. In column 2, we estimate the effect of M&As on wages for routine occupations compared to non-routine occupations, and find a point estimate suggesting an economically larger decline in wages for routine workers, although the difference is not statistically significant.

In columns 3-4, Table 5, we instead focus on high-technology occupations, while controlling for changes in the employment of non-high-technology occupations at the same establishment in the same year. Specifically, we define $HighTech$ to take a value of one for high-technology occupations in a given establishment and zero for non-high-technology occupations. We then interact $HighTech$ with $Post_t \cdot M\&A_i$ and estimate the effect of the M&A on high-technology employment share and wages within establishments. Consistent with technology increasing the demand for these occupations, column 3 shows a greater increase in the share of high-technology employment compared to the employment share of non-high-technology occupations. In column 4, we show that wages for high-technology workers increase by 4.97% compared to non-high-technology workers, suggesting greater demand for high-technology workers post M&A.

Next, we consider a sample of M&A deals that were announced but subsequently cancelled for reasons exogenous to the target's labor needs (Seru, 2014; Malmendier, Opp and Saidi, 2016). To this end, we start with all M&A deals announced over our sample period that were subsequently withdrawn. We then read Factiva news articles explaining the reasons for the cancellation and retain the sample of deals where the M&A was either blocked by regulators, typically for anti-trust concerns, or because the acquirer was acquired ex-post and had to withdraw the deal. This leaves us with a small sample of deals cancelled for reasons exogenous to the target's labor demand.[18] We are able to identify 58 establishments in the OEWS survey data with cancelled M&A deals and this forms our 'pseudo treated' group. Following the same matching procedure as described in Section

[18]The other most common reasons for why deals get cancelled include: the management of the target rejecting the deal; disagreement on the price; changes in market or industry conditions; and bad news being revealed for the target. However, these reasons are arguably not exogenous to the target's labor demand and therefore we choose not to consider them.

2.1, we create a control sample which excludes establishments involved in completed or cancelled M&As over our sample period.

Table 6 repeats the specification in column 3, Table 2, controlling for establishment and industry times year fixed effects.[19] We examine whether there are occupational or wage changes consistent with our prior analysis, using this sample of 'pseudo-treated' deals and their matched control establishments. Across all measures, we cannot replicate the same pattern as in our baseline results. In fact, all coefficients are either statistically and economically zero or have the opposite sign from what our hypotheses predict. To mitigate the concern that the null results are due to the small sample size used in this analysis, we replicate our baseline analysis using equally small samples. In this regard, for each of our dependent variables, we randomly pick 2% of the treated-control pairs in our baseline sample and estimate a specification with establishment and industry-year fixed effects. We repeat this process 1000 times and average the estimated coefficients. Despite the small sample size, we are able to produce estimates that are very close in terms of magnitude to the full sample estimates.[20] Thus, our placebo findings reinforce the notion that our baseline results capture the effect of M&As and not of some other confounding variable as omitted variables should impact target firms associated with completed M&As and the cancelled M&As in our sample equally.

Finally, we address the concern that labor market changes we document at M&A target establishments may be offset by opposing changes at the acquirers' establishments.

[19] We do not estimate results where we also account for state times year fixed effects due to the small sample size in this analysis.

[20] The average coefficient estimates from this procedure are as follows: -0.051 for *RTI*; 0.009 for *Share HighTech*; 0.007 for *Wages*; 0.044 for *StdWages*. The sample mean of all four coefficients is significantly different from 0 at the 1% level.

If this were the case, then the labor market changes we document would not materially affect firm-level labor outcomes and could be deemed as less important. To address this concern, we repeat our baseline analysis in the combined sample of acquirer and target establishments that can be matched to the OEWS dataset and their respective control establishments.[21] We present this analysis in Internet Appendix Table IA3. With the exception of establishment average wages, where the effect is positive but not statistically significant, we find similar occupational and wage effects in this expanded sample, which suggests that the labor reallocation we document post M&A, and its implications for wage inequality, captures changes that aggregate up to the post-M&A firm-level.

3.4 Mechanisms: Investment in technology

The occupational and wage changes we document post-M&A at target establishments are consistent with the effects of technology adoption. To further bolster this argument, in this section, we present direct evidence of increasing investments in technology post M&A.

Mirroring our baseline methodology, we compare changes in IT investments at target establishments before and after the M&A compared to a matched control sample. Table 7 presents the results.[22] In column 1, we focus on the overall IT budget (log-transformed). We control for establishment fixed effects, interacted (four-digit NAICS) industry and

[21] Control establishments are sampled from the set of establishments in OEWS which are not involved in M&As. For each acquirer (target) establishment, we find a control establishment that: 1) operates in the same four-digit NAICS industry as the acquirer (target) establishment and appears in the OEWS survey the same year as the treated establishment, 2) is sampled again within one year of the treated establishment's post-M&A observation, 3) is the nearest best match in terms of size to the treated establishment, as measured by number of employees. We allow matched control establishments to repeat.

[22] We do not control for offshorability in both Tables 7 and 8, which use IT investment data from CiTDB, as we do not observe occupation in the CiTDB data.

year fixed effects, and interacted state and year fixed effects in all columns. In column 1, we show that IT spending increases by 5.4% post M&A, compared to a matched set of control establishments, and this increase is statistically significant at the 1% level. In column 2, we further examine whether establishments become more capital intensive post M&A which would be consistent with the argument that technology is labor-saving. We thus normalize IT budget by the number of employees in the establishment, provided in CiTDB, and take a logarithm of the normalized value. We continue to find a positive and significant result, both statistically and economically.

In columns 3 and 4, Table 7, we present a dynamic estimation for the technology investment analysis. Specifically, we create separate dummy variables for years before and after the M&A event. Pre_2 is equal to one for the observation observed two-years prior to the M&A, and zero otherwise. $Post_0$ is the the observation observed in the effective year of the M&A. $Post_{+1}$ and $Post_{+2}$ are the latter two observations following M&As.[23,24] We augment our baseline specification by interacting these variables with $M\&A_i$. We find no evidence of pre-trends prior to the M&A, while both total IT budget and IT budget per employee increase post M&A.[25]

So far, our results provide direct evidence that M&As are followed by greater technology adoption. Still, they do not address why M&As encourage technology adoption—a question we discuss next. We explore three non-mutually exclusive mechanisms that may explain why M&As facilitate technology adoption: 1) firms which can integrate technol-

[23] Within our technology investment sample, each establishment is observed exactly five times in a five-year window around the M&A and each observation is separated by one year.

[24] Given the regressions include establishment fixed effects, we must exclude one observation. We omit the observation right before the M&A event from the estimation.

[25] We cannot replicate the cancelled deals robustness test with the CiTDB data as we are able to match only 7 establishments with 6 deals cancelled for exogenous reasons in this sample.

ogy more efficiently can acquire targets less able to do so; 2) financial constraints may have prevented the target (pre-M&A) from adopting all cost-effective technology; and 3) M&As can resolve agency conflicts which may have prevented the adoption of cost-effective technology. We test these mechanisms using the CiTDB sample which allows us to directly observe investment in technology.

The first mechanism builds upon the observation that firms do not all simultaneously adopt a new technology, once available, even if it is cost-effective to do so (Gort, 1969). Failure to adopt a cost-effective technology may be tied to multiple frictions, such as the lack of skilled labor necessary to implement the technology. Non-adopters will then become takeover targets by tech-savvy acquirers and M&As will be followed by increased technology adoption at targets (Bartelsman and Doms, 2000).

We proxy for tech-savvy acquirers using pre-acquisition IT investment, as measured in the CiTDB. Specifically, we create a dummy variable, $TechSavvy\_Acq_i$ which is 1 if the ex-ante IT spending at the acquirer is greater than its industry median, and zero otherwise. We interact $TechSavvy\_Acq_i$ with $\text{Post}_t \cdot \text{M\&A}_i$ and test the effect of M&As on technology adoption, as proxied by total IT budget and IT budget per employee (log-transformed) at the target. We include establishment fixed effects to control for time-invariant establishment characteristics, interacted industry and year fixed effects to control for time-varying industry shocks, and state times year fixed effects to control for time-varying local shocks. We present the results in Table 8, columns 1-2. We find a positive effect of M&As on total IT budget and per employee IT budget which is more pronounced for the more tech-savvy acquirers. These results indicate that targets acquired by more technologically advanced firms invest more in technology post merger, consistent with the argument that these tech-savvy acquirers have a better ability to implement technology.

Second, we investigate variation in the treatment effect using pre-treatment differences in financial constraints at the target. Given that typically technology adoption requires higher up-front costs as compared to employing labor to accomplish the same tasks, some firms experiencing financial constraints may not have been able to adopt available cost-effective technology. Given that M&As can relieve financial constraints at the target (Erel, Yang and Weisbach, 2015), we predict that technology adoption post-M&A will be relatively greater at financially constrained targets. To proxy for financial constraints at the target (which include both public and private firms), we use firm size (Hadlock and Pierce 2010). We create an indicator variable, $SmallTarget_i$, which is 1 if the ex-ante employment at the target is below the sample median, and zero otherwise. We augment our baseline specification by including an interaction between $SmallTarget_i$ and $\text{Post}_t \cdot \text{M\&A}_i$. As observed in columns 3-4, targets which appear to be more financially constrained ex-ante are associated with relatively greater ex-post technology adoption.

Third, we propose that M&As can alleviate agency issues at the target, thereby facilitating technology adoption. For example, manager-worker alliances at the target (Bertrand and Mullainathan 2003; Pagano and Volpin, 2005) could discourage investment in technology, which typically comes with layoffs of routine workers. We find evidence in support for this mechanism in Table 8, columns 5-6. We identify unsolicited M&As from SDC Platinum and create a dummy which is 1 for unsolicited deals, and zero otherwise ($Unsolicited_i$). We augment our baseline specification by including an interaction between $\text{Post}_t \cdot \text{M\&A}_i$ and $Unsolicited_i$. Consistent with the fact that M&As following those unsolicited bids are more likely to address agency conflicts, we find greater IT investment following these types of M&As. Both interaction coefficients are economically large and statistically significant.

In sum, we find evidence in support for all three mechanisms. M&As facilitate technology adoption both by alleviating frictions that discourage firms from adopting available technologies, such as financial constraints or the presence of agency conflicts, and due to the greater ability of the acquiring firm to implement technology more efficiently.

4 External validity: Industry analysis

So far, we have presented evidence showing that labor market changes at target establishments following M&As appear to be associated with greater adoption of automation technologies. We also showed that these changes impact the post-M&A firm, as they still hold in the combined sample of target and acquirer establishments. We will next move one step further and demonstrate that these labor changes aggregate up to the industry-level.

4.1 Industry analysis: Data

As in our baseline analysis, we collect data on horizontal M&As from SDC. We use deals announced from 1980 through 2010 of a U.S. target and U.S. acquirer, for which we can confirm the acquirer completed a purchase of a majority stake.[26] We define *Merger intensity* as the count of horizontal deals in a given decade and industry, normalized by all horizontal deals in that decade. This normalization controls for changes in the scope of

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

coverage of SDC over time.

We collect data on occupational employment from the Integrated Public Use Microdata Service (IPUMS) 5% extract for 1980, 1990, 2000 and the 2010 American Community Survey (ACS).[27,28] IPUMS provides detailed surveys of the American population drawn from federal censuses and the ACS. IPUMS was created to facilitate time-series analysis and, as such, has unique industry (IND1990) and occupational (OCC1990) identifiers, defined so 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.

We map NAICS industries from SDC to IPUMS industries, using the crosswalk provided by IPUMS, as detailed in the Internet Appendix. Following this approach, we end up with 132 industries and more than 300 occupations in each Census-year. Our IPUMS sample consists of individuals who are between 18 and 64 years old 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

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

[28] For more information, see Ruggles et al., (2015).

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*). Wages are adjusted to year 2001 dollars using the Consumer Price Index of all urban consumers in order to be comparable to the establishment-level analysis. IPUMS also provides data on workers' education allowing us to define workers with a graduate education (at least 5 years of post-secondary education). We aggregate all variables at the industry-Census year level by computing employment-weighted averages.

We measure RTI as in the baseline analysis, using data from Autor and Dorn (2013). We merge these data with IPUMS using the occupation crosswalks detailed earlier. Following these steps, we can characterize occupations in a given industry-year in terms of their routine intensity.[29] We define all variables used in our analysis in the Appendix.

Table 9 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%-0.57% of the overall merger activity. The industry average RTI score decreases over time from 1.35 in 1980 to 1.17 in 2010. We find that 12-13% of the workforce in our average industry is employed in a high-technology occupation. The average hourly wage is $16.8 in 1980 and $18.89 in 2010. Moreover, we show an increase in the standard deviation of wages within a given industry, consistent with the fact that inequality has increased over time.

[29] Internet Appendix Table IA4 provides some examples of our sample industries with high and low routine task intensity. Industries with high routine task intensity occupations include accounting and legal services. On the other hand, industries with low routine task intensity include taxicab services and elementary and secondary schools.

4.2 Industry analysis: Results

To parallel our establishment-level results, we examine how industry routine task intensity, high-technology employment, and wages change following M&A activity. We thus estimate the following specification:

$$y_{j,t} = \alpha_t + \alpha_j + \gamma \cdot \log(\text{Merger Intensity})_{j,(t-10,t-1)} + \beta \cdot X_{j,t} + \epsilon_{j,t} \quad (2)$$

where t indexes years and j indexes industries. $X_{j,t}$ controls for average offshorability of tasks, time-varying at the industry-level. *Merger Intensity* is our proxy of M&A activity at the industry.[30] α_j is an industry fixed effect to control for industry time-invariant characteristics; α_t is a year fixed effect to control for differences across time. The IPUMS data are 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.[31] Our outcome measures y are measured every decade in 1990, 2000, and 2010. Standard errors are clustered at the industry level to take into account correlation in industries over time.

Column 1, Table 10, examines routine task intensity as our outcome variable. An increase in industry M&A intensity is associated with a decline in the industry routine task intensity. These results suggest that high industry M&A intensity is associated with tasks becoming subsequently less routine task intensive, consistent with our hypothesis

[30] Internet Appendix Table IA5 shows that the key results are robust to using M&A transaction values to define *Merger Intensity*. Specifically, we define M&A activity as the logarithm of one plus the total transaction values of horizontal deals made in a given (four-digit NAICS) industry-decade normalized by total transaction values of all horizontal deals made in the decade. We use the M&A count as opposed to transaction values in our baseline analysis due to the high number of observations with missing data on transaction values.

[31] Internet Appendix Table IA6 shows that the key results are robust to defining M&A activity over the first six year of each decade.

of routine-biased technological change. At the same time, this process of automation can also increase relative demand for high-technology employees as technology tends to be complementary to skilled labor, leading to an “upskilling” of affected industries. Thus, column 2, Table 10, looks at the share of high-technology employment within a given industry. The result is consistent with skill-biased technological change taking place following M&As.

Next, we test whether these occupational changes have any implications for wages. In column 3, we explore predictions related to hourly wages. We use the log of the industry average hourly wage as the dependent variable and find an increase in the average wage in affected industries. Note that 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 columns. To test the effect on wage polarization following M&A activity, we examine the standard deviation of hourly wages in column 4. Within industries, an increase in M&A activity by 1% increases wage disparity by 1.4%. Consistent with our establishment-level findings, we report increases in wage dispersion within an industry following higher M&A activity.

Overall, the industry-level results parallel the trends we documented at the establishment level. These results indicate that establishment-level changes in labor demand and compensation appear to aggregate to the industry level. These results are not consistent with an argument that changes at a given M&A firm are offset by counter-balancing changes at non-M&A peer firms absorbing the redundant labor from the M&A firms. These results also confirm that our within-establishment evidence can be generalized to industry-wide changes in labor outcomes and inequality.

5 Conclusion

We show new evidence that M&As bring changes in the nature of jobs performed at the firm that are consistent with greater adoption of technology post M&A. We find that M&As are followed by an employment reduction in occupations with higher routine task intensity at the target. At the same time, we also observe an ex-post increase in the demand for high-skill workers following M&As. 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 mirrored in wages: we observe an increase in the average wage and, most importantly, an increase in the overall wage inequality within establishments. We also directly confirm that M&As are followed by higher investment in technology, especially when they are associated with tech-savvy acquirers, financially constrained targets, or targets with greater agency conflicts. Lastly, we are able to generalize our findings at the industry-level, where we find that industries impacted by high M&A activity exhibit similar changes in labor outcomes and wages as those identified within establishments.

A key implication of our findings is that the impact of M&As on target firm workers is heterogeneous. Workers engaged in highly routine activities fare the worst, while high-skill non-routine workers may see expanded employment opportunities following the M&A. These results also imply that the labor market effects of M&As are more nuanced than the simple cost-cutting argument where layoffs are a source of operational synergies following M&As. However, we need to emphasize a caveat of our analysis: Our results are unique to the sample of employed workers. As such, they are consistent with patterns of increasing skill premium and increasing income inequality documented in the macro economy. 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 for only those employees who remain employed in the firm or industry.

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Appendix: Variable definitions

1. Establishment-level variables from OEWS and SDC

Employment is the number of employees at an establishment.

Routine Task Intensity (RTI) measures routine intensity of tasks in the OEWS establishment. It is defined as the occupational employment weighted average of routine task intensity scores in each establishment-year. Following Autor and Dorn (2013), routine task intensity for occupation occ is defined as $RTI_{occ} = lnR_{occ,1980} - lnA_{occ,1980} - lnM_{occ,1980}$, where $R_{occ,1980}$, $A_{occ,1980}$ and $M_{occ,1980}$ are the routine, abstract, and manual inputs, respectively, by occupation, indexed by occ, in 1980. Then, RTI_{occ} is merged to the OEWS data using the SOC occupation codes. The data on occupational routine, abstract, and manual inputs are available at https://www.ddorn.net/data/occ1990dd_task_alm.zip.

High-tech Employment Share (Share HighTech) is the share of employment of high-technology workers in the OEWS establishment. High-technology occupations include scientific, engineering, and technician 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://www.bls.gov/opub/mlr/2005/07/art6full.pdf.

Average Hourly Wages (Wages) is the logarithm of the average hourly wage in each establishment-year. The OEWS data report 12 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 the hourly wage of workers in that wage bin-occupation. Then we take the occupational employment-weighted mean of hourly wages of all occupations in the establishment as a proxy of establishment-level hourly wages. These wages correspond to the hourly wages of salaried workers and do not include non-production bonuses or employer costs of non-wage benefits. All wages are inflated to year 2001.

Std. Dev. of Hourly Wages (StdWages) is the logarithm of the occupational employment-weighted standard deviation of hourly wages in each establishment and year.

$Offshorability$ captures the degree to which the tasks performed in a given establishment-year require either face-to-face interaction or on-site operation. It is defined as the employment weighted average of occupational offshorability scores, which are available at David Dorn's website: https://www.ddorn.net/data/occ1990dd_task_offshore.zip. Occupational offshorabilty scores are merged to OEWS data using SOC occupation codes. The crosswalks between SOC occupation codes and $occ1990dd$ occupation codes are available at David Dorn's website: https://www.ddorn.net/data.htm.

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

$Post_t$ is an indicator equal to one for years post-M&A and zero otherwise.

Pre_{-n} is an indicator equal to one for the n^{th} observation of the establishment observed in OEWS prior to the M&A,where $n = 2 or 3$, and zero otherwise.

$Post_{+n}$ is an indicator equal to one for the n^{th} observation of the establishment observed in OEWS post-M&A, where $n = 1, 2, or\ 3$, and zero otherwise.

Occupation Type is an indicator equal to one for routine (high-technology) occupations, and zero otherwise in column 1-2 (3-4), Table 5. Following Autor and Dorn (2013), an occupation is routine if it is in the top employment-weighted third of occupational routine task intensity in the 1980 5% state sample maintained by IPUMS USA (https://usa.ipums.org/usa/sampdesc.shtml#us1980a). High-technology occupations are described above when defining *Share HighTech*.

Occupational Employment Share measures the employment share of routine (or non-routine) occupations within the OEWS establishment in column 1, Table 5. It is defined as the logarithm of one plus the total employment of routine (or non-routine) occupations in establishment i and year t divided by the total employment in the same establishment-year. *Occupational Employment Share* measures the employment share of high-technology (or non-high-technology) occupations within the OEWS establishment in column 3, Table 5. It is defined as the logarithm of one plus the total employment of technology (or non-high-technology) in establishment i and year t divided by the total employment in the same establishment-year.

Occupational Wage is the logarithm of establishment average hourly wage of routine (or non-routine) occupations within the establishment in column 2, Table 5. *Occupational Wage* is the logarithm of establishment average hourly wage of high-technology (or non-high-technology) occupations within the establishment in column 4, Table 5.

pseudo $M\&A_i$ is an indicator equal to one if establishment i observed in the OEWS belongs to a firm that was the target of a withdrawn deal. We include only those deals that were withdrawn either because they were blocked by regulators or because the acquirer was acquired ex-post and had to withdraw the deal.

2. Establishment-level variables from CiTDB and SDC

$Employment$ is the number of employees at an establishment.

IT budget is the logarithm of one plus the budget for IT in the CiTDB establishment.

IT Budget Per Employee (IT budget/Emp) is the logarithm of one plus the budget for IT normalized by the number of employees in the CiTDB establishment.

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

$Post_t$ is an indicator equal to one for years post-M&A and zero otherwise.

Pre_{-2} is an indicator equal to one for the observation of the establishment observed two years prior to the M&A, and zero otherwise.

$Post_n$ is an indicator equal to one for the n^{th} observation of the establishment observed in the CiTDB after the M&A, where $n = 0,\ 1,\ or\ 2$, and zero otherwise.

$TechSavvy\_Acq_i$ is an indicator equal to one if the average IT budget at the acquirer establishments within the two years prior to the M&A is greater than the industry (four-digit NAICS) median, and zero otherwise.

$SmallTarget_i$ is an indicator equal to one if the average target employment within the two years prior to the M&A is below the sample median, and zero otherwise.

$Unsolicited_i$ is an indicator equal to one if the M&A deal is unsolicited, and zero otherwise.

3. Industry-level variables from IPUMS USA and SDC

log(Merger Intensity) captures the intensity of M&A activity in an industry-decade. It is the logarithm of one plus the number of horizontal deals made in each (four-digit NAICS) industry-decade, normalized by the number of all horizontal deals, in the decade.

Routine Task Intensity (RTI) measures routine intensity of tasks in a given industry-year. It is defined as the occupational employment weighted average of routine task intensity scores in a given industry-year. Following Autor and Dorn (2013), routine task intensity for occupation occ is defined as $RTI_{occ} = lnR_{occ,1980} - lnA_{occ,1980} - lnM_{occ,1980}$, where $R_{occ,1980}$, $A_{occ,1980}$ and $M_{occ,1980}$ are the routine, abstract, and manual inputs, respectively, by occupation, indexed by occ, in 1980. Then RTI_{occ} are merged to the occupations in IPUMS using the occupation crosswalks provided on David Dorn's website (https://www.ddorn.net/data.htm). The data on occupational routine, abstract, and manual inputs are available at https://www.ddorn.net/data/occ1990dd_task_alm.zip.

High-technology Employment Share (Share HighTech) is defined as the employment share of high-technology workers in each industry-year. High-technology occupations include scientific, engineering, and technician 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://www.bls.gov/opub/mlr/2005/07/art6full.pdf

Average Hourly Wages (Wages) is the logarithm of the average hourly wage in each industry-year. It is employment-weighted average of hourly wages of workers in that industry. 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 2001 following the instruction provided by IPUMS (https://cps.ipums.org/cps/cpi99.shtml).

Standard Deviation of Hourly Wages(StdWages) is the logarithm of the employment-weighted standard deviation of hourly wages in each industry-year.

Offshorability captures the degree to which the tasks performed in a given industry-year require either face-to-face interaction or on-site operation. It is defined as the employment-weighted average of occupational offshorability, which is available at David Dorn's website: https://www.ddorn.net/data/occ1990dd_task_offshore.zip. Occupational-level offshorabilty is merged to occupations in IPUMS using the crosswalks provided on David Dorn's website: https://www.ddorn.net/data.htm.

Table 1. Summary statistics

This table reports the mean and standard deviation of key variables from the Occupational Employment and Wage Statistics program (OEWS) administered by the Bureau of Labor Statistics (Panel A) and the Ci Technology Database (CiTDB) by Harte Hanks. Each observation is measured at the establishment level. In both panels, columns 1-3 present summary statistics for all establishments. Columns 4-6 and 7-9 present summary statistics for establishments without M&A (controls) and with M&A (treated), respectively, in the years before an M&A. The last column reports the p-value of the differences in means (clustered by firm) between control and treated groups pre-treatment and the level of significance. All variable definitions are provided in the Appendix.

Panel A. OEWS										
				Establishments before M&A						
	All Establishments			Without M&A			With M&A			
	(1) N	(2) Mean	(3) Std. Dev.	(4) N	(5) Mean	(6) Std. Dev.	(7) N	(8) Mean	(9) Std. Dev.	(10) p-value
Employment	20,056	139	344	5,014	139	334	5,014	147	366	0.43
Routine Task Intensity	20,056	1.64	1.18	5,014	1.61	1.13	5,014	1.66	1.22	0.38
High-tech Employment Share	20,056	0.06	0.17	5,014	0.07	0.18	5,014	0.07	0.18	0.82
Average Hourly Wages ($)	20,056	16.92	9.42	5,014	16.55	8.92	5,014	16.98	9.45	0.29
Std. Dev. of Hourly Wages	19,713	8.82	6.72	4,943	8.70	6.50	4,939	8.45	6.32	0.27
Offshorability	20,056	0.33	0.74	5,014	0.33	0.74	5,014	0.34	0.75	0.70

Panel B. CiTDB										
				Establishments before M&A						
	All Establishments			Without M&A			With M&A			
	(1) N	(2) Mean	(3) Std. Dev.	(4) N	(5) Mean	(6) Std. Dev.	(7) N	(8) Mean	(9) Std. Dev.	(10) p-value
Employment	35,070	56	158	7,014	54	159	7,014	58	156	0.62
IT Budget ($)	35,070	291,311	751,554	7,014	241,028	624,146	7,014	257,001	660,923	0.74
IT Budget Per Employee ($)	35,070	8,906	12,514	7,014	9,645	15,446	7,014	9,326	15,066	0.86

Table 2. M&As and target occupational composition

This table presents estimates of changes in occupational composition at establishments of M&A targets compared to control establishments. The dependent variable in columns 1-4 is the employment weighted average of routine task intensity defined at the establishment level. The dependent variable in columns 5-8 is the share of high-technology employment defined at the establishment level. $Post_t$ is estimated but not reported for brevity. The sample consists of establishments targeted in horizontal M&As from 2001 through 2017 and those of matched control establishments. All variables are defined in the Appendix. Standard errors are reported in parentheses and clustered at the firm level. Significance levels are indicated by *, ** and *** and correspond to the 10%, 5% and 1% significance level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	RTI	RTI	RTI	RTI	Share HighTech	Share HighTech	Share HighTech	Share HighTech
$Post_t \cdot M\&A_i$	-0.0902***	-0.0660***	-0.0567***	-0.0558***	0.0049*	0.0067**	0.0072**	0.0096***
	(0.0205)	(0.0178)	(0.0172)	(0.0175)	(0.0029)	(0.0029)	(0.0028)	(0.0031)
$Offshorability$		0.669***	0.680***	0.681***		0.0492***	0.0440***	0.0459***
		(0.0283)	(0.0289)	(0.0278)		(0.0048)	(0.0051)	(0.0051)
Year FE	Yes	Yes			Yes	Yes		
Establishment FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry · Year FE			Yes	Yes			Yes	Yes
State · Year FE				Yes				Yes
Observations	20,056	20,056	19,081	18,971	20,056	20,056	19,328	19,218
R^2	0.853	0.883	0.911	0.922	0.843	0.850	0.886	0.899

Table 3. M&As and target wage inequality

This table presents estimates of changes in average wages and wage inequality at establishments of M&A targets compared to control establishments. The dependent variable in columns 1-4 is the log-transformed average hourly wage at the establishment level. The dependent variable in columns 5-8 is the log-transformed standard deviation of hourly wages at the establishment level. $Post_t$ is estimated but not reported for brevity. The sample consists of establishments targeted in horizontal M&As from 2001 through 2017 and those of matched control establishments. All variables are defined in the Appendix. Standard errors are reported in parentheses and clustered at the firm level. Significance levels are indicated by *, ** and *** and correspond to the 10%, 5% and 1% significance level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Wages	Wages	Wages	Wages	StdWages	StdWages	StdWages	StdWages
$Post_t \cdot M\&A_i$	0.0166**	0.0166**	0.0125*	0.0125*	0.0454***	0.0460***	0.0392***	0.0396**
	(0.0074)	(0.0074)	(0.0068)	(0.0073)	(0.0151)	(0.0151)	(0.0150)	(0.0153)
$Offshorability$		-0.0011	-0.0007	-0.0018		0.0147	0.0020	-0.0035
		(0.0083)	(0.0092)	(0.0090)		(0.0178)	(0.0205)	(0.0176)
Year FE	Yes	Yes			Yes	Yes		
Establishment FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry · Year FE			Yes	Yes			Yes	Yes
State · Year FE				Yes				Yes
Observations	20,056	20,056	19,081	18,971	19,137	19,137	18,090	17,970
R^2	0.893	0.893	0.920	0.930	0.810	0.811	0.858	0.879

Table 4. Robustness: Dynamics in labor outcomes

This table presents estimates of occupational and wage changes at establishments of M&A targets in the periods before and after the M&A compared to control establishments. The dependent variable is the average of routine task intensity at the establishment, in column 1; the share of high-technology employment, in column 2; the log-transformed average hourly wage, in column 3; and the log-transformed standard deviation of hourly wages, in column 4. Pre_{-n} is an indicator equal to one for the n^{th} observation of the establishment observed in OEWS $before$ the M&A, and zero otherwise. $Post_{+n}$ is an indicator equal to one for the n^{th} observation of the establishment observed in OEWS $after$ the M&A, and zero otherwise. The first observation prior to/at the M&A is the omitted coefficient, depending on which one is covered by OEWS. Pre_{-n} and $Post_{+n}$ are estimated but not reported for brevity. The sample consists of OEWS establishments targeted in horizontal M&As from 2001 through 2017 and those of matched control establishments. All variables are defined in the Appendix. Standard errors are reported in parentheses and clustered at the firm level. Significance levels are indicated by *, ** and *** and correspond to the 10%, 5% and 1% significance level, respectively.

	(1)	(2)	(3)	(4)
	RTI	Share HighTech	Wages	StdWages
$Pre_{-3} \cdot M\&A_i$	-0.0816	0.0024	-0.0827**	-0.0865
	(0.0883)	(0.0162)	(0.0362)	(0.0840)
$Pre_{-2} \cdot M\&A_i$	0.0148	-0.0007	0.0133	0.0458
	(0.0567)	(0.0105)	(0.0211)	(0.0441)
$Post_{+1} \cdot M\&A_i$	-0.0814***	0.0119**	0.0349***	0.0577**
	(0.0315)	(0.0050)	(0.0124)	(0.0274)
$Post_{+2} \cdot M\&A_i$	-0.1050***	0.0067	0.0298*	0.0065
	(0.0408)	(0.0056)	(0.0154)	(0.0314)
$Post_{+3} \cdot M\&A_i$	-0.0979**	0.0095	0.0109	0.0183
	(0.0482)	(0.0068)	(0.0177)	(0.0426)
Offshorablility	0.6290***	0.0481***	0.0013	-0.0343
	(0.0404)	(0.0070)	(0.0129)	(0.0268)
Establishment FE	Yes	Yes	Yes	Yes
Industry · Year FE	Yes	Yes	Yes	Yes
State · Year FE	Yes	Yes	Yes	Yes
Observations	8,549	8,549	8,549	8,194
R^2	0.893	0.862	0.907	0.833

Table 5. Occupational changes: Within-establishment estimates

This table presents estimates of changes in employment shares and wages within establishments of M&A targets compared to control establishments. The dependent variables are the employment share (columns 1 and 3) and the log-transformed establishment average wage (columns 2 and 4) of a given *Occupation Type*. *Occupation Type* refers to routine (versus non-routine) occupations in columns 1 and 2, and to high-technology (versus non-high-technology) occupations in columns 3 and 4. $Post_t$, $M\&A_i$ and their interaction are absorbed by establishment-year fixed effects. *Occupation Type* and its interactions with $Post_t$ or $M\&A_i$ are estimated but not reported for brevity. The sample consists of establishments targeted in horizontal M&As from 2001 through 2017 and those of matched control establishments. All variables are defined in the Appendix. Standard errors are reported in parentheses and clustered at the firm level. Significance levels are indicated by *, ** and *** and correspond to the 10%, 5% and 1% significance level, respectively.

	Routine		High-technology	
	(1)	(2)	(3)	(4)
	Occupational Employment Share	Occupational Wage	Occupational Employment Share	Occupational Wage
$Post_t \cdot M\&A_i \cdot$ *Occupation Type*	-0.0290**	-0.0170	0.0099*	0.0497***
	(0.0126)	(0.0124)	(0.0058)	(0.0182)
Establishment · Year FE	Yes	Yes	Yes	Yes
Observations	40,112	32,950	40,112	11,818
R^2	0.014	0.810	0.864	0.784

Table 6. Robustness: Cancelled M&As

This table presents estimates of occupational and wage changes at establishments of M&A targets that were announced and subsequently withdrawn compared to control establishments. Cancelled M&A deals (*pseudo M&A*) are included in the sample if they were blocked by regulators or the bidder was acquired ex-post by a third party. The dependent variable is the average of routine task intensity at the establishment, in column 1; the share of high-technology employment, in column 2; the log-transformed average hourly wage, in column 3; and the log-transformed standard deviation of hourly wages, in column 4. $Post_t$ is estimated but not reported for brevity. The sample consists of OEWS establishments targeted in cancelled horizontal M&As from 2001 through 2017 and those of matched control establishments. All variables are defined in the Appendix. Standard errors are reported in parentheses and clustered at the firm level. Significance levels are indicated by *, ** and *** and correspond to the 10%, 5% and 1% significance level, respectively.

	(1)	(2)	(3)	(4)
	RTI	Share HighTech	Wages	StdWages
$Post_t \cdot pseudo\ M\&A_i$	-0.0082	-0.0238	-0.0495	-0.0693
	(0.1620)	(0.0222)	(0.0545)	(0.1430)
$Offshorability$	0.5900***	-0.0050	-0.0557	-0.0743
	(0.1240)	(0.0188)	(0.0450)	(0.1380)
Establishment FE	Yes	Yes	Yes	Yes
Industry · Year FE	Yes	Yes	Yes	Yes
Observations	232	232	232	216
R^2	0.913	0.753	0.841	0.768

Table 7. M&As and investment in IT

This table presents estimates of changes in IT investment at establishments of M&A targets compared to control establishments. Columns 3 and 4 present the dynamics of the changes in IT investment at target establishments in the years before and after the M&A compared to control establishments. The dependent variable in columns 1 and 3 is the logarithm of one plus the budget $ for IT. In columns 2 and 4, the dependent variable is the logarithm of one plus the budget $ for IT normalized by the number of employees in the establishment. In columns 1 and 2, $Post_t$ is an indicator equal to one for years post-M&A and zero otherwise. In columns 3 and 4, Pre_{-2} is an indicator equal to one for the observation of the establishment observed two years *before* the M&A, and zero otherwise; $Post_n$ is an indicator equal to one for the n^{th} observation of the establishment observed *after* the M&A, where $n = 0,\ 1,\ or\ 2$, and zero otherwise; the first observation prior to the M&A is the omitted coefficient. $Post_t$, Pre_{-2} or $Post_n$ are estimated but not reported for brevity. The sample consists of establishments in the CiTDB data that are targeted in horizontal M&As between 2010 and 2015 and those of matched control establishments. All variables are defined in the Appendix. Standard errors are reported in parentheses and clustered at the firm level. Significance levels are indicated by *, ** and *** and correspond to the 10%, 5% and 1% significance level, respectively.

	(1)	(2)	(3)	(4)
	IT budget	IT budget/Emp	IT budget	IT budget/Emp
$Post_t \cdot M\&A_i$	0.0544***	0.0451**		
	(0.0192)	(0.0192)		
$Pre_{-2} \cdot M\&A_i$			-0.0007	0.0095
			(0.0212)	(0.0214)
$Post_0 \cdot M\&A_i$			0.0476**	0.0407**
			(0.0202)	(0.0202)
$Post_1 \cdot M\&A_i$			0.0635***	0.0606**
			(0.0239)	(0.0240)
$Post_2 \cdot M\&A_i$			0.0502**	0.0476**
			(0.0238)	(0.0239)
Establishment FE	Yes	Yes	Yes	Yes
Industry · Year FE	Yes	Yes	Yes	Yes
State · Year FE	Yes	Yes	Yes	Yes
Observations	35,070	35,070	35,070	35,070
R^2	0.946	0.912	0.946	0.912

Table 8. M&As and investment in IT: Cross-sectional heterogeneity

This table presents estimates of changes in IT investment at establishments of M&A targets compared to control establishments, further interacting $Post_t \cdot M\&A_i$ with $TechSavvy\_Acq_i$ in columns 1-2, $SmallTarget_i$ in columns 3-4, $Unsolicited_i$ in columns 5-6. $TechSavvy\_Acq_i$ is equal to one if ex-ante IT spending at the acquirer is greater than the industry median, and zero otherwise. $SmallTarget_i$ is equal to one if the ex-ante employment at the target is below the sample median, and zero otherwise. $Unsolicited_i$ is equal to one if the M&A deal is unsolicited, and zero otherwise. The dependent variables in columns 1, 3, and 5 are the logarithm of one plus the $ budget for IT. In columns 2, 4 and 6, the dependent variables are the logarithm of one plus the budget $ for IT normalized by the number of employees in the establishment. The interactions between $M\&A_i$ and $TechSavvy\_Acq_i$, $SmallTarget_i$, and $Unsolicited_i$ are absorbed by the fixed effects and the interactions between $Post_t$ and $M\&A_i$, $TechSavvy\_Acq_i$, $SmallTarget_i$, or $Unsolicited_i$ are estimated but not reported for brevity. The sample consists of establishments in the CiTDB data that are targeted in horizontal M&As between 2010 and 2015 and those of matched control establishments. All variables are defined in the Appendix. Standard errors are reported in parentheses and clustered at the firm level. Significance levels are indicated by *, ** and *** and correspond to the 10%, 5% and 1% significance level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
	IT budget	IT budget/Emp	IT budget	IT budget/Emp	IT budget	IT budget/Emp
$Post_t \cdot M\&A_i \cdot TechSavvy\_Acq_i$	0.0978**	0.0941**				
	(0.0445)	(0.0439)				
$Post_t \cdot M\&A_i \cdot SmallTarget_i$			0.0823**	0.0922**		
			(0.0358)	(0.0360)		
$Post_t \cdot M\&A_i \cdot Unsolicited_i$					0.158*	0.192**
					(0.0917)	(0.0897)
Establishment FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry · Year FE	Yes	Yes	Yes	Yes	Yes	Yes
State · Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	25,840	25,840	35,070	35,070	35,070	35,070
R^2	0.945	0.913	0.946	0.912	0.946	0.912

Table 9. Industry-level analysis: 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 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 the Appendix.

	1980	1990	2000	2010
Merger Intensity (%)		0.56	0.46	0.57
		[1.18]	[1.65]	[2.10]
Routine Task Intensity	1.35	1.21	1.17	1.17
	[.63]	[.58]	[.57]	[.63]
High-technology Employment Share	0.121	0.134	0.123	0.135
	[0.905]	[0.101]	[0.118]	[0.135]
Average Hourly Wage ($)	16.80	17.11	18.46	18.89
	[3.53]	[3.81]	[4.42]	[5.52]
Standard Deviation of Hourly Wages	11.27	12.95	16.74	15.16
	[2.01]	[3.07]	[4.23]	[4.83]
Offshorability	0.12	0.12	0.13	0.16
	[0.43]	[0.44]	[0.45]	[0.45]

Table 10. M&As and labor outcomes: Industry-level analysis

This table presents estimates of occupational and wage changes at the (four-digit NAICS) industry j and time t following M&As. In column 1, the dependent variable is the average routine task intensity; in column 2, the dependent variable is the share of high-technology employment; in column 3, the dependent variable is the log-transformed average hourly wage; and in column 4, the dependent variable is the log-transformed standard deviation of hourly wages. The timeline starts in 1980 and ends in 2010 with one observation per decade for each industry. All variables are defined in the Appendix. Standard errors are reported in parentheses and clustered at the industry level. Significance levels are indicated by *, ** and *** and correspond to the 10%, 5% and 1% significance level, respectively.

	(1)	(2)	(3)	(4)
	RTI	Share HighTech	Wage	StdWages
$log(Merger\ Intensity)_{j,(t-10,t-1)}$	-1.316***	0.514**	1.088**	1.407**
	(0.469)	(0.131)	(0.497)	(0.406)
$Offshorability$	0.375	0.0612	-0.0217	0.0098
	(0.324)	(0.0379)	(0.0822)	(0.151)
Year FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Observations	396	396	396	396
R^2	0.956	0.969	0.959	0.885

Mergers and Acquisitions, Technological Change, and Inequality

INTERNET APPENDIX

Table IA1. M&As and target high-technology employment

This table presents estimates of changes in employment of high-technology occupations at establishments of M&A targets compared to control establishments. The dependent variable in column 1 is the establishment-level employment in high-technology occupations including scientific, engineering and technician occupations; the dependent variable in column 2 is the establishment-level employment of computer and mathematical scientists and managers; the dependent variable in column 3 is the establishment-level employment of technicians, engineers and engineering managers; the dependent variable in column 4 is the establishment-level employment of life, physical, and social science technicians and natural sciences managers. $Post_t$ is estimated but not reported for brevity. The sample consists of establishments of firms targeted in horizontal M&As from 2001 through 2017 and those of matched control establishments. Standard errors are reported in parentheses and clustered at the firm level. Significance levels are indicated by *, ** and *** and correspond to the 10%, 5% and 1% significance level, respectively.

	(1)	(2)	(3)	(4)
	HighTech Emp	CS and Math Emp	Engineering Emp	LS and Physics Emp
$Post_t \cdot M\&A_i$	0.0180	-0.0193	0.0537***	0.0144
	(0.0213)	(0.0202)	(0.0196)	(0.0109)
$Offshorability$	0.2380***	0.2270***	0.0682***	0.0098
	(0.0270)	(0.0263)	(0.0180)	(0.0108)
Establishment FE	Yes	Yes	Yes	Yes
Industry · Year FE	Yes	Yes	Yes	Yes
State · Year FE	Yes	Yes	Yes	Yes
Observations	19,218	19,218	19,218	19,218
R^2	0.924	0.907	0.892	0.870

Table IA2. Robustness: M&As and target wage inequality

This table presents estimates of changes in wage inequality at establishments of M&A targets compared to control establishments. In Panel A, the dependent variable is the log-transformed ratio of the 90th percentile of wages to the 10th percentile of wages at the establishment-year level. In Panel B, the dependent variable is the log-transformed ratio of the 75th percentile of wages to the 25th percentile of wages at the establishment-year level. In Panel C, the dependent variable is the log-transformed ratio of the 90th percentile of wages to the 50th percentile of wages at the establishment-year level. $Post_t$ is estimated but not reported for brevity. The sample consists of establishments of firms targeted in horizontal M&As from 2001 through 2017 and those of matched control establishments. Standard errors are reported in parentheses and clustered at the firm level. Significance levels are indicated by *, ** and *** and correspond to the 10%, 5% and 1% significance level, respectively.

	Panel A			
	(1)	(2)	(3)	(4)
	Wages 90/10	Wages 90/10	Wages 90/10	Wages 90/10
$Post_t \cdot M\&A_i$	0.0316***	0.0322***	0.0316***	0.0287***
	(0.0114)	(0.0113)	(0.0101)	(0.0108)
$Offshorability$		0.0148	0.0092	0.0086
		(0.0112)	(0.0124)	(0.0116)
Year FE	Yes	Yes		
Establishment FE	Yes	Yes	Yes	Yes
Industry · Year FE			Yes	Yes
State · Year FE				Yes
Observations	20,056	20,056	19,081	18,971
R^2	0.743	0.743	0.806	0.830

Panel B				
	(1)	(2)	(3)	(4)
	Wages 75/25	Wages 75/25	Wages 75/25	Wages 75/25
$Post_t \cdot M\&A_i$	0.0265***	0.0268***	0.0276***	0.0286***
	(0.0080)	(0.0080)	(0.0075)	(0.0078)
$Offshorability$		0.0085	0.0100	0.0082
		(0.0075)	(0.0084)	(0.0084)
Year FE	Yes	Yes		
Establishment FE	Yes	Yes	Yes	Yes
Industry · Year FE			Yes	Yes
State · Year FE				Yes
Observations	20,056	20,056	19,081	18,971
R^2	0.704	0.704	0.772	0.799

Panel C				
	(1)	(2)	(3)	(4)
	Wages 90/50	Wages 90/50	Wages 90/50	Wages 90/50
$Post_t \cdot M\&A_i$	0.0179**	0.0183**	0.0207**	0.0206**
	(0.0088)	(0.0088)	(0.0081)	(0.0086)
$Offshorability$		0.0098	0.0040	0.0044
		(0.0081)	(0.0088)	(0.0087)
Year FE	Yes	Yes		
Establishment FE	Yes	Yes	Yes	Yes
Industry · Year FE			Yes	Yes
State · Year FE				Yes
Observations	20,056	20,056	19,081	18,971
R^2	0.693	0.693	0.765	0.793

Table IA3. Robustness: M&As and acquirer and target labor outcomes

This table presents estimates of changes in labor outcomes at establishments of both M&A targets and acquirers compared to control establishments. In column 1, the dependent variable is the average routine task intensity (RTI) at the establishment; in column 2, the dependent variable is the share of high-technology employment; in column 3, the dependent variable is the log-transformed average hourly wage; in column 4, the dependent variable is the log-transformed standard deviation of hourly wages. $Post_t$ is estimated but not reported for brevity. The sample consists of establishments of firms targeted and establishments of acquirers in M&As from 2001 through 2017 and those of matched control establishments. Standard errors are reported in parentheses and clustered at the firm level. *** indicates p < 0.01, ** indicates p < 0.05, and * indicates p < 0.1.

	(1)	(2)	(3)	(4)
	RTI	Share HighTech	Wages	StdWages
$Post_t \cdot M\&A_i$	-0.0838***	0.0072***	0.0036	0.0220*
	(0.0161)	(0.0022)	(0.0058)	(0.0119)
$Offshorability$	0.803***	0.0332***	0.0008	0.0123
	(0.0310)	(0.0034)	(0.0065)	(0.0129)
Establishment FE	Yes	Yes	Yes	Yes
Industry · Year FE	Yes	Yes	Yes	Yes
State · Year FE	Yes	Yes	Yes	Yes
Observations	40,129	40,129	40,129	37,664
R^2	0.907	0.885	0.913	0.858

Table IA4. Industries ranked by level of routine task intensity (RTI)

This table ranks (four-digit NAICS) industries by RTI. Panel A ranks the industries with the highest RTI by decade (in descending order). Panel B ranks the industries with the lowest RTI by decade (in ascending order). The four-digit NAICS codes are included in parentheses.

1980	1990	2000	2010
Panel A. Industries with highest RTI			
legal services (5411)	legal services (5411)	legal services (5411)	legal services (5411)
accounting, auditing, and bookkeeping services (5412)	accounting, auditing, and bookkeeping services (5412)	offices of dentists (6212)	offices of dentists (6212)
offices of dentists (6212)	offices of dentists (6212)	accounting, auditing, and bookkeeping services (5412)	accounting, auditing, and bookkeeping services (5412)
nondepository credit intermediation, activities related to credit intermediation (5223-5224)	nondepository credit intermediation, activities related to credit intermediation (5223-5224)	personal care services (8121)	personal care services (8121)
personal care services (8121)	personal care services (8121)	beer, wine, and liquor stores (4453)	beer, wine, and liquor stores (4453)
Panel B. Industries with lowest RTI			
taxicab service (4853)	taxicab service (4853)	taxicab service (4853)	taxicab service (4853)
elementary and secondary schools (6111)	elementary and secondary schools (6111)	transit and ground passenger transportation (4851-4859)	transit and ground passenger transportation (4851-4859)
transit and ground passenger transportation (4851-4859)	transit and ground passenger transportation (4851-4859)	elementary and secondary schools (6111)	elementary and secondary schools (6111)
child day care services (6244)	child day care services (6244)	timber tract operations, forest nurseries and gathering of forest products (1131-1132)	timber tract operations, forest nurseries and gathering of forest products (1131-1132)
timber tract operations, forest nurseries and gathering of forest products (1131-1132)	timber tract operations, forest nurseries and gathering of forest products (1131-1132)	child day care services (6244)	child day care services (6244)

Table IA5. Industry-level analysis robustness: Defining M&A intensity using transaction values

This table repeats specifications in Table 10, except that $Merger\ Intensity_{j,(t-10,t-1)}$ is defined based on M&A transaction values (instead of M&A counts). Standard errors are reported in parentheses and clustered at the industry level. Significance levels are indicated by *, ** and *** and correspond to the 10%, 5% and 1% significance level, respectively.

	(1)	(2)	(3)	(4)
	RTI	Share HighTech	Wage	StdWages
$log(Merger\ Intensity)_{j,(t-10,t-1)}$	-1.316***	0.369**	1.088**	1.407**
	(0.469)	(0.147)	(0.497)	(0.406)
$Offshorability$	0.375	0.0127	-0.0217	0.0098
	(0.324)	(0.0223)	(0.0822)	(0.151)
Year FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Observations	396	396	396	396
R^2	0.956	0.963	0.959	0.885

Table IA6. Industry-level analysis robustness: Defining M&A intensity using the first six years of each decade

This table repeats specifications in Table 10, except that $Merger\ Intensity_{j,(t-10,\ t-4)}$ is based on M&A transaction values over the first six years of each decade(instead of over the ten years of each decade). Standard errors are reported in parentheses and clustered at the industry level. Significance levels are indicated by *, ** and *** and correspond to the 10%, 5% and 1% significance level, respectively.

	(1)	(2)	(3)	(4)
	RTI	Share HighTech	Wage	StdWages
$log(Merger\ Intensity)_{j,(t-10,\ t-4)}$	-1.847***	0.558***	1.651***	1.796***
	(0.569)	(0.172)	(0.302)	(0.554)
$Offshorability$	0.376	0.0605	-0.0226	0.0083
	(0.324)	(0.0378)	(0.0821)	(0.150)
Year FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Observations	396	396	396	396
R^2	0.970	0.969	0.960	0.886

Mapping M&A deals from SDC to OEWS

The OEWS program is a federal-state cooperative program between the Bureau of Labor Statistics (BLS) and State Workforce Agencies (SWAs). The program surveys nonfarm establishments in the U.S. semiannually.[1] Each establishment is surveyed at most once every three years and has a 9-digit unique and time-invariant identifier ($UDBNum$) that allows researchers to track the establishment's employment and wages over time. For each establishment, the OEWS program also reports its parent firm's 9-digit Federal Employer Identification Number (EIN) and legal name (L_Name), which may change over time. SDC includes information on 6-digit CUSIP codes and company names of targets and acquirers involved in M&A deals.

To match M&A deals to the OEWS, we take the following steps. First, we get firms' EINs from Compustat and match them to target and acquirer companies in the SDC using CUSIP codes. For companies that get more than one match, we manually check each match and only keep the ones matched with company names.

Second, we link M&A deals to the establishments in the OEWS using target EINs. By taking this step, approximately 15% of the M&A deals are matched to the OEWS. The matching rate is low for two reasons: 1) most target firms are not publicly listed and cannot be matched with Compustat provided EINs; 2) firms may not have a consistent and unique EIN across different databases. Specifically, firms may use one EIN in Securities and Exchange Commission (SEC) filings and a different EIN (or EINs) in filings with the state Unemployment Insurance (UI) tax system.[2] The former is used in the Compustat

[1]See more details at https://www.bls.gov/oes/oes_emp.htm.

[2]Firms that span across states may use numerous EINs in the UI system. See more details about linking

database, and the latter is used in the OEWS.

To improve the matching between the SDC and the OEWS data, we use a name matching procedure for M&A deals that cannot be matched by target EINs. We start with standardizing firm names provided in the SDC and OEWS (e.g., lowering cases and stripping out common endings and special characters, such as "Inc," ".com," "L.P.," and "@"). We run a fuzzy matching algorithm (reclink2) developed by Wasi and Flaaen (2015) on the standardized firm names to identify possible matching candidates. We review candidates with a matching score above 90% and manually pick the matches.

Finally, we keep matches only if we observe the target establishment strictly in the OEWS before and after the M&A deal is completed. In the end, we identify a total of 1,740 horizontal M&A deals in the OEWS survey covering 5,014 establishments from 2001 to 2017.

firms with establishments in BLS microdata in Handwerker and Mason (2013).

Industry mapping between IPUMS and SDC data

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 perform the following steps.

First, we map the variable INDNAICS from ACS 2008-2014 samples to NAICS 2007 using a crosswalk provided by IPUMS.[3] About 4% 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 four digits. This crosswalk provides a one-to-one mapping between INDNAICS and IND1990.

Second, 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 those 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 2212 and to NAICS 2213. NAICS

[3] The crosswalk is available at the following website: https://usa.ipums.org/usa/volii/indnaics18.shtml

2212 and NAICS 2213 map only 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 to identify all possible such matches. Industries that 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 this paper as meta-industries, as they may include more than one unique IND1990 and more than one unique four-digit NAICS 2007. We have 132 unique meta-industries. Of the 224 unique industries in IND1990, we can successfully map 178 industries into our meta-industries or 79.5% of the unique IND1990 industries in IPUMS. Our mapping includes 209 unique four-digit NAICS 2007.

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