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Mergers and Acquisitions, Technological Change and Inequality

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August 2025

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Abstract

Mergers and acquisitions (M&As) are an important mechanism through which technology is adopted by firms. Firms with greater technological skill acquire less tech-savvy firms and, subsequently, increase technology investment at the target. This has important implications for labor reallocation following M&As. We show that target establishments become less routine intensive post-M&A, especially when a target had greater routine occupational employment, compared to its acquirer, ex-ante. We also provide evidence consistent with targets investing in information technology which tends to displace more office routine occupations. Such labor reallocation impacts wages, resulting in higher pay inequality within target establishments.

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

JEL Classifications: G34, J24, J31, O33

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Mergers and Acquisitions, Technological Change, and Inequality*

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Abstract

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1. Introduction

Several studies on mergers and acquisitions (M&As) have documented important labor reallocation effects on employment and wages. These changes have been associated with new owners breaking implicit contracts impacting employment and wages (Shleifer and Summers, 1988) as well as acquirers targeting firms with surplus employment and subsequently raising shareholder value through redundancies (Shleifer and Vishny, 1988). In addition, M&As can change the optimal allocation of a firm's assets (Maksimovic et al., 2011) leading to asset sales and employment shifts. This paper documents a novel channel through which post-merger labor reallocation occurs: Acquirers transfer technological knowledge to targets, who then adopt more advanced technology ex-post with implications for labor demand.

Our hypothesis is based on the idea that acquiring firms tend to possess more technological know-how than target firms in the same industry and that these technology-specific skills can be transferred following a horizontal merger. This is rather intuitive if we think that acquiring firms tend to be large in scale and have greater access to financing (Erel et al., 2015), characteristics also common among firms that have invested significantly in technology.[1] Moreover, such investments have important implications for labor allocation as technology (e.g., automation) tends to replace workers performing routine tasks, namely those tasks that are repetitive in nature (e.g., Autor et al., 2003; Autor and Dorn, 2013; Kogan et al., 2023).

To the extent that technologically advanced acquirers implement more sophisticated technology at targets, we should observe that the share of routine occupations declines at target establishments post merger, compared to a matched set of control establishments. To this end, we use data provided by the Occupational Employment and Wage Statistics program (OEWS), administered by the Bureau of Labor Statistics (BLS). The OEWS contains detailed information on occupational employment and wages. Using a

[1] For example, large and cash-rich firms are more likely to adopt technology in the U.S. (Bessen, 2020; Zolas et al., 2020), while established firms with better access to financing have been the primary buyers of new capital in the economy (Ma et al., 2022).

sample of 2,924 target establishments in OEWS associated with 1,159 horizontal M&A events spanning 2001-2017, we indeed find that the employment share of workers in high routine occupations declines relatively more at target establishments post-M&A, compared to matched non-M&A establishments. Moreover, the magnitudes of these effects are economically important, with an average decline in the routine employment share by 1.9 percentage points, or 5.3% relative to the pre-treatment mean–equivalent to approximately an annual rate of 1.23%.[2] Comparing our baseline estimates with the decline in routine employment share across OEWS establishments over the same time period, M&A targets reduce routine employment share annually at a rate approximately 1.5 times higher than that of the broader economy.

To further test our hypothesis, we explore treatment heterogeneity. We show that M&As, where targets have greater ex-ante routine employment shares relative to acquirers, are those in which we observe a larger decline in routine employment share at the target by 4 percentage points (or 0.93 percentage points annually). This is a large decline when compared to the baseline average treatment effect of 1.9 percentage points (or an annual reduction of 0.44 percentage points). We find similar results when we instead exploit heterogeneity based on acquirer wages being higher than target wages pre-treatment, with such wage differences likely reflecting the relative skill of employees in the acquirer-target pair. We also examine establishment-level data on information technology (IT) investment from the Ci Technology Database (CiTDB). Consistent with the labor results, we find that the percentile rank of investment in IT (IT per employee) increases post-M&A by 2.1 (2.3) percentage points annually on average, compared to controls, in deals where acquirers have ex-ante greater investments in IT per employee relative to targets.

Furthermore, we show that these patterns are not just in the relative share of routine employment but also in the overall level of employment. In the presence of zeros in the employment distribution, we transform employment levels into percentiles by measuring the rank of each observation within its relevant sample each year following Chen

[2]In our sample, the average post-treatment period is 4.3 years.

and Roth (2023) and Delius and Sterck (2024). We show that not only do target firms reallocate away from routine occupations post-M&A, but the majority of post-M&A employment reductions are concentrated in these routine occupations. Specifically, we find that relative to control establishments, the percentile rank of routine employment at target establishments declines by 2.3 percentage points (0.53 percentage points annually) post-M&A. In contrast, the percentile rank of non-routine employment does not decline significantly. The net effect is an average decline in the percentile rank of overall employment in target establishments of 1.6 percentage points (or 0.37 percentage points in annual terms), driven primarily by lower demand for routine employment. Within routine occupations, we find a significant decline in the percentile ranks of routine cognitive employment, consistent with information technology replacing routine cognitive tasks typically performed by white-collar office workers, and an insignificant decline in the percentile ranks of routine manual employment often associated with the adoption of robots and machinery replacing production workers.

We also examine changes to employment in technology-related occupations post-M&As driven by the notion that technology should increase the productivity (and demand for labor) of employees who use, develop, and maintain technology (e.g., Autor et al., 2003; Autor and Dorn, 2013; Goos et al., 2014; Kogan et al., 2023). On average, the percentile rank of tech-oriented occupations increases by 1.76 percentage points (or 0.41 percentage points annually) post-M&As at target establishments relative to controls. Decomposing it further, we find that the increase is mainly driven by engineering occupations. Specifically, we document a 2.26-percentage-point increase (or 0.53 percentage points in annual terms) in the average percentile rank of engineering employment and a positive but insignificant effect on the average percentile rank of non-engineering employment. As such, our evidence points toward technology-related occupations benefiting post M&As.

To better understand which occupations are responsible for such shift, we dig deeper into employment changes among granular occupations defined using the finest classification by Dorn (2009) for which we can measure routine intensiveness. Among the 25 occupations experiencing the highest decline in employment percentiles, routine occupations are over-represented, including roles like shipping clerks, interviewers, surveyors, data entry keyers, and bill and account collectors. In contrast, among the top occupations experiencing the highest increase in employment percentiles, technical occupations are over-represented, along with management-related and professional occupations, such as electrical engineers, engineering technicians, health technologists, HR specialists, and financial specialists. These occupations are directly linked to or benefit from the use of technology.

It is possible that an omitted variable, such as declines in demand (Hershbein and Kahn, 2018; Jaimovich and Siu, 2020), industry shocks (Harford, 2005), or regulatory changes (Tuzel and Zhang, 2021; Bena et al., 2022) may lead to both M&As and changes in labor demand. We present several pieces of evidence that mitigate the possibility that demand, industry, regulatory, or other shocks could explain both the observed changes in optimal firm boundaries and the adoption of technology. First, we carefully match M&A targets to control establishments to reduce selection bias caused by the non-random nature of the target selection process. In our specifications, we further control for time-invariant establishment characteristics by including establishment fixed effects, time-varying industry characteristics by including industry-year fixed effects, and time-varying local characteristics by including state-year fixed effects. Second, we plot the dynamic coefficient estimates around the M&A events and document no significant pre-treatment trends prior to the M&A, providing support for the validity of a parallel trends assumption. Third, we show robust results with alternative matching algorithms, where we additionally require that the target and matched control establishments both belong to a narrower band of ex-ante measures of routine employment.

Although our results collectively support the importance of the technology channel, it is possible that alternative mechanisms may also be at play. First, target firms might receive takeover bids when they are further behind the technological frontier, but would have made similar technological adjustments ex-post irrespective of the M&A. Second, M&As may result in redundancies of duplicate employees if there are economies of scale and such opportunities may be concentrated among routine occupations. Third, our results might be driven by acquirers' greater expertise and supportive infrastructure to offshore their production, rather than by their greater technological skill. We perform several robustness analyses to address these concerns. Although such analyses cannot fully exclude the role of these other potential motivations, collectively, they suggest that these alternative mechanisms cannot entirely explain our main findings.

Our results on occupational employment changes at M&A targets also have implications for wages. We find that mean establishment wages increase following M&As, likely driven by lower relative demand for routine employment and, overall, upskilling within the establishment. On average, we find a 2.4% (an annual rate of 0.56%) increase in the mean wage at treated establishments post-M&A, compared to matched control establishments.[3] We also find that M&As are associated with more unequal pay, consistent with the observed occupational shift away from routine (typically mid-skill) occupations, and toward tech-oriented (typically high-skill) occupations. In economic terms, the increase in standard deviation in wages at the average target establishment post M&A exceeds that of a similar control establishment by 3.2% (or 0.74% annually).

Our paper contributes to several strands of the literature. First, it contributes to the finance literature on the labor outcomes of M&As. Existing studies argue that a new owner can break implicit contracts with employees associated with wage and employment expectations and thereby transfer the surplus resulting from decreased wages and/or worker employment to shareholders (Shleifer and Summers, 1988; Gugler and Yurtoglu, 2004; John et al., 2015). Shleifer and Vishny (1988) argue that acquirers may be motivated to target firms where existing agency conflict has led to surplus employment, subsequently raising shareholder value with post-merger layoffs. Maksimovic et al. (2011) arrive at a similar prediction but without requiring agency conflicts at the target. They argue that due to new boundaries of the firm post-M&A, value gains can be achieved by

[3] Note that the wage changes we capture could be driven by changes among continuing or new employees reflecting upskilling of occupations due to automation (Dunne et al., 2004; Hershbein and Kahn, 2018; Kogan et al., 2023) or by compositional occupational shifts occurring post-M&As. However, in the absence of individual wage data, these changes are less informative about the effect of technology on the earnings of impacted workers as in Kogan et al. (2020, 2023).

reshuffling assets, and mechanically, plant divestitures will lead to employment declines. More recently, the literature has explored other labor-related motivations for M&As, including acquiring targets to access the firm's labor as in Ouimet and Zarutskie (2020), or as a means to expand internal labor markets as in Tate and Yang (2024), and has documented significant ex-post changes to the acquirer's workforce as well (Gehrke et al., 2021).

The empirical literature tends to find that M&As are generally followed by lower employment at the target (Lichtenberg and Siegel, 1990; Conyon et al., 2002; Li, 2013; Dessaint et al., 2017; Lagaras, Forthcoming), and/or declines in employee compensation (Pontiff et al., 1990; Rosett, 1990; Babenko et al., 2021; He and le Maire, 2025; Lagaras, Forthcoming). However, several papers have shown more mixed results regarding employment and/or wages (Brown and Medoff, 1988; Kaplan, 1989; McGuckin and Nguyen, 2001; Gugler and Yurtoglu, 2004; Huttunen, 2007; Lehto and Böckerman, 2008; Siegel and Simons, 2010; Kubo and Saito, 2012).[4] Our paper is more closely related to Li (2013), who uses plant-level data in manufacturing and shows that layoffs post-M&As are concentrated among non-production workers. While our results are not necessarily contradictory, as we also observe relatively larger employment declines in non-production occupations (such as clerical and administrative occupations), our interpretation is different. We argue that the occupational changes we observe are the result of greater automation technology adoption at the target. Li (2013), instead, interprets the results as consistent with acquirers improving efficiency at their targets by replacing targets' management teams. It is also important to note that Li's sample includes the 1980s, when automation was less developed and takeovers motivated by weak governance were more common. Overall, we contribute to the literature on M&A and labor by proposing a new mechanism through which labor restructuring occurs following M&As. 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 after M&As.

[4] See also Nishesh et al. (2024) for a discussion of the literature on labor and M&As.

We also build on the literature on how technology is adopted by firms. Several frictions can create variation as to *when* firms automate, such as macroeconomic conditions (Hershbein and Kahn, 2018; Jaimovich and Siu, 2020), regulatory changes that change the relative price of the production inputs (Geng et al., 2022; Tuzel and Zhang, 2021; Bena et al., 2022; Dai and Qiu, 2023), shocks to the labor supply (Lewis, 2011; Bena and Simintzi, Forthcoming; Ouimet et al., 2025), agency conflicts (Atkin et al., 2017), or financial constraints (Midrigan and Xu, 2014; Ersahin, 2020). Technology adoption will in turn impact firms' expected returns (Zhang, 2019) or valuation (Bena et al., 2022) and will change workers' labor outcomes (Frydman and Papanikolaou, 2018; Kogan et al., 2020, 2023). In our paper, we instead show that M&As act as a catalyst for technology adoption, as acquiring firms that better implement automation technologies take over targets less able to do so. Following the M&A, these automation-savvy acquirers adopt greater technology at the target, resulting in compositional and wage shifts at these firms. Similar to Kogan et al. (2023), we find that technology has nuanced effects on the impacted labor with significant heterogeneity across groups.

2. Data

2.1. 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). These data come from a semiannual survey of individual establishments in the U.S. Each establishment is surveyed at most once every three years. The median time between two observations of an establishment is 3.5 years. The surveyed establishments are selected in a manner that allows 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.[5]

For each establishment-year, we observe employment in 800 different occupational

[5] See more details at the BLS website, https://www.bls.gov/oes/oes_emp.htm.

categories represented by 6-digit Standard Occupational Classification (SOC) codes.[6] 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, we observe each establishment's location (by county), EIN, name, legal name (ultimate owner), industry, and a time-invariant establishment identifier used to track establishments that have switched owners over time.

Although OEWS is a unique source of detailed occupational employment in the U.S., we need to acknowledge certain limitations as well. First, in case of missing observations, BLS imputes missing values using data from establishments with similar characteristics, such as industry, employment levels, state, and ownership. Second, we cannot observe all establishments of a given firm. However, both of the aforementioned issues are not unique to either treated or control establishments in our analysis. Third, while OEWS surveys establishments of both private and publicly listed firms, it over-samples larger establishments. This limits our ability to reach conclusions about smaller establishments but ensures that our results are based on a sample of economically important entities. While we acknowledge the limitations of the data and the potential of these limitations to introduce noise, or even bias our results if there is systematic selection, the OEWS ultimately is the only administrative establishment-level dataset that provides complete and detailed occupational employment for a representative sample of U.S. establishments over time.

To construct the sample, we identify horizontal M&A deals in which the acquirer and target are U.S.-based and operate in the same 4-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.[7] The sample starts in 2001, the earliest year in which the identifier needed to link OEWS establishments over time is available. We require each matched establishment to be surveyed in OEWS at least once before and

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

[7] In the Internet Appendix B1, we document the detailed steps for matching M&A deals from SDC to OEWS.

once after the M&A. We identify a total of 1,159 horizontal M&A deals in the OEWS survey, covering 2,924 establishments during our sample time period. Internet Appendix Figure IA. A.1 shows that our deals cover a wide range of industries (Panel A) and a wide range of geographies (Panels B and C). The industry and geographical distribution of our sample deals (Figure IA. A.1) are similar to those that could not be matched to OEWS (Figure IA. A.2).

Control establishments are sampled from the set of establishments in OEWS that were not involved in M&As during our sample period. For each target establishment, i) we match on a set of observable characteristics, and ii) we keep up to two matched control establishments. Specifically, we follow a two-step process. We first require all potentially matched control establishments to match by 4-digit NAICS industry code as well as by decile of establishment total employment and decile of average hourly wages (as measured in the first pre-M&A observation). In addition, treated and control establishments need to be observed at least once before and once after the M&A. We require treated and control establishments to be observed in the same year prior to the M&A. We also require observations in the first post-M&A year of treated and control establishments to occur within a year of each other. Second, we keep up to two matches with the nearest propensity score constructed using a linear probability model based on the first pre-M&A year establishment RTI, high-tech employment share, offshorability, log of employment, log of average hourly wages, and log of the standard deviation of hourly wages.[8] Internet Appendix Table IA. A.1 presents the distribution of observation counts across periods in our baseline sample.[9]

To measure occupational shifts consistent with technology adoption, we examine the routine task intensiveness of occupations performed at establishments following Autor and Dorn (2013).[10] Specifically, we employ three measures: i) RSH, the employment share

[8] Similar matching approaches have been used in the literature, as described in Graham et al. (2023) and Lagaras (Forthcoming).

[9] To assess whether smaller sample sizes in the pre-treatment period impact our estimates, we show in the Internet Appendix Table IA. A.2 the robustness estimates of our baseline analysis using shorter event windows.

[10] Since occupations involve multiple tasks (routine, abstract, and manual) at different average frequencies, Autor and Dorn (2013) create an index that measures routine task intensity by occupation.

of routine occupations, where an occupation is routine if it is in the top employment-weighted quartile of routine task intensity within the 2000 American Community Survey (ACS) distribution;[11] ii) RTI, the occupational employment-weighted average of routine task intensity; and iii) *Routine Employment Percentile*, the percentile rank of establishment employment within routine occupations in the sample distribution for a given year.[12]

Following Hecker (2005), we also identify tech-oriented occupations, which include engineers; engineering technicians; life and physical scientists and technicians; computer and mathematical scientists; and managers of computer, information systems, engineering, and natural science. Workers in these occupations engage in tasks related to research; design and develop equipment, products, and production processes; apply technology; and manage these activities. We group these tech-oriented occupations into engineering and non-engineering occupations. Workers in engineering occupations develop, apply, and maintain hardware devices and software systems. Non-engineering occupations include the rest of tech-oriented occupations focused on theoretical research and increasing scientific knowledge, such as life and physical scientists, and computer and mathematical scientists.[13]

To measure establishment wages and inequality, we start by 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 employment-weighted average of the upper and lower bounds of the wage bin as the nominal wage for each

This index increases in the importance of the routine inputs and decreases in the importance of the abstract and manual inputs of a given occupation. Following Autor and Dorn (2013), routine task intensity for occupation o is defined as $RTI_o = lnR_o - lnA_o - lnM_o$, where R_o, A_o and M_o are the routine, abstract, and manual inputs, respectively, by occupation, indexed by o. Routine task intensity scores are defined at $occ1990dd$ level, an occupational classification system developed by Dorn (2009).

[11] Zhang (2019) defines routine-task labor based on the RTI distribution in the 1990 Census, and Autor and Dorn (2013) define routine occupations based on the RTI distribution in the 1980 Census. We use 2000 ACS because our sample starts in 2001. ACS data is publicly available at IPUMS USA website, `https://usa.ipums.org/usa/`.

[12] We do not directly use employment levels due to the presence of both skewness and observations with zero values (Cohn, Liu, and Wardlaw 2022; Chen and Roth 2023). Instead, for each observation, we calculate its percentile rank of employment, using all observations in that regression sample in that year. This approach avoids making any distributional property assumptions as in Chen and Roth (2023).

[13] Detailed SOC codes of tech-oriented, engineering, and non-engineering occupations are documented in Appendix Table A.1.

establishment-occupation-year and adjust for inflation to real wages in 2001 dollars. The establishment wage is measured as the employment-weighted mean of occupational wages. Within-establishment inequality is measured by the employment-weighted standard deviation of occupational wages.

Last, 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 Appendix Table A.1.

Table 1 reports summary statistics for our sample establishments in OEWS data. The average establishment in our sample has 185 employees. On average, 35.6% of employees in an establishment are in routine occupations. The average establishment has a routine task intensity of 1.6. On average, 55 employees in an establishment are employed in routine occupations and 16 employees are in high-technology occupations. Our sample firms have an average real wage of \$17.52 per hour. This is comparable to the mean hourly U.S. wage in 2001 of \$16.4.[14] Finally, we report an average standard deviation of hourly wages equal to \$9.4. In Table 1, columns 4-10, 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 treated and control establishments across characteristics. The last column of Table 1 reports the means of pooled treated and control establishments in the pre-treatment period.[15]

2.2. 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 telecom-

[14] See the BLS report for more information at https://www.bls.gov/oes/bulletin_2001.pdf

[15] The lack of significant difference in pre-treatment characteristics between our treated and control groups is reassuring, given the clear selection of more routine establishments as M&A targets when comparing within all establishments in the same industry and year observed in the OEWS (Internet Appendix Table IA. A.3).

munication technologies at establishments across the U.S. CiTDB generates its data using annual surveys of establishments. 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. Existing literature has also used data from the CiTDB (or its predecessors) to measure information technologies (e.g., Brynjolfsson and Hitt, 2003; Tambe and Hitt, 2014; Zhang, 2019; Tuzel and Zhang, 2021; Dai and Qiu, 2023).

To construct the technology investment sample, we take the following steps. For each treated establishment, we measure the pre-M&A period beginning three years before the M&A effective year and extend the sample through two years after the M&A effective year. 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 six-year timeline around the M&A event. To create the control sample, we start with the set of establishments observed across a six-year window and that are not identified as a target firm during our sample period. We require control firms to match on (4-digit NAICS) industry, type of establishment, decile of establishment total employment, and decile of revenue per employee (as measured in the first year prior to the M&A).[16] We keep up to two matches with the nearest propensity score, constructed using a linear probability model based on the first pre-M&A year establishment log of employment, log of revenue per employee, log of IT budget, and log of IT budget per employee. This gives us a sample of 3,438 unique establishments (treated and control) covering 165 (4-digit NAICS) industries and all states. Our sample timeline is 2009-2015, since we require each establishment to have six years of observations to match with the OEWS sample.[17]

Internet Appendix Table IA. A.4 reports summary statistics for our establishments in the CiTDB sample. The average establishment in our sample has 110 employees, and spends \$496 thousand in total and \$8,455 per employee on IT. The *IT budget* variable includes a firm's budget spent, on average, on hardware equipment (18%), software

[16] CiTDB identifies four different types of establishments: branch, headquarters, stand-alone and ultimate headquarters. The majority of our matched establishments are branches (80%).

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

(27.8%), IT-related services (37.1%), storage technologies (3.9%), and communication services (11.8%). 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 column 10. We find no significant differences between treated and control establishments across these variables.

We show that our IT measure correlates significantly with other measures that capture investment in automation or capital (more broadly) at the firm and industry levels, using the universe of our CiTDB data. To do this, we aggregate IT spending and employment data from CiTDB to the firm level. We then match CiTDB variables with firm-level patenting data from the United States Patent and Trademark Office (USPTO) and process innovation data from Bena and Simintzi (Forthcoming) using firm names. In Internet Appendix Table IA. A.5, column 1, we present correlations between percentile ranks of firms' IT budget per employee and percentile ranks of their total number of patents filed in a given year, controlling for year fixed effects. We show a positive and significant correlation, consistent with the intuition that firms that patent more tend to be leaders in technology adoption. In column 2, we examine correlations between percentile ranks of firms' IT budget per employee and the share of process innovation in a given year. Bena and Simintzi (Forthcoming) show that process innovation measures labor-saving innovation. The share of process innovation is defined only if the firm receives at least one patent in a given firm-year, thus reducing the sample. We document a positive correlation between percentile ranks of firms' IT budget per employee and their share of process innovation, after controlling for year fixed effects.

In Table IA. A.5, columns 3-5, we instead examine industry-level correlations between IT spending per worker from CiTDB data and capital spending per worker from NBER-CES manufacturing database over 2009-2015. We first aggregate IT spending and employment data from CiTDB to the 4-digit NAICS level. We then regress the logarithm of industry-level investment per worker or equipment per worker from NBER-CES on the logarithm of IT spending per worker aggregated from CiTDB, controlling for year fixed effects. We show a significant positive association between IT spending per worker and equipment per worker (or investment per worker) for the manufacturing sector. In column 6, we also show a significant negative correlation between CiTDB IT spending per worker and the share of production workers within manufacturing industries, as automation increases investment in capital and reduces reliance on production labor.

3. Occupational Composition

To test our hypothesis regarding changes in technology use at targets post-M&A, we examine changes in the share of routine employment at establishments. Our tests are based on the well-documented fact that technology adoption tends to replace tasks that are routine and highly repetitive in nature (e.g., Autor et al., 2003; Autor and Dorn, 2013). We use OEWS data to examine changes in the occupational composition of target establishments, compared to similar establishments that did not experience an M&A. To this end, we estimate the following OLS specification at the establishment-year level:

$$y_{i,t} = \gamma_1 \cdot Post_t \cdot M\&A_i + \gamma_2 \cdot Post_t + \alpha_i + \alpha_t + \beta \cdot X_{i,t} + \epsilon_{i,t}, \tag{1}$$

where i denotes establishments and t denotes years. $y_{i,t}$ represents the employment share of routine occupations (RSH); $Post_t$ equals one for years after the effective year of M&As, zero otherwise; $M\&A_i$ equals one for establishments of targets in horizontal M&As, zero otherwise;[18] α_i represents establishment fixed effects, and α_t represents year fixed effects; $X_{i,t}$ controls for changes in *Offshorability* of a given establishment that could affect both the probability of M&As and labor outcomes. In more restrictive specifications, we further control for interacted 4-digit NAICS industry and year fixed effects ($\alpha_{j,t}$) to absorb time-varying industry shocks, and for interacted state and year fixed effects ($\alpha_{s,t}$) to absorb time-varying local shocks. In all specifications, we cluster standard errors at the firm level.[19]

[18] $M\&A_i$ is absorbed by establishment fixed effects. $Post_t$ is estimated because control establishments can repeat and match with different treated establishments.

[19] Column 1 of Internet Appendix Table IA. A.2 presents robustness where we double cluster standard errors by firm and year.

Table 2, Panel A, presents the results. Column 1 shows that M&As are associated with a reduction in the share of routine employment 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 RSH declining by 2.38 percentage points, or 6.6% (=-0.0238/0.358) relative to the pre-treatment mean reported in Table 1, column 11. In annual terms, this suggests an average annual decrease of approximately 0.55 percentage points (=-0.0238/4.3), or a 1.54% (=-0.0055/0.358) annual decline relative to the pre-treatment sample.[20] In column 2, we control for the potential of establishments offshoring their production — which may also be associated with lower demand for routine jobs — and continue to find a statistically significant decline in RSH. In this specification, we report a 1.82-percentage-point decrease in routine employment share, which suggests an average annual decrease of approximately 0.42 percentage points (=-0.0182/4.3), or a 1.17% (=-0.0042/0.358) annual decline relative to the pre-treatment mean.

Note that we report a positive correlation between the percentage of offshorable jobs and the change in routine task intensity. This is consistent with the fact that more offshorable tasks tend to be more routine intensive.[21] We next repeat the estimation, additionally controlling for (4-digit NAICS) industry-year fixed effects (Table 2, Panel A, column 3) and both industry-year and state-year fixed effects (Table 2, Panel A, 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 magnitude and are statistically significant at the 1% level, suggesting that neither industry nor local shocks drive our findings.[22]

[20] Given that the median period between two observations is 3.5 years in our sample and we assume that M&As happen in year 2 between two surveyed years, on average, the post-treatment period in our sample is 4.3 years ($= 1.5\ years \times 46\% + 5\ years \times 27.6\% + 8.5\ years \times 26.4\%$) based on the observation count distribution reported in Table IA. A.1. An average decline of 2.38-percentage-point in RSH post-M&A represents an average decline over 4.3 years or 0.55 percentage points (=-0.0238/4.3) decline per year.

[21] Goos et al. (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 0.49 and significant at the 1% level.

[22] Due to the survey nature of our data, we observe longer event windows than the typical study. To address the concern that confounding factors may impact our baseline estimates, we perform several robustness tests in Internet Appendix Table IA. A.2. In columns 2 and 3, we show that our results are

To put these magnitudes into context, we compare our coefficient estimates to economy-wide trends, as measured using national SOC-level employment data from OEWS over the same years.[23] Annually, RSH in the broader economy declines by 0.85%, on average. This contrasts to our estimates from Table 2, Panel A, column 3, which suggests that RSH declines at target firms by an additional 1.89 percentage points (or 0.44 percentage points in annual terms), on average, post-merger. This indicates an annual decline of 1.23% (=-0.0044/0.358) relative to the pre-treatment mean. In other words, target firms in our sample exhibit an average decline in RSH at a rate about 1.5 times greater than the baseline rate expected during these years.

In the absence of truly exogenous mergers, it is important to 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 each observation before and after the M&A event. Pre_n is an indicator equal to one for the n^{th} observation of the establishment in OEWS $before$ the M&A, zero otherwise. $Post_n$ is an indicator equal to one for the n^{th} observation of the establishment in OEWS $after$ the M&A, zero otherwise. The first observation prior to or measured during the year of the M&A event is the omitted coefficient.[24,25] We augment our baseline specification by interacting these variables with $M\&A_i$ and plot the dynamic coefficient estimates in Figure 1.

In Panel A, where we consider RSH as our dependent variable, we observe that prior to the M&A the estimated coefficients are statistically insignificant and economically small. In contrast, we estimate large and persistent declines in our coefficients of interest post-M&A. Specifically, relative to the control establishments, we observe an average

robust to keeping only one or up to two observations in the post period, respectively. In columns 4-6, we show consistent effects within shorter event windows with 4, 5, and 6 calendar years before and after the effective year of M&As, respectively. In columns 7-8, we show insignificant time series variance in our treatment effect by checking if our estimates change before and after 2008, which is the midpoint of our sample period.

[23] The data is publicly available at the BLS website, https://www.bls.gov/oes/tables.htm.

[24] Each establishment in OEWS is surveyed at most once within three years, so the observations in $Post_1$ and $Post_2$ are separated by at least three years. Similarly, the observations in Pre_1, Pre_2 and Pre_3 are separated by at least three years.

[25] Each establishment in our OEWS sample can be observed up to three times before and up to five times post-M&A. Few establishments in our sample can be observed more than three times after M&As; observations after the second post-observation are therefore estimated and presented in a lump sum.

decline of 1.25 percentage points, or 3.5% (=-0.0125/0.358) in RSH relative to the pre-treatment mean, at target establishments in the year of the first post-M&A observation ($Post_1$), and the change is statistically significant at the 10% level. In the year of the second post-M&A observation, on average, RSH declines by 2.8 percentage points, or 7.8% (=-0.028/0.358) relative to the pre-treatment mean, at target establishments. For years of and after the third post-M&A observation, on average, target RSH declines by 2.6 percentage points, or 7.3% (=-0.026/0.358) relative to the pre-treatment mean, at target establishments relative to the controls. On a yearly basis, the estimates for $Post_1$, $Post_2$ and $Post_{3\ plus}$ represent approximately 2.3% (=-3.5%/1.5), 1.6% (=-7.8%/5) and 0.9% (=-7.3%/8.5) reductions relative to the mean before the treatment, respectively.[26]

The fact that the declines of our coefficient estimates are persistent in the longer run is consistent with the hypothesis that we are capturing permanent shifts to targets' production processes. Moreover, our results suggest that it takes time for firms to shift their production processes from labor to capital. Similar longer-run effects are observed in other papers studying firms' technology adoption decisions. For example, Brynjolfsson and Hitt (2003) find that the productivity and output effects of computerization are maximized over periods of five to seven years. Bena et al. (2022) show that innovative firms' adoption of cost-saving technology following increases in labor adjustment costs is maximized four years after state-level legal changes and remains persistently higher than the control group.

Table 2, Panel B considers, instead, the routine task intensity of the establishment (RTI). This variable allows us to take advantage of all the information in the continuous measure of routine task intensity. In column 1, we show that the routine task intensity of the average target establishment declines by 8.42 percentage points post-M&A, or an annual rate of 1.96 percentage points (=-0.0842/4.3), a change that is statistically significant at the 1% level. We continue to find similar declines in target establishments' routine task intensity after additionally controlling for offshorability

[26] The median period between two observations is 3.5 years in our sample and we assume that M&As happen in year 2 between two surveyed years, so the estimates for $Post_1$, $Post_2$ and $Post_{3\ plus}$ represent effects of M&As over 1.5 years, 5 years and 8.5 years, respectively.

(column 2), industry-specific changes (column 3), or state-specific changes (column 4). Finally, we examine changes in percentile ranks of establishment routine employment levels (*Routine Employment Percentile*) in Panel C, as opposed to relative employment captured in *RSH*, following the same specifications. We find that, compared to controls, the average percentile rank of target establishment employment within routine occupations is reduced by 2.4 percentage points (column 4), or 0.56 percentage points in annual terms (=-0.024/4.3), following the M&A. The change is statistically significant at the 1% level.

Moreover, we continue to observe no significant pre-trends when considering dynamic coefficient estimates for *RTI* and *Routine Employment Percentile*, as reported in Figure 1, Panels B and C, respectively. We observe that the coefficient estimates prior to the M&A are close to zero and statistically insignificant, while there is a persistent decline following the M&A. Relative to the control establishments, in Panel B, we observe average decreases in *RTI* of 2.8%, 4.7%, and 6.7% (or 1.9%, 0.9%, and 0.8% in annual terms) relative to the pre-treatment mean, by the first ($Post_1$), second ($Post_2$) and third plus ($Post_{3\ plus}$) observations post-M&A, respectively. These coefficient estimates are statistically significant at the 5% level. Panel C shows that, relative to control establishments, the target establishments experience average decreases of 1.5, 3, and 3.1 percentage points in *Routine Employment Percentile*, or declines of 3.1%, 6.3% and 6.5% (or 2.1%, 1.3% and 0.8% in annual terms) relative to the pre-treatment mean, respectively.

To enhance our understanding of the types of technology that could lower the demand for routine labor in M&A targets, we further characterize routine employment as routine manual and routine cognitive and estimate employment changes for those occupational subgroups in Table 3, columns 4-5. Specifically, routine cognitive (routine manual) corresponds to an occupation that is routine and its cognitive (manual) task score is within the top quartile of the employment-weighted distribution, using employment data from the 2000 ACS.[27] Routine cognitive occupations include accountants and auditors, bank tellers

[27] Occupational task scores can be downloaded from Daron Acemoglu's website, `https://www.dropbox.com/s/835jzwyo0o0x0xn/task-construct(1).zip?e=1&dl=0`.

and data entry keyers—namely office occupations that are replaceable by IT technology. Routine-manual occupations include assemblers of electrical equipment and production helpers, which would involve robots and machines replacing production workers. We show that although employment declines post-M&A for both routine manual and routine cognitive occupations, the decline in routine cognitive employment percentile rank is economically larger and statistically significant.

While we focus on shifts in routine occupational employment, technology adoption associated with M&As has additional implications for occupations complementary to technology (Kogan et al., 2023). To test this, we examine the effect of M&As on employment of tech-oriented occupations and present results in Table 3. Column 6 shows a statistically significant and positive effect. Further decomposing this broader occupational category into engineering and non-engineering occupations, we find a large and significant increase in the engineering employment percentile rank at targets post-M&A (column 7), while the effect on non-engineering employment percentile rank is positive but not statistically significant (column 8).[28] Engineering occupations, such as industrial, mechanical, civil, electrical, and electronic engineers, apply, integrate, and maintain technology. Non-engineering occupations, such as life, computer, and math scientists, are high-skill occupations that conduct research and innovate new technology.

4. Mechanisms

4.1. Investment in Technology

The occupational changes we document post-M&A at target establishments are consistent with the effects of increased investment in automation. Our argument relies on the hypothesis that acquirers, which are large, not financially constrained, and thereby more likely to be tech-savvy, implement more advanced automation technologies at targets that tend to be much smaller, financially constrained, and as such are less likely to be tech-savvy. Target firms may not have the managerial or technical human cap-

[28] Following Hecker (2005), "Engineering" occupations include engineering managers, SOC 11–9040; engineers, SOC 17–2000; drafters, engineering, and mapping technicians, SOC 17–3000. Appendix Table A.1 reports detailed classifications of tech-oriented, engineering, and non-engineering occupations.

ital necessary to implement or scale these automation technologies, may be financially constrained (thus limiting their ability to acquire technologies that often require high up-front costs), or may refrain from implementing automation technologies that may lead to labor redundancies due to implicit labor contracts. While we are agnostic about the specific frictions that produce the observed technological differences between firms in the economy, we argue that the existence of such differences leads to opportunities for more technologically skilled firms to acquire firms that have been less able to implement such technologies.[29]

To bolster our theoretical argument, in this section, we present evidence that the decline in the share of routine employment at M&A targets is driven by deals in which the acquirer is more likely to have a significantly greater technological advantage relative to the target. As we cannot observe this directly, we infer the likelihood of relative acquirer technological advantage using occupational differences between acquirers and targets. To this end, we present two sets of results.

First, given the large literature in labor economics, which shows that displacement of routine employment and technology adoption are highly correlated (Autor et al. 2003; Autor and Dorn 2013; Zhang 2019; Kogan et al. 2023), we proxy for a firm's relative position on the technological frontier using their relative share of routine occupational employment. Specifically, we define $\mathbb{1}_{TargetRSH>AcquirerRSH}$ to be equal to one if the ex-ante routine employment share (RSH) at the target exceeds that at the acquirer, and zero otherwise.[30,31] Our coefficient of interest is γ_3 in the following specification, which exploits variation in $\mathbb{1}_{TargetRSH>AcquirerRSH}$ between acquirers and targets:

[29] This idea that differences between acquirers and targets drive M&As has been theorized in the literature. For example, Jovanovic and Rousseau (2002) argue that acquirers are better managed firms than targets, and mergers can create synergies due to the optimal reallocation of physical assets to more efficient managers.

[30] Target (or Acquirer) RSH is defined as the ratio of routine employment to total employment, where total (or routine) employment are aggregated by taking the sum of employment (or routine employment) using the first observation prior to the M&A across establishments matched to the target (or acquirer). As we do not observe an acquirer for the control establishments, $\mathbb{1}_{TargetRSH>AcquirerRSH}$ equals 0 for these establishments.

[31] In our sample, variable $\mathbb{1}_{TargetRSH>AcquirerRSH}$ has a mean of 16.5% and standard deviation of 37%.

$$RHS_{i,t} = \gamma_1 \cdot Post_t \cdot M\&A_i + \gamma_2 \cdot Post_t$$
$$+ \gamma_3 \cdot Post_t \cdot M\&A_i \cdot \mathbb{1}_{TargetRSH>AcquirerRSH} + \alpha_i + \alpha_{j,t} + \beta \cdot X_{i,t} + \epsilon_{i,t}, \quad (2)$$

where i represents an establishment and t represents a year. $Post_t$ equals one for years after the effective year of the M&A, zero otherwise. $M\&A_i$ equals one for establishments of targets in horizontal M&As, zero otherwise. Control variables are the same as the ones described in Equation 1.[32] Standard errors are clustered at the firm level.[33]

We present these results in Table 4, column 1. Although the baseline coefficient $Post_t \cdot M\&A_i$ is insignificant and economically zero, the interaction coefficient $Post_t \cdot M\&A_i \cdot \mathbb{1}_{TargetRSH>AcquirerRSH}$, which exploits variation within the treated sample, is negative and statistically significant. It also shows an economically significant decline in routine employment share equal to 4 percentage points (=0.0086-0.0484) (or an annual rate of 0.9 percentage points), compared to the average 1.9 percentage point (or an annual rate of 0.4 percentage points) decline in Table 2, column 3. These results suggest that our baseline findings are driven by M&A deals in which the target is more reliant on routine employment, relative to the acquirer. To the extent that lower routine employment shares of the acquirer indicate greater technology adoption, these results are consistent with the intuition that M&As facilitate technology transfers from acquirers to targets.

In Table 4, columns 2-3, we use alternative measures to create acquirer-target comparisons pre-M&A. Specifically, we rely on relative occupational differences to proxy for technological differences between the acquirer and target. First, we argue that higher average wages will tend to reflect the higher skills most commonly observed at firms further on the technological frontier (Wallskog et al. 2024). To this end, we consider $\mathbb{1}_{AcquirerWage>TargetWage}$ in column 2, defined as one if the pre-M&A average hourly wages at an acquirer firm exceeds that of its target, zero otherwise. In column 3, we instead consider $\mathbb{1}_{AcquirerTechWage>TargetTechWage}$, defined as one if the pre-M&A average hourly wages

[32] $M\&A_i$, $\mathbb{1}_{TargetRSH>AcquirerRSH}$ and their interaction are absorbed by establishment fixed effects. $\mathbb{1}_{TargetRSH>AcquirerRSH} \cdot Post_t$ is absorbed by $Post_t \cdot M\&A_i$, since $\mathbb{1}_{TargetRSH>AcquirerRSH}$ exploits variation only withing the treated sample.

[33] In Internet Appendix Table IA. A.6, we repeat the robustness of the analysis presented in this Section using instead continuous measures of heterogeneity.

of tech-oriented workers at an acquirer firm exceeds that of its target, zero otherwise.[34] This measure focuses on the relative wages or productivity of tech-oriented workers, which should also capture ex-ante differences in skill between acquirers and targets. In both cases, we find similar results, where an ex-ante difference in wages between the acquirer and the target is associated with greater relative declines in routine employment shares for M&A targets, consistent with our hypothesis.[35]

Second, we follow a similar approach of exploring cross-sectional variation in treatment, but instead use proprietary data from the CiTDB database, which allows us to measure dollars spent on information technology (IT) at the establishment level. Our measure follows the literature showing that investments in IT have played a key role in displacing routine intensive occupations (Bartel et al., 2007; Autor and Dorn, 2013; Webb, 2020; Dillender and Forsythe, 2022).

To this end, we estimate Equation 2 on the technology investment sample described in section 2.2 using the percentile ranks of establishment IT budget levels and IT budgets per employee as our dependent variables. Although IT investment is admittedly not a comprehensive measure of technology, it has several advantages. First, it is available at the establishment level for a large number of both private and public firms, thereby allowing us to measure it at targets around the M&A. Second, IT investments are ideally suited to measure the job loss specifically identified in our data, which is larger for routine cognitive tasks. To proxy for ex-ante differences in IT intensities between acquirers and targets, we define $\mathbb{1}_{AcquirerIT>TargetIT}$ to be equal to one if the IT budget per worker at the acquirer exceeds that of its target in the first year prior to the M&A, zero otherwise.[36] Results are reported in Table 4, columns 5 and 6. Consistent with our hypothesis, we find a relatively higher target IT investment post-M&A in deals where acquirers are more IT intensive relative to their targets before the M&A. Specifically, targets acquired by firms

[34] Variable $\mathbb{1}_{AcquirerWage>TargetWage}$ has a sample mean (standard deviation) of 16% (36.7%). Variable $\mathbb{1}_{AcquirerTechWage>TargetTechWage}$ has a sample mean (standard deviation) of 14% (34.7%).

[35] Note, we cannot exclude the possibility that these measures could also be impacted by different costs of living across locations or other firm characteristics that co-vary with wages.

[36] Our measure of IT investment has a particularly low match rate with the OEWS sample, given the differences in time period and sampling frequency and the fact that both samples are surveys; thus we cannot run this analysis within the OEWS sample.

with relatively greater IT intensity experience an annual increase in the percentile rank of their IT budget (IT budget per employee) by 2.12 (2.26) percentage points, on average, as compared to controls.[37,38] Although IT does not include all automation investments, such as investment in robots, robot penetration has been minimal for the majority of industries during this sample period (Benmelech and Zator, 2022). That being said, our estimates should be interpreted as a lower bound on the effect of M&As on technology adoption.

4.2. Alternative Explanations and Robustness

So far, our results point towards the role of technology in explaining the occupational changes at targets post-M&A. In this section, we discuss alternative explanations that could also be consistent with our baseline findings.

First, due to the positive correlation in the data between tasks that are routine and tasks that are offshorable, a decline in routine task intensive jobs will mechanically lead to a decline in offshorability or vice-versa. This is of specific concern if acquirers have greater expertise and supportive infrastructure to offshore and, subsequently, increase offshoring activities at the targets. To this end, we show that our baseline results are robust to controlling for offshorability, a control we include throughout our analyses. In addition, in Table IA. A.8, we show that our baseline estimates are robust to controlling for offshorability-specific trends captured by *Offshorability*-by-year fixed effects.

To further examine whether this alternative mechanism could be driving our findings, we revisit the specification in Table 4, column 1, but instead, run a horserace using the indicator variable for whether the target has relatively greater routine employment and a new indicator variable, $\mathbb{1}_{TargetOffshor>AcquirerOffshor}$, reflecting if the target has relatively

[37] In Internet Appendix Table IA. A.7 we replicate the analysis in Table 4, columns 5 and 6, using instead other sub-components of IT spending, including hardware, software, IT services, storage and communication services. We find similar results across these different IT categories.

[38] Devos et al. (2008) shows that firms reach operational synergies post-M&As by reducing investments. We also argue that there is operational restructuring post M&As, as targets implement technology changing their production processes. Such operational restructuring has direct implications on labor restructuring post M&A—an aspect not studied by Devos et al. (2008). Also, our measure is more specific to automation, and our mechanism has nothing to say about other types of investments, such as investment in buildings or land.

greater offshoreable employment. We present the results in Table 5, column 1. The intuition behind this test is that an acquirer with superior offshoring ability ex-ante, as proxied by a lower relative share of offshorable employment, would be more likely to increase offshoring at the target. This could drive our results, given the positive correlation between offshoreable and routine occupations. In this case, we would predict a negative and significant coefficient on $Post_t \cdot M\&A_i \cdot \mathbb{1}_{TargetOffshor>AcquirerOffshor}$. Instead, we estimate this coefficient to be positive and statistically insignificant, while the coefficient on $Post_t \cdot M\&A_i \cdot \mathbb{1}_{TargetRSH>AcquirerRSH}$, capturing our main mechanism of target-acquirer routine occupational differences, remains negative, statistically significant, and economically similar to the coefficient in Table 4, column 1.[39] These results suggest that greater offshoring ability at the acquirer is not, at least primarily, driving our results.

Second, our results could conceivably capture layoffs of employees who are redundant post-merger, but through a mechanism unrelated to technology. Such layoffs could be driven by economies of scale. To the extent that the acquirer and target had employees engaged in a similar function, they may need fewer of these employees at the combined firm. If such duplicate employees are overrepresented in routine occupations, this could explain our results.

To test this alternative mechanism, we augment the specification in Table 4, column 1, by adding new interaction terms proxying for the degree of occupational similarity between acquirer and target prior to the M&A. We report these results in Table 5, columns 2 and 3. Specifically, in column 2, we define $\mathbb{1}_{HighOccOverlap}$, an indicator equal to one if the shares of target employment in occupations that exist in both the target and its acquirer in the year of the first observation before the M&A exceeds the sample median, zero otherwise, and interact it with $Post_t \cdot M\&A_i$. In column 3, we define $\mathbb{1}_{HighOccSimilarity}$, an indicator equal to one if the cosine-similarity score of occupations at the target and its acquirer exceeds the sample median in the first year observed prior to the M&A,

[39] Internet Appendix Table IA. A.9 presents robustness, where we instead consider continuous measures of heterogeneity.

zero otherwise, and interact it with $Post_t \cdot M\&A_i$.[40,41] If our results are driven by such a redundancy mechanism, we should find a negative and significant coefficient on these interaction terms in Table 5, columns 2 and 3. Instead, we observe insignificant coefficients on $Post_t \cdot M\&A_i \cdot \mathbb{1}_{HighOccOverlap}$ and $Post_t \cdot M\&A_i \cdot \mathbb{1}_{HighOccSimilarity}$, respectively.[42] Importantly, the coefficient on $Post_t \cdot M\&A_i \cdot \mathbb{1}_{TargetRSH>AcquirerRSH}$ remains negative, statistically significant and economically similar to the coefficient in Table 4, column 1. It is worth emphasizing that interacting $Post_t \cdot M\&A_i$ with $\mathbb{1}_{TargetRSH>AcquirerRSH}$ should pick up the deals, where, if anything, larger asymmetries exist in routine occupations within the acquirer-target pair, conceptually the opposite of what the redundancy story would predict.

While it is challenging to perfectly rule out this alternative interpretation, collectively, the evidence lends no support for that channel being an important driver of our baseline findings. Moreover, in Section 5, where we examine granular occupational changes post-M&A, we provide further evidence that alternative explanations do not seem key to our findings.

Third, a key concern for our analysis is that an omitted variable, such as a demand, industry, regulatory, or other shock, may drive both M&A activity and the associated labor changes that we document in the data. The linkage between such shocks and technology adoption has been well established in the literature (e.g., Mitchell and Mulherin, 1996; Ahern and Harford, 2014; Hershbein and Kahn, 2018; Jaimovich and Siu, 2020; Tuzel and Zhang, 2021; Bena et al., 2022). Given that mergers are not random events, we next present robustness analyses that mitigate concerns that our results might be driven by shocks that could lead to changes in both optimal firm boundaries and technology adoption.

[40] The cosine-similarity score is a measure that evaluates the similarity between occupational profiles at target and acquirer constructed based on vectors of text descriptions of their SOC occupations and employment shares in each occupation. Detailed construction steps are described in Appendix Table A.1.

[41] The sample means are 16.2% for $\mathbb{1}_{TargetOffshor>AcquirerOffshor}$, 19% for $\mathbb{1}_{HighOccOverlap}$, and 18.4% for $\mathbb{1}_{HighOccSimilarity}$.

[42] Internet Appendix Table IA. A.9 presents robustness, where we instead consider continuous measures of heterogeneity.

To this end, as explained in Section 2.1, we match treated and control establishments along several observable characteristics available in the OEWS data pre-treatment. While matching on observable characteristics does not negate the presence of unobservable omitted variables, it is reassuring that we compare establishments that are similar in terms of ex-ante observable characteristics (Table 1). We further show that our coefficient estimates do not change materially after controlling for industry and local specific trends, suggesting that unobserved shocks at the industry or local levels are not likely to drive our findings. Moreover, as shown in Figure 1, we present evidence consistent with the parallel trends hypothesis of the difference-in-differences, which supports a causal interpretation of our findings.

We further show that both our baseline coefficient estimates and our dynamic analysis are robust to an alternative matching estimator, where we additionally require that the target and matched control establishments belong to a narrower band of ex-ante measures of routine employment. Specifically, we limit the sample to matched treated-control pairs where the averaged ex-ante *RTI* (*RSH*, *Routine Employment Percentile*) in all pre-periods for control observations falls within a 25% range of the averaged ex-ante *RTI* (*RSH*, *Routine Employment Percentile*) for treated observations. We present these results in Table 6 and Figure IA. A.3 and show that our baseline estimates are robust and continue to exhibit no significant pre-trends.

Fourth, we follow the M&A literature and consider a placebo sample of M&A deals that were announced but subsequently canceled for reasons exogenous to the target's labor needs (Seru, 2014; Malmendier et al., 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 in which the M&A was either blocked by regulators, typically for antitrust concerns, or because the acquirer was acquired ex-post and had to withdraw the deal. This leaves us with a small sample of deals canceled for reasons exogenous to the target's labor demand. We identify 30 establishments in the OEWS survey data with canceled M&A deals, which form our "pseudo treated" group. Following the same matching procedure described in Section 2.1, we create a control sample that excludes establishments involved in completed or canceled M&As over our sample period. Internet Appendix Table IA. A.10 repeats the specification in Table 2, Panel A, column 3, controlling for establishment and industry times year fixed effects. Across all our routine measures, we cannot replicate the same pattern as in our baseline results. In fact, all coefficients display the opposite sign from what our hypotheses predict.

Fifth, M&A targets might be low-technology firms that would mean-revert to the technological frontier irrespective of the M&A. Under this alternative scenario, M&As are not a necessary catalyst for targets to adopt technology, but instead capture a selection of firms in the process of converging to the frontier. To address this specific concern, we repeat our baseline analysis including an interaction between our routine measure and year fixed effects. This additional control captures mean-reversion for the dependent variable, further mitigating the assumption that dynamic selection concerns drive our results. We present these results in Internet Appendix Table IA. A.11. We find that our coefficient estimates remain robust, alleviating this concern.

Finally, we address the concern that our results could be driven by survivorship bias due to the fact that firms far from the technological frontier would close down and thus might not be observed throughout our sample period. To mitigate this concern, our baseline analysis requires that each treated and control establishment in our sample must be observed at least once during the years before (or during the year of) the M&A and once during the years after the M&A. In Table IA. A.12, we also show that our results are robust when we keep only those treated and control establishments that have the same number of observations before and after M&As, i.e., the same survival periods.

5. Granular Occupational Employment Changes

Our baseline results indicate that M&A targets become less routine following M&As, compared to observably similar establishments. In this section, we provide a detailed analysis of the occupational employment profiles impacted post-merger, digging into the specific occupations that are impacted the most, and discussing the nature of technology adoption consistent with the observed changes in occupational demand.

First, we examine employment changes at targets following M&A in 23 broad occupation groups defined by Dorn (2009) and Autor and Dorn (2013). For each occupation group, we estimate the following regression specification:

$$y_{o,i,t} = \gamma_{1,o} \cdot Post_t \cdot M\&A_i + \gamma_{2,o} \cdot Post_t + \alpha_i + \alpha_{j,t} + \beta \cdot X_{i,t} + \epsilon_{o,i,t}, \tag{3}$$

where o represents the occupation group o at establishment i and t represents a year. $y_{o,i,t}$ is the percentile rank of an establishment's employment within occupation group o in the sample distribution for a given year; $Post_t$ equals one for years after the effective year of the M&A, zero otherwise; $M\&A_i$ equals one for establishments of targets in horizontal M&As, zero otherwise;[43] $\alpha_{j,t}$ represents industry-by-year fixed effects; $X_{i,t}$ represents offshorability of a given establishment i. Standard errors are clustered at the firm level.

Figure 2 plots the coefficient estimates ranked from the largest increase in the employment percentile rank to the largest decrease. At the bottom of the plot, we observe a large relative employment decline post M&A for *Retail Sales Occupations*, which represent 9.2% of sample employment prior to the M&A. This occupation group consists of occupations such as cashiers, door-to-door sales, models, news vendors and sales demonstrators, promoters, retail salespeople and sales clerks, and street sales. This group's average routine task intensity score, weighted by occupational employment in the 2000 ACS, ranks at the 90$^{\text{th}}$ percentile of the score distribution. In other words, occupations in this group involve many routine tasks that can be performed more efficiently by computers or IT software. Similarly, we observe that *Administrative Support Occupations*—the most routine intensive occupation group in our sample—exhibits a large decline in post M&A employment. This occupation group represents 24.4% of sample employment prior to the M&A and involves occupations such as bank tellers, billing clerks and related financial records processing, bookkeepers and accounting and auditing clerks, file clerks, hotel clerks, library assistants, payroll and timekeeping clerks, proofreaders, records clerks,

[43] $M\&A_i$ is absorbed by establishment fixed effects. $Post_t$ is estimated because control establishments can repeat and match with different treated establishments.

secretaries and stenographers, and typists.

In contrast, we observe increases in percentile ranks of employment within occupation groups that are more skilled and less routine, such as *Management Related Occupations*, *Professional Specialty Occupations*, and *Technicians and Related Support Occupations*. *Management Related Occupations* include occupations that support managers, such as HR specialists, purchasing agents, wholesale and retail trade buyers, business agents, construction inspectors, compliance officers, and management support. *Professional Specialty Occupations* include electrical engineers, industrial engineers and mechanical engineers, civil engineers, computer systems analysts, and computing scientists. *Technicians and Related Support Occupations* involves occupations such as biological technicians, chemical technicians, computer software developers, engineering technicians, health technologists, and technicians, n.e.c. (not elsewhere classified), and programmers of numerically controlled machine tools. Overall, occupations in *Management Related Occupations*, *Professional Specialty Occupations* and *Technicians and Related Support Occupations* are associated with developing, using, and maintaining technology.

Although Figure 2 presents a nice visual of which occupational groups are most impacted by M&A, the broad categorization of these groups might obscure variations in granular occupational demand. To provide a more comprehensive analysis, we break down the 23 broad occupational groups in Figure 2 into more granular 320 distinct $occ1990dd$ non-farming occupations. $occ1990dd$ is the most detailed classification available for determining RTI scores.[44,45]

In Table 7 Panel A (Panel B), we present the top 25 granular $occ1990dd$ occupations that experience the largest post-M&A decline (increase) in percentile ranks of employ-

[44] Table IA. A.13 lists the 23 occupation group titles and the corresponding granular $occ1990dd$ occupations classified under each occupation group. The $occ1990dd$ occupation classification aggregates U.S. Census occupation codes to a balanced panel of occupations for 2000, 2005, and 2010 Census *occ*. The detailed methodology for constructing $occ1990dd$ and crosswalks between $occ1990dd$ and *occ* can be found at David Dorn's website, `https://www.ddorn.net/data.htm`. We match $occ1990dd$ with 2000 and 2010 SOC occupation codes observed in OEWS using crosswalks between *occ* and SOC downloaded from `https://usa.ipums.org/usa/volii/occtooccsoc18.shtml`.

[45] Autor and Dorn (2013) provide detailed occupational task scores that capture the degree of abstract, manual and routine of tasks conducted by each $occ1990dd$ occupation. Therefore, we also use the $occ1990dd$ classification to construct our baseline measures of routine task intensity at the establishment level as described in section 2.1.

ment, along with the coefficient estimates and standard errors estimated by Equation 3 as well as indicators highlighting their characteristics. While we do not focus on statistical significance in this analysis, given the limited statistical power due to smaller sample sizes, the rankings of granular occupations with the largest changes in post-M&A employment provide further insights on how labor demand evolves following these deals.

Overall, we observe that routine occupations are disproportionately represented among the top decliners. Specifically, in Table 7, Panel A, we observe that 60% of occupations that experience the largest relative decline post-M&A are routine. This reflects a significant overrepresentation of routine occupations, namely, occupations in the top quartile of the routine task intensity distribution.

We also observe that the majority of the routine occupations that experience a drop in employment are routine cognitive and fewer are routine manual. These results are consistent with Table 3, columns 4-5, which show that although employment declines post-M&A for both routine manual and routine cognitive occupations, the decline in routine cognitive employment is economically larger and statistically significant. These most impacted occupations are likely office routine occupations replaced by information technology (IT). This reflects a pattern of IT technology adoption that started before our sample period and continued well into the 2000s. As reported in Bessen (2020), proprietary software investment increased substantially between 1995 and 2016. Tambe and Hitt (2014) also find that "the measured marginal product of IT spending is higher from 2000-2006 than in any previous period, suggesting that firms, and especially large firms, have been continuing to develop new, valuable IT-enabled business process innovations". The less routine intensive occupations comprising the list in Table 7, Panel A, tend to be lower-skill occupations involving a greater proportion of manual tasks (e.g., stock and inventory clerks); or occupations that, although they are less routine in nature (i.e., they are not in the top quartile of the routine task intensity distribution), are also significantly affected by IT adoption (e.g., retail salespersons and sales clerks).

In contrast, Panel A of Table 7 also shows that occupations experiencing the largest employment declines post-M&A do not exhibit characteristics that align with alternative explanations for our findings. Prior research, such as John et al. (2015), Dessaint et al. (2017), and Tian and Wang (2020), suggests that M&A activity is more prevalent when unions and worker protections are weaker, enabling labor efficiencies. However, only three of the 25 occupations with the greatest employment declines are non-unionized (*Non-unionized*). Moreover, Li (2013) argues that acquirer firms with superior expertise can enhance managerial efficiency, which may lead to managerial slack and, consequently, layoffs in target management teams.[46] Yet, in our data, only one of the 25 occupations experiencing the largest declines falls within the *Executive, Admin, and Managerial* occupational group, which oversees other people's work. Finally, we create a new measure of occupation scalability to capture the idea that some roles are inherently more "scalable" post-merger, meaning firms can operate effectively with fewer employees than the combined pre-merger workforce, leading to overhead reductions. If scalability were a key factor, we would expect an over-representation of highly scalable occupations in this sample.[47] However, only three of the 25 occupations with the largest employment declines are classified as highly scalable (*Scalable*).[48]

On the other hand, occupations that tend to be high-skill and non-routine overwhelmingly dominate the top increase list (Table 7, Panel B). Specifically, several of those occupations correspond to management-related specialists (e.g., HR, management analysts, and financial specialists), technicians and related support occupations (e.g., engineering technicians, health technologists, and technicians), and professional specialty occupations, such as electrical engineers, pharmacists, or medical scientists. Tasks performed in these occupations are related to developing or using technology.

[46] Relatedly, Jensen and Ruback (1983) suggests that M&As improve efficiency by creating competition in managing resources and replacing target firms' management teams.

[47] We explain how we construct the measure of occupational scalable task intensity and identify highly scalable occupations in Internet Appendix B2.

[48] In Internet Appendix Table IA. A.14, we present correlations between the change in employment percentile post-M&A for the 320 $occ1990dd$ occupational groups estimated from Equation 3 and these occupational characteristics. We confirm the negative relationship between routine task intensity (RTI) and estimated changes in employment percentile rank after controlling for occupational offshorability. In contrast, employment percentile changes do not correlate significantly with *Union Share*, *Executive, Admin, and Managerial Occs*, and *Scalability*, suggesting that redundancies due to overhead layoffs do not fit the patterns we observe in our sample.

6. Wages

Our hypothesis that implementing more advanced technology at M&A targets impacts occupational employment also embodies implications for wages. Following M&As, we tend to observe increased demand by the target firm for occupations complementary to technology and softer demand for occupations that involve routine tasks. Moreover, technology transforms employment within occupations, leading to upskilling and higher productivity (Bartel, Ichniowski, and Shaw, 2007; Hershbein and Kahn, 2018; Dillender and Forsythe, 2022; Kogan et al., 2023). Such productivity increases and compositional employment changes in M&A targets should shift mean wages higher and increase wage inequality within establishments.

In Table 8, Panel A, we examine the effect of M&As on the 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 affect our results. In column 1, we find a 2.5% (or 0.6% in annual terms) increase in treated establishments' average hourly wage compared to the control sample, statistically significant at the 1% level. The estimated coefficients remain significant both statistically and economically across specifications after controlling for offshorability, interacted industry-year fixed effects, and state-year fixed effects.

In Table 8, Panel B, 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 1 shows a 3.3% (or 0.8% in annual terms) increase in the standard deviation of wages at target establishments compared to matched control establishments, significant at the 5% level. The coefficient remains robust in terms of magnitude and significance across all specifications we consider.[49]

Both the shift in the nature of tasks performed at the establishment and within-

[49] A growing literature studies pay inequality within firms (e.g. Mueller, Ouimet, and Simintzi, 2017; Song et al., 2018; Huneeus et al., 2021; Wallskog et al., 2024). We add to this literature by showing that pay inequality within firms increases following M&As and argue that this is consistent with associated technology adoption.

establishment wage inequality are consistent with the notion that labor restructuring following M&As reflects nuanced changes in production processes involving the adoption of labor-saving technologies. Post-M&A changes involve a complex restructuring of the labor force at the expense of routine occupations that get displaced by technology investments.

7. Conclusion

We present novel evidence that M&As change the nature of jobs performed at the target firm, consistent with greater adoption of technology post-M&A. We find that M&As are followed by an employment reduction in routine intensive occupations at the target, particularly those easily replaceable by IT capital. Our results support the hypothesis that technologically skilled firms acquire targets that are less able to implement such technologies, and at which the acquiring firms subsequently increase that implementation. We provide evidence consistent with this mechanism and show that our effects are driven primarily by deals in which acquirers, prior to the M&A, have a smaller reliance on routine occupational employment and a greater reliance on higher-wage employees, suggesting a technological advantage. Moreover, the observed post-merger effects do not appear to be fully accounted for by alternative motives for M&As that might also be at play, such as redundancies of duplicate employees post-M&A or by targets outsourcing production. The changes observed in occupational distributions are also mirrored in wages: We observe increases in the average wage and overall wage inequality within establishments. We also directly confirm that M&As are followed by higher investment in IT technology when they involve acquirers with higher relative IT investments prior to the M&A.

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 poorly, while occupations using or implementing more advanced technology may see expanded employment opportunities following the M&A. These results also imply that the labor market effects of M&As appear more nuanced than the traditional cost-cutting argument whereby layoffs are a source of operational synergies following M&As.

References

Ahern, K. R., Harford, J., 2014. The importance of industry links in merger waves. The Journal of Finance 69, 527–576.

Atkin, D., Chaudhry, A., Chaudry, S., Khandelwal, A. K., Verhoogen, E., 2017. Organizational barriers to technology adoption: Evidence from soccer-ball producers in Pakistan. The Quarterly Journal of Economics 132, 1101–1164.

Autor, D. H., Dorn, D., 2013. The growth of low-skill service jobs and the polarization of the US labor market. American Economic Review 103, 1553–97.

Autor, D. H., Levy, F., Murnane, R. J., 2003. The skill content of recent technological change: An empirical exploration. The Quarterly Journal of Economics 118, 1279–1333.

Babenko, I., Du, F., Tserlukevich, Y., 2021. Will I get paid? Employee stock options and mergers and acquisitions. Journal of Financial and Quantitative Analysis 56, 29–64.

Bartel, A., Ichniowski, C., Shaw, K., 2007. How does information technology affect productivity? Plant-level comparisons of product innovation, process improvement, and worker skills. The Quarterly Journal of Economics 122, 1721–1758.

Barth, E., Bryson, A., Davis, J. C., Freeman, R., 2016. It's where you work: Increases in the dispersion of earnings across establishments and individuals in the United States. Journal of Labor Economics 34, S67–S97.

Bena, J., Ortiz-Molina, H., Simintzi, E., 2022. Shielding firm value: Employment protection and process innovation. Journal of Financial Economics 146, 637–664.

Bena, J., Simintzi, E., Forthcoming. Machines could not compete with Chinese labor: Evidence from U.S. firms' innovation. Review of Finance.

Benmelech, E., Zator, M., 2022. Robots and firm investment. Working Paper 29866, National Bureau of Economic Research.

Bessen, J., 2020. Industry concentration and information technology. The Journal of Law and Economics 63, 531–555.

Brown, C., Medoff, J. L., 1988. The impact of firm acquisitions on labor. In: *Corporate Takeovers: Causes and Consequences*, National Bureau of Economic Research, Inc., NBER Chapters, pp. 9–32.

Brynjolfsson, E., Hitt, L., 2003. Computing productivity: Firm-level evidence. The Review of Economics and Statistics 85, 793–808.

Chen, J., Roth, J., 2023. Logs with zeros? Some problems and solutions. The Quarterly Journal of Economics 139, 891–936.

Cohn, J. B., Liu, Z., Wardlaw, M. I., 2022. Count (and count-like) data in finance. Journal of Financial Economics 146, 529–551.

Conyon, M., Girma, S., Thompson, S., Wright, P., 2002. The impact of mergers and acquisitions on company employment in the United Kingdom. European Economic Review 46, 31–49.

Dai, X., Qiu, Y., 2023. Minimum wage hikes and technology adoption: Evidence from U.S. establishments. Journal of Financial and Quantitative Analysis p. 1–39.

Delius, A., Sterck, O., 2024. Cash transfers and micro-enterprise performance: Theory and quasi-experimental evidence from Kenya. Journal of Development Economics 167, 103232.

Dessaint, O., Golubov, A., Volpin, P., 2017. Employment protection and takeovers. Journal of Financial Economics 125, 369–388.

Devos, E., Kadapakkam, P.-R., Krishnamurthy, S., 2008. How do mergers create value? a comparison of taxes, market power, and efficiency improvements as explanations for synergies. The Review of Financial Studies 22, 1179–1211.

Dillender, M., Forsythe, E., 2022. Computerization of white collar jobs. Working Paper 29866, National Bureau of Economic Research.

Dorn, D., 2009. Essays on inequality, spatial interaction, and the demand for skills. Dissertation, University of St. Gallen.

Dunne, T., Foster, L., Haltiwanger, J., Troske, K., 2004. Wage and productivity dispersion in United States manufacturing: The role of computer investment. Journal of Labor Economics 22, 397–429.

Erel, I., Jang, Y., Weisbach, M. S., 2015. Do acquisitions relieve target firms' financial constraints? The Journal of Finance 70, 289–328.

Ersahin, N., 2020. Creditor rights, technology adoption, and productivity: Plant-level evidence. The Review of Financial Studies 33, 5784–5820.

Frydman, C., Papanikolaou, D., 2018. In search of ideas: Technological innovation and executive pay inequality. Journal of Financial Economics 130, 1–24.

Gehrke, B., Maug, E., Obernberger, S., Schneider, C., 2021. Post-merger Restructuring of the Labor Force. IZA Discussion Papers 14409, Institute of Labor Economics (IZA).

Geng, H. G., Huang, Y., Lin, C., Liu, S., 2022. Minimum wage and corporate investment: Evidence from manufacturing firms in China. Journal of Financial and Quantitative Analysis 57, 94–126.

Goos, M., Manning, A., Salomons, A., 2014. Explaining job polarization: Routine-biased technological change and offshoring. American Economic Review 104, 2509–26.

Graham, J. R., Kim, H., Li, S., Qiu, J., 2023. Employee costs of corporate bankruptcy. The Journal of Finance 78, 2087–2137.

Gugler, K., Yurtoglu, B., 2004. The effects of mergers on company employment in the USA and Europe. International Journal of Industrial Organization 22, 481–502.

Harford, J., 2005. What drives merger waves? Journal of Financial Economics 77, 529–560.

He, A. X., le Maire, D., 2025. Managing inequality: Manager-specific wage premiums and selection in the managerial labor market. Review of Economics and Statistics pp. 1–46.

Hecker, D., 2005. High-technology employment: a NAICS-based update. Monthly Labor Review by U.S. Bureau of Labor Statistics.

Hershbein, B., Kahn, L. B., 2018. Do recessions accelerate routine-biased technological change? Evidence from vacancy postings. American Economic Review 108, 1737–72.

Huneeus, F., Kroft, K., Lim, K., 2021. Earnings inequality in production networks. Working Paper 28424, National Bureau of Economic Research.

Huttunen, K., 2007. The effect of foreign acquisition on employment and wages: Evidence from Finnish establishments. The Review of Economics and Statistics 89, 497–509.

Jaimovich, N., Siu, H., 2020. Job polarization and jobless recoveries. The Review of Economics and Statistics 102, 129–147.

Jensen, M. C., Ruback, R. S., 1983. The market for corporate control: The scientific evidence. Journal of Financial Economics 11, 5–50.

John, K., Knyazeva, A., Knyazeva, D., 2015. Employee rights and acquisitions. Journal of Financial Economics 118, 49–69.

Jovanovic, B., Rousseau, P. L., 2002. The Q-theory of mergers. American Economic Review 92, 198–204.

Kaplan, S., 1989. The effects of management buyouts on operating performance and value. Journal of Financial Economics 24, 217–254.

Kogan, L., Papanikolaou, D., Schmidt, L. D., Seegmiller, B., 2023. Technology and labor displacement: Evidence from linking patents with worker-level data. Working Paper 31846, National Bureau of Economic Research.

Kogan, L., Papanikolaou, D., Schmidt, L. D. W., Song, J., 2020. Technological innovation and labor income risk. Working Paper 26964, National Bureau of Economic Research.

Kubo, K., Saito, T., 2012. The effect of mergers on employment and wages: Evidence from Japan. Journal of the Japanese and International Economies 26, 263–284.

Lagaras, S., Forthcoming. M&As, employee costs and labor reallocation. Journal of Finance.

Lehto, E., Böckerman, P., 2008. Analysing the employment effects of mergers and acquisitions. Journal of Economic Behavior & Organization 68, 112–124.

Lewis, E., 2011. Immigration, skill mix, and capital skill complementarity. The Quarterly Journal of Economics 126, 1029–1069.

Li, X., 2013. Productivity, restructuring, and the gains from takeovers. Journal of Financial Economics 109, 250–271.

Lichtenberg, F. R., Siegel, D., 1990. The effect of ownership changes on the employment and wages of central office and other personnel. The Journal of Law & Economics 33, 383–408.

Ma, S., Murfin, J., Pratt, R., 2022. Young firms, old capital. Journal of Financial Economics 146, 331–356.

Maksimovic, V., Phillips, G., Prabhala, N., 2011. Post-merger restructuring and the boundaries of the firm. Journal of Financial Economics 102, 317–343.

Malmendier, U., Opp, M., Saidi, F., 2016. Target revaluation after failed takeover attempts: Cash versus stock. Journal of Financial Economics 119, 92–106.

McGuckin, R. H., Nguyen, S. V., 2001. The impact of ownership changes: a view from labor markets. International Journal of Industrial Organization 19, 739–762.

Midrigan, V., Xu, D. Y., 2014. Finance and misallocation: Evidence from plant-level data. American Economic Review 104, 422–58.

Mitchell, M. L., Mulherin, J., 1996. The impact of industry shocks on takeover and restructuring activity. Journal of Financial Economics 41, 193–229.

Mueller, H. M., Ouimet, P. P., Simintzi, E., 2017. Within-firm pay inequality. The Review of Financial Studies 30, 3605–3635.

Nishesh, N., Ouimet, P., Simintzi, E., 2024. Labor and corporate finance. In: *Handbook of Corporate Finance*, Edward Elgar Publishing, chap. 17, pp. 647–673.

Ouimet, P., Simintzi, E., Ye, K., 2025. The impact of the opioid crisis on firm value and investment. The Review of Financial Studies.

Ouimet, P., Zarutskie, R., 2020. Acquiring labor. The Quarterly Journal of Finance 10, 2050011.

Pontiff, J., Shleifer, A., Weisbach, M. S., 1990. Reversions of excess pension assets after takeovers. RAND Journal of Economics 21, 600–613.

Rosett, J. G., 1990. Do union wealth concessions explain takeover premiums? the evidence on contract wages. Journal of Financial Economics 27, 263–282.

Seru, A., 2014. Firm boundaries matter: Evidence from conglomerates and R&D activity. Journal of Financial Economics 111, 381–405.

Shleifer, A., Summers, L. H., 1988. Breach of trust in hostile takeovers. In: *Corporate Takeovers: Causes and Consequences*, National Bureau of Economic Research, Inc., NBER Chapters, pp. 33–68.

Shleifer, A., Vishny, R. W., 1988. Value maximization and the acquisition process. Journal of Economic Perspectives 2, 7–20.

Siegel, D. S., Simons, K. L., 2010. Assessing the effects of mergers and acquisitions on firm performance, plant productivity, and workers: new evidence from matched employer-employee data. Strategic Management Journal 31, 903–916.

Song, J., Price, D. J., Guvenen, F., Bloom, N., von Wachter, T., 2018. Firming up inequality. The Quarterly Journal of Economics 134, 1–50.

Tambe, P., Hitt, L. M., 2014. Job hopping, information technology spillovers, and productivity growth. Management Science 60, 338–355.

Tate, G., Yang, L., 2024. The human factor in acquisitions: Cross-industry labor mobility and corporate diversification. The Review of Financial Studies 37, 45–88.

Tian, X., Wang, W., 2020. Hard marriage with heavy burdens: Organized labor as takeover deterrents. The Review of Corporate Finance Studies 10, 306–346.

Tuzel, S., Zhang, M. B., 2021. Economic stimulus at the expense of routine-task jobs. The Journal of Finance 76, 3347–3399.

Wallskog, M., Bloom, N., Ohlmacher, S. W., Tello-Trillo, C., 2024. Within-firm pay inequality and productivity. Working Paper 32240, National Bureau of Economic Research.

Webb, M., 2020. The impact of artificial intelligence on the labor market. Working Paper.

Zhang, M. B., 2019. Labor-technology substitution: Implications for asset pricing. The Journal of Finance 74, 1793–1839.

Zolas, N., Kroff, Z., Brynjolfsson, E., McElheran, K., Beede, D. N., Buffington, C., Goldschlag, N., Foster, L., Dinlersoz, E., 2020. Advanced technologies adoption and use by U.S. firms: Evidence from the annual business survey. Working Paper 28290, National Bureau of Economic Research.

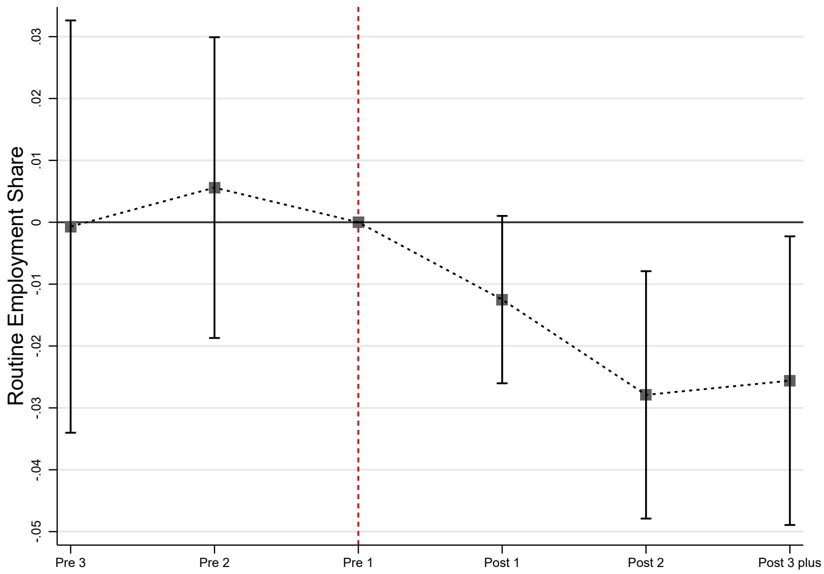
Figure 1. Dynamic effects of M&A on measures of routineness

The figures plot the dynamic effects of M&A on the routineness of tasks performed at target establishments estimated by the following equation:

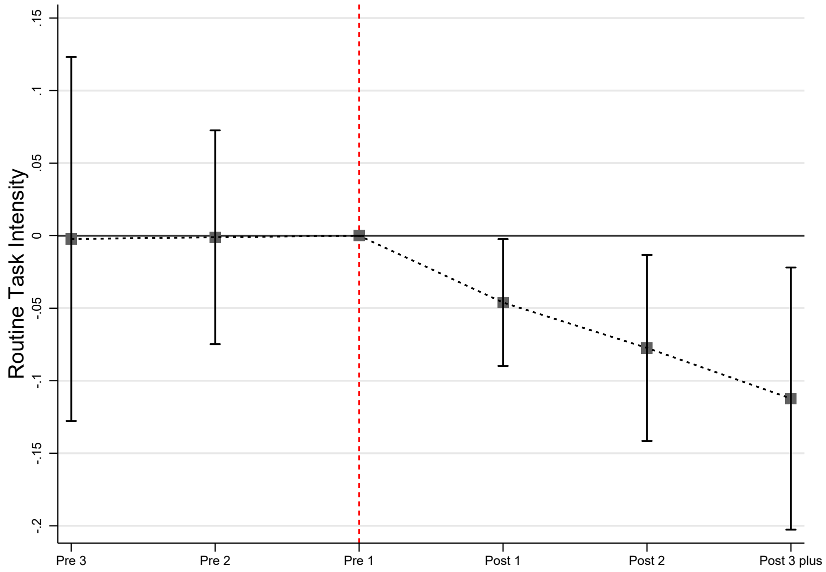
$$y_{i,t} = \sum_{n=2}^{3} \phi_{Pre_n} 1_{t=t(Pre_n)} \cdot M\&A_i + \sum_{n=1}^{3+} \phi_{Post_n} 1_{t=t(Post_n)} \cdot M\&A_i$$

$$+ \sum_{n=2}^{3} \mu_{Pre_n} 1_{t=t(Pre_n)} + \sum_{n=1}^{3+} \mu_{Post_n} 1_{t=t(Post_n)} + \alpha_i + \alpha_{j,t} + \beta \cdot X_{i,t} + \epsilon_{i,t},$$

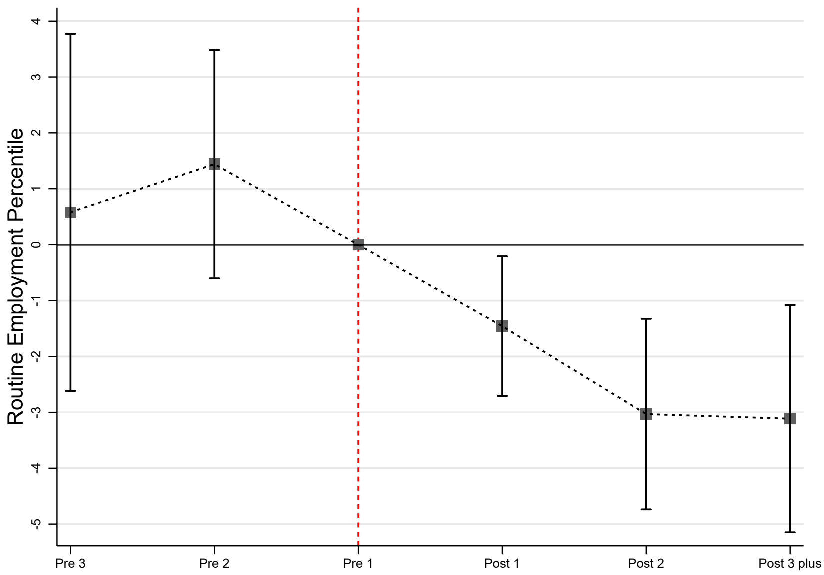
where i represents an establishment and t represents a year. $y_{i,t}$ is measured by the employment share of routine occupations (RSH) in Panel A, the employment-weighted average routine task intensity (RTI) in Panel B, and the percentile rank of employment of routine occupations ($Routine\ Employment\ Percentile$) in Panel C. $M\&A_i$ equals one for establishments of targets in horizontal M&As from 2001 through 2017, zero otherwise. $1_{t=t(Pre_n)}$ equals one for the year of the n^{th} observation observed $before$ the M&A effective year, zero otherwise. $1_{t=t(Post_n)}$ equals one for the year of the n^{th} observation observed $after$ the M&A effective year, zero otherwise. The first observation prior to/at the M&A ($1_{t=t(Pre_1)}$) is the omitted coefficient, depending on which one is covered by OEWS. α_i represents establishment fixed effects, and $\alpha_{j,t}$ represents 4-digit NAICS-by-year fixed effects. $X_{i,t}$ represents *Offshorability* of a given establishment year. $M\&A_i$ is absorbed by establishment fixed effects. Each figure plots estimates of ϕ_{Pre_n} and ϕ_{Post_n} along with 95% confidence intervals. Standard errors are clustered at the firm level.



Panel A. RSH



Panel B. RTI



Panel C. Routine Employment Percentile Rank

Figure 2. M&A and occupational employment

The figure plots effects of M&As on percentile ranks of employment for occupation groups defined by Autor and Dorn (2013). For each occupation group, the coefficient estimate (i.e., $\gamma_{1,o}$) is estimated using Equation 3, where the dependent variable is specified as the percentile rank of establishment employment for the occupation group within the year's sample distribution. Coefficient estimates are plotted in square dots. Horizontal bands represent 95% confidence intervals. Standard errors are clustered at the firm level. The sample consists of OEWS establishments targeted in horizontal M&As from 2001 through 2017 and those of matched control establishments.

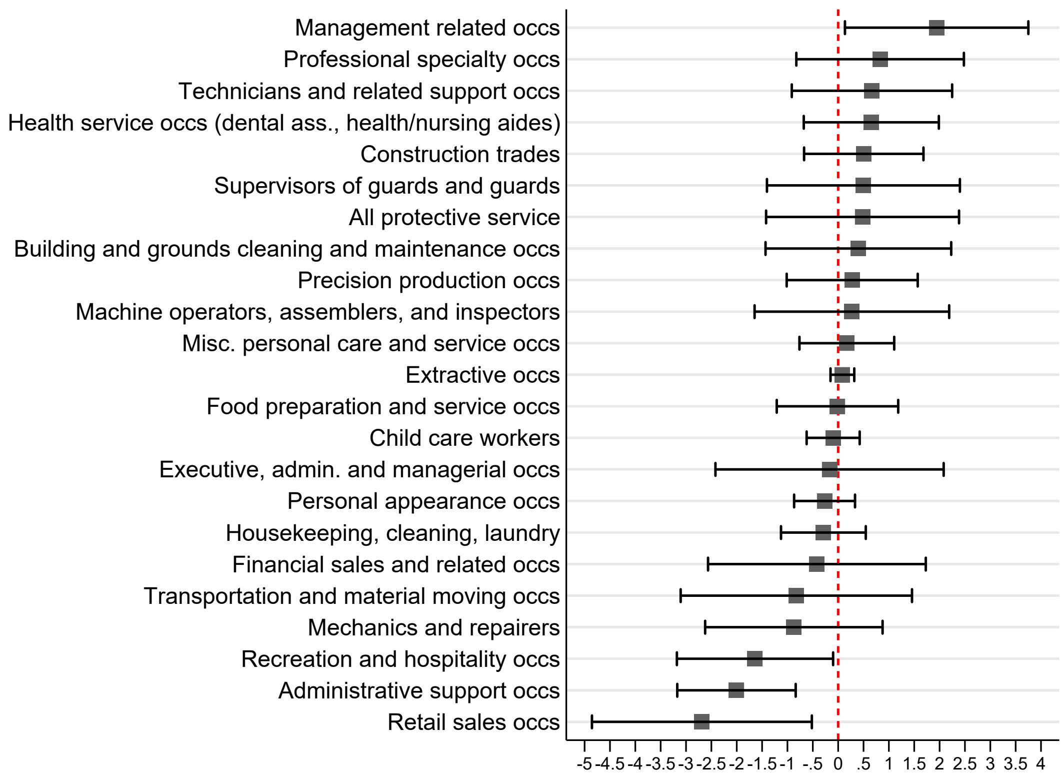


Table 1
Summary statistics

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. Each observation is measured at the establishment level. Columns 1-3 present summary statistics for all establishments. Columns 4-6 and 7-9 present summary statistics for establishments with M&A (treated) and without M&A (controls), respectively, in the years before an M&A. Column 10 reports the *p*-value of the differences in means (clustered by firm) between treated and control groups pre-treatment and the level of significance. The last column reports the mean of all establishments' key variables in the pre-treatment period. All variable definitions are provided in Appendix Table A.1.

				Establishments before M&A							
	All Establishments			With M&A			Without 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	(11) Mean
Total Employment	25,588	185.0	444.2	4,016	186.5	472.6	5,831	187.2	453.1	0.97	186.9
Routine Employment Share	25,588	0.356	0.285	4,016	0.364	0.289	5,831	0.353	0.282	0.47	0.358
Routine Employment	25,588	55.81	173.1	4,016	56.55	152.2	5,831	52.28	119.7	0.39	54.02
Routine Task Intensity	25,588	1.672	1.211	4,016	1.693	1.266	5,831	1.626	1.223	0.35	1.653
Offshorability	25,588	0.352	0.723	4,016	0.387	0.732	5,831	0.347	0.748	0.18	0.363
Tech-oriented Employment	25,588	15.93	88.32	4,016	17.40	86.70	5,831	19.36	111.6	0.47	18.56
Engineering Employment	25,588	6.328	44.02	4,016	5.478	43.43	5,831	6.947	52.07	0.32	6.348
Routine-manual Employment	25,588	9.829	64.17	4,016	11.42	65.49	5,831	8.990	39.72	0.11	9.981
Routine-cognitive Employment	25,588	39.33	123.4	4,016	41.51	124.2	5,831	36.98	90.65	0.28	38.83
Average Hourly Wages ($)	25,588	17.52	9.668	4,016	17.56	9.309	5,831	17.57	9.130	0.98	17.57
Std. Dev. of Hourly Wages ($)	25,458	9.358	6.792	4,012	9.032	6.213	5,808	9.331	6.457	0.27	9.209

Table 2
M&As and target routine occupation composition

This table presents estimates of changes in routine occupation composition at M&A target establishments compared to control establishments. The effects are estimated using Equation 1. The dependent variable in Panel A is the employment share of routine occupations (RSH) defined at the establishment level. In Panel B, the dependent variable is the employment-weighted average of routine task intensity (RTI) defined at the establishment level. The dependent variable in Panel C is the percentile rank of an establishment's routine employment within a sample year distribution. An occupation is routine if it is in the top employment-weighted quartile of RTI in the 2000 ACS sample distribution. $M\&A_i$ is absorbed by fixed effects. $Post_t$ 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. Standard errors are reported in parentheses and clustered at the firm level. Industries are classified by 4-digit NAICS. All variable definitions are provided in Appendix Table A.1. Significance levels are indicated by *, ** and *** and correspond to 10%, 5%, and 1% significance levels, respectively.

	(1)	(2)	(3)	(4)
	Panel A. RSH			
$Post_t \cdot M\&A_i$	-0.0238***	-0.0182**	-0.0189***	-0.0180***
	(0.0078)	(0.0075)	(0.0067)	(0.0065)
Offshorability		0.1550***	0.1615***	0.1609***
		(0.0076)	(0.0082)	(0.0081)
Observations	25,588	25,588	25,040	25,007
R^2	0.740	0.776	0.813	0.824
	Panel B. RTI			
$Post_t \cdot M\&A_i$	-0.0842***	-0.0612***	-0.0638***	-0.0656***
	(0.0250)	(0.0231)	(0.0209)	(0.0206)
Offshorability		0.6318***	0.6497***	0.6454***
		(0.0279)	(0.0296)	(0.0290)
Observations	25,588	25,588	25,040	25,007
R^2	0.819	0.852	0.877	0.884
	Panel C. Routine Employment Percentile			
$Post_t \cdot M\&A_i$	-2.496***	-2.115***	-2.285***	-2.436***
	(0.681)	(0.654)	(0.600)	(0.586)
Offshorability		10.50***	10.84***	10.73***
		(0.561)	(0.623)	(0.607)
Observations	25,588	25,588	25,040	25,007
R^2	0.828	0.843	0.868	0.876
Year FE	YES	YES		
Establishment FE	YES	YES	YES	YES
Industry · Year FE			YES	YES
State · Year FE				YES

Table 3
M&As and target employment

This table presents estimates of changes in percentile ranks of employment within various occupation groups at M&A target establishments compared to control establishments. The dependent variables in columns 1-3 are percentile ranks of a given establishment's total employment, routine employment, and non-routine employment in the sample distribution for a given year, respectively. In column 4 (5), the dependent variable is the percentile ranks of a given establishment's employment for routine manual (routine cognitive) occupations within the year's sample distribution. Routine manual (routine cognitive) occupations are the routine occupations with routine manual (routine cognitive) task scores in the top-employment weighted quartile of the 2000 ACS sample distribution. Columns 6-8 report post-M&A changes in tech-oriented occupations classified following Hecker (2005). The dependent variables in columns 6-8 are percentile ranks of a given establishment's employment for tech-oriented occupations, engineering occupations, and the rest of tech-oriented occupations (i.e., non-engineering) in the sample distribution for a given year, respectively. $M\&A_i$ is absorbed by fixed effects. $Post_t$ 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. Standard errors are reported in parentheses and clustered at the firm level. Industries are classified by 4-digit NAICS. All variable definitions are provided in Appendix Table A.1. Significance levels are indicated by *, ** and *** and correspond to 10%, 5%, and 1% significance levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Total Employment Percentile	Routine Employment Percentile	Non-routine Employment Percentile	Routine-manual Employment Percentile	Routine-cognitive Employment Percentile	Tech-oriented Employment Percentile	Engineering Employment Percentile	Non-engineering Employment Percentile
$Post_t \cdot M\&A_i$	-1.6451***	-2.2851***	-0.6832	-1.1876	-1.8849***	1.7614**	2.2622***	1.2865
	(0.4513)	(0.5995)	(0.4735)	(1.0480)	(0.5953)	(0.7704)	(0.8730)	(0.8193)
Offshorability	0.6711**	10.8357***	-4.8758***	0.9733	12.7662***	5.1427***	1.7875**	5.5608***
	(0.2993)	(0.6226)	(0.4718)	(0.8389)	(0.5819)	(0.8365)	(0.7745)	(0.7698)
Observations	25,040	25,040	25,040	25,040	25,040	25,040	25,040	25,040
R^2	0.943	0.868	0.921	0.736	0.855	0.816	0.792	0.777
Establishment FE	YES	YES	YES	YES	YES	YES	YES	YES
Industry · Year FE	YES	YES	YES	YES	YES	YES	YES	YES

Table 4
Mechanism: Treatment heterogeneity analysis

This table presents estimates of changes in routine employment share (RSH) at M&A target establishments compared to control establishments, further interacting $Post_t \cdot M\&A_i$ with dummy variables $\mathbb{1}_{TargetRSH>AcquirerRSH}$ in column 1, $\mathbb{1}_{AcquirerWage>TargetWage}$ in column 2, and $\mathbb{1}_{AcquirerTechWage>TargetTechWage}$ in column 3. The dependent variable in columns 1-3 is the employment share of routine occupations, where an occupation is routine if it is in the top employment-weighted quartile of RTI in the 2000 ACS sample distribution. Columns 4-5 present estimates of changes in percentile ranks of IT spending and IT spending per employee at target establishments compared to control establishments, further interacting $Post_t \cdot M\&A_i$ with $\mathbb{1}_{AcquirerIT>TargetIT}$. The sample used in columns 1-3 consists of establishments targeted in horizontal M&As from 2001 through 2017 and those of matched control establishments in the OEWS sample. The sample used in columns 4-5 consists of establishments targeted in horizontal M&As from 2009 through 2015 and those of matched control establishments in the CiTDB sample. The estimates are generated by Equation 2. $M\&A_i$ and its interaction with $\mathbb{1}_{TargetRSH>AcquirerRSH}$ ($\mathbb{1}_{AcquirerWage>TargetWage}$, $\mathbb{1}_{AcquirerTechWage>TargetTechWage}$, or $\mathbb{1}_{AcquirerIT>TargetIT}$) is absorbed by establishment fixed effects. The interaction between $Post_t$ and $\mathbb{1}_{TargetRSH>AcquirerRSH}$ ($\mathbb{1}_{AcquirerWage>TargetWage}$, $\mathbb{1}_{AcquirerTechWage>TargetTechWage}$, or $\mathbb{1}_{AcquirerIT>TargetIT}$) is absorbed by $Post_t \cdot M\&A_i$. $Post_t$ is estimated but not reported for brevity. *Offshorability* is not included in the estimation in columns 4-5 because we do not observe occupational offshorability data in the CiTDB sample. Industries are classified by 4-digit NAICS. All variable definitions are provided in Appendix Table A.1. Standard errors are reported in parentheses and clustered at the firm level. Significance levels are indicated by *, ** and *** and correspond to 10%, 5%, and 1% significance levels, respectively.

	(1)	(2)	(3)	(4)	(5)
	RSH	RSH	RSH	IT Budget Percentile	IT Budget/Emp Percentile
$Post_t \cdot M\&A_i$	0.0086	0.0075	0.0201	-0.285	-1.905*
	(0.0150)	(0.0148)	(0.0216)	(0.872)	(0.992)
$Post_t \cdot M\&A_i \cdot \mathbb{1}_{TargetRSH>AcquirerRSH}$	-0.0484**				
	(0.0213)				
$Post_t \cdot M\&A_i \cdot \mathbb{1}_{AcquirerWage>TargetWage}$		-0.0456**			
		(0.0213)			
$Post_t \cdot M\&A_i \cdot \mathbb{1}_{AcquirerTechWage>TargetTechWage}$			-0.0690**		
			(0.0333)		
$Post_t \cdot M\&A_i \cdot \mathbb{1}_{AcquirerIT>TargetIT}$				2.404**	4.166***
				(1.047)	(1.307)
Offshorability	0.1636***	0.1640***	0.1279***		
	(0.0178)	(0.0177)	(0.0274)		
Observations	6,468	6,468	3,063	15,983	15,983
R^2	0.835	0.835	0.810	0.871	0.840
Establishment FE	YES	YES	YES	YES	YES
Industry · Year FE	YES	YES	YES	YES	YES

Table 5
Testing alternative explanations

This table presents estimated changes in routine employment share (RSH) at M&A target establishments compared to control establishments, interacting $Post_t \cdot M\&A_i$ with $\mathbb{1}_{TargetRSH>AcquirerRSH}$ in each column and further augmenting the specification interacting $Post_t \cdot M\&A_i$ with $\mathbb{1}_{TargetOffshor>AcquirerOffshor}$, $\mathbb{1}_{HighOccOverlap}$, and $\mathbb{1}_{HighOccSimilarity}$ in columns 1-3, respectively. The dependent variable is the employment share of routine occupations at target establishments, where an occupation is routine if it is in the top employment-weighted quartile of RTI in the 2000 ACS sample distribution. $M\&A_i$ and its interaction with $\mathbb{1}_{TargetRSH>AcquirerRSH}$ ($\mathbb{1}_{TargetOffshor>AcquirerOffshor}$, $\mathbb{1}_{HighOccOverlap}$, or $\mathbb{1}_{HighOccSimilarity}$) is absorbed by establishment fixed effects. The interaction between $Post_t$ and $\mathbb{1}_{TargetRSH>AcquirerRSH}$ ($\mathbb{1}_{TargetOffshor>AcquirerOffshor}$, $\mathbb{1}_{HighOccOverlap}$, or $\mathbb{1}_{HighOccSimilarity}$) is absorbed by $Post_t \cdot M\&A_i$. $Post_t$ is estimated but not reported for brevity. The sample consists of establishments in OEWS data that are targeted in horizontal M&As from 2001 through 2017 and those of matched control establishments. Industries are classified by 4-digit NAICS. All variable definitions are provided in Appendix Table A.1. Standard errors are reported in parentheses and clustered at the firm level. Significance levels are indicated by *, ** and *** and correspond to 10%, 5%, and 1% significance levels, respectively.

	(1)	(2)	(3)
	RSH	RSH	RSH
$Post_t \cdot M\&A_i$	0.0074	0.0212	-0.0050
	(0.0160)	(0.0175)	(0.0145)
$Post_t \cdot M\&A_i \cdot \mathbb{1}_{TargetRSH>AcquirerRSH}$	-0.0500**	-0.0494**	-0.0509**
	(0.0233)	(0.0212)	(0.0207)
$Post_t \cdot M\&A_i \cdot \mathbb{1}_{TargetOffshor>AcquirerOffshor}$	0.0045		
	(0.0226)		
$Post_t \cdot M\&A_i \cdot \mathbb{1}_{HighOccOverlap}$		-0.0237	
		(0.0203)	
$Post_t \cdot M\&A_i \cdot \mathbb{1}_{HighOccSimilarity}$			0.0311
			(0.0206)
Offshorability	0.1637***	0.1637***	0.1632***
	(0.0180)	(0.0178)	(0.0178)
Observations	6,468	6,468	6,468
R^2	0.835	0.835	0.835
Establishment FE	YES	YES	YES
Industry · Year FE	YES	YES	YES

Table 6
Robustness: Keeping the nearest matches

This table presents estimates of changes in routine occupation composition at M&A target establishments compared to control establishments within a subset of treated and control pairs with the nearest match in a given outcome variable ex-ante. In Panel A (B or C), the sample keeps pairs in which a given treated establishment's average *RTI* (*RSH* or *Routine Employment Percentile*) observed in years prior to the M&A is within the 25% range of its matched control establishments. In each panel, the dependent variable is the employment share of routine occupations in column 1, the average of routine task intensity at the establishment in column 2, and the percentile rank of establishment routine employment within the year's sample distribution in column 3. $M\&A_i$ is absorbed by fixed effects. $Post_t$ 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. Standard errors are reported in parentheses and clustered at the firm level. Industries are classified by 4-digit NAICS. All variable definitions are provided in Appendix Table A.1. Significance levels are indicated by *, ** and *** and correspond to 10%, 5%, and 1% significance levels, respectively.

	Panel A. Nearest pre-RTI			Panel B. Nearest pre-RSH			Panel C. Nearest pre-Routine Employment Percentile		
	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
	RSH	RTI	Routine Employment Percentile	RSH	RTI	Routine Employment Percentile	RSH	RTI	Routine Employment Percentile
$Post_t \cdot M\&A_i$	-0.0339***	-0.0803***	-2.4600***	-0.0278***	-0.0773**	-2.8865***	-0.0169**	-0.0390	-2.1692***
	(0.0094)	(0.0286)	(0.7103)	(0.0088)	(0.0303)	(0.6844)	(0.0078)	(0.0259)	(0.6102)
Offshorability	0.1451***	0.5538***	9.7393***	0.1665***	0.5738***	10.6287***	0.1658***	0.5966***	10.6324***
	(0.0155)	(0.0453)	(1.2186)	(0.0122)	(0.0461)	(1.1312)	(0.0113)	(0.0408)	(0.8718)
Observations	10,994	10,994	10,994	9,212	9,212	9,212	14,038	14,038	14,038
R^2	0.849	0.906	0.894	0.868	0.912	0.901	0.846	0.902	0.895
Establishment FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
Industry · Year FE	YES	YES	YES	YES	YES	YES	YES	YES	YES

Table 7
Top 25 occupations by employment changes

This table presents the top 25 occupations with the highest *decline* in employment percentile ranks in Panel A and the top 25 occupations with the highest *increase* in employment percentile ranks in Panel B after M&As. Occupations are classified by *occ*1990*dd* codes constructed by Dorn (2009). For each occupation, we estimate the effect of M&A on its employment percentile rank (defined based on the year's sample distribution) using Equation 3 with establishment and 4-digit NAICS-by-year fixed effects. The last two columns of each panel report coefficient estimates of the $Post \cdot M\&A$ term and standard errors, which are clustered at the firm level. The sample consists of establishments targeted in horizontal M&As from 2001 through 2017 and those of matched control establishments. In Panel A, an occupation is routine (routine manual, routine cognitive, or scalable) if its routine task intensity (routine manual task, routine cognitive task, or scalable task intensity) score is in the top-employment weighted quartile of the 2000 ACS sample distribution. Internet Appendix B2 describes the construction of scalable task intensity measure. An occupation is defined as non-unionized when its workers indicate no union membership in the 2000 Current Population Survey. *Executive, Admin, and Managerial* include *occ*1990*dd* occupations between codes 3 and 22 defined by Dorn (2009) and Autor and Dorn (2013). In Panel B, following the same literature, *Management Related* include *occ*1990*dd* occupations between codes 23 and 37. *Technicians and Related Support* include *occ*1990*dd* occupations between codes 203 and 235. *Professional Specialty* include *occ*1990*dd* occupations between codes 43 and 200.

Panel A. Top 25 occupations by employment percentile rank decline

Rank	Occupation Codes	Occupation Title	Routine	Routine Manual	Routine Cognitive	Non-unionized	Executive, Admin and Managerial	Scalable	Coefficient Estimates	Std. Error
1	275	Retail salespersons and sales clerks							-3.47	1.27
2	364	Shipping and receiving clerks	1						-3.19	1.11
3	316	Interviewers, enumerators, and surveyors	1		1				-1.95	1.44
4	365	Stock and inventory clerks							-1.86	0.88
5	274	Salespersons, n.e.c.							-1.82	1.04
6	427	Protective service, n.e.c.							-1.73	0.72
7	549	Mechanics and repairers, n.e.c.							-1.67	0.88
8	385	Data entry keyers	1		1				-1.65	0.79
9	379	General office clerks	1		1				-1.61	1.18
10	255	Financial service sales occupations	1			1			-1.59	0.70
11	335	File clerks	1						-1.46	0.82
12	459	Recreation facility attendants							-1.42	0.72
13	178	Lawyers and judges	1					1	-1.22	0.58
14	389	Administrative support jobs, n.e.c.	1						-1.18	0.86
15	23	Accountants and auditors	1		1			1	-1.15	0.92
16	303	Office supervisors							-1.08	1.19
17	166	Economists, market and survey researchers							-1.02	0.68
18	378	Bill and account collectors	1		1	1			-0.93	0.73
19	356	Mail clerks, outside of post office	1	1					-0.85	0.55
20	873	Production helpers	1	1					-0.81	0.54
21	344	Billing clerks and related financial records processing	1		1				-0.80	0.85
22	33	Purchasing managers, agents, and buyers, n.e.c.							-0.77	0.83
23	686	Butchers and meat cutters	1	1					-0.76	0.35
24	338	Payroll and timekeeping clerks	1		1				-0.75	0.85
25	4	Chief executives, public administrators, and legislators				1	1	1	-0.72	0.93

Panel B. Top 25 occupations by employment percentile rank increase

Rank	Occupation Codes	Occupation Title	Management Related	Technicians and Related Support	Professional Specialty	Coefficient Estimates	Std. Error
1	55	Electrical engineers		1		1.73	0.89
2	415	Supervisors of guards				1.64	0.87
3	96	Pharmacists		1		1.41	0.77
4	59	Engineers and other professionals, n.e.c.		1		1.41	0.63
5	433	Supervisors of food preparation and service				1.33	0.97
6	328	Human resources clerks, excl payroll and timekeeping				1.05	1.55
7	774	Photographic process workers				1.04	0.71
8	803	Supervisors of motor vehicle transportation				0.91	1.09
9	27	Personnel, HR, training, and labor rel. specialists	1			0.89	1.27
10	25	Other financial specialists	1			0.83	0.95
11	368	Weighers, measurers, and checkers				0.80	0.56
12	376	Customer service reps, invest., adjusters, excl. insur.				0.73	1.41
13	13	Managers and specialists in marketing, advert., PR				0.67	1.38
14	447	Health and nursing aides				0.64	0.68
15	214	Engineering technicians			1	0.63	0.72
16	75	Geologists		1		0.61	0.26
17	348	Telephone operators				0.59	0.80
18	208	Health technologists and technicians, n.e.c.			1	0.57	0.50
19	453	Janitors				0.55	0.95
20	235	Technicians, n.e.c.			1	0.54	0.33
21	26	Management analysts	1			0.54	0.93
22	106	Physicians' assistants		1		0.51	0.29
23	518	Industrial machinery repairers				0.50	0.48
24	319	Receptionists and other information clerks				0.49	1.15
25	37	Management support occupations	1			0.48	1.01

Table 8
M&As and target wage inequality

This table presents estimates of changes in average wages and standard deviation of wages at M&A target establishments compared to control establishments. The effects are estimated using Equation 1. The dependent variable in Panel A is the log-transformed average hourly wage at the establishment level. The dependent variable in Panel B is the log-transformed standard deviation of hourly wages at the establishment level. $M\&A_i$ is absorbed by fixed effects. $Post_t$ 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. Standard errors are reported in parentheses and clustered at the firm level. Industries are classified by 4-digit NAICS. All variable definitions are provided in Appendix Table A.1. Significance levels are indicated by *, ** and *** and correspond to 10%, 5%, and 1% significance levels, respectively.

	Panel A			
	(1)	(2)	(3)	(4)
	Wages	Wages	Wages	Wages
$Post_t \cdot M\&A_i$	0.0251***	0.0251***	0.0241***	0.0245***
	(0.0080)	(0.0080)	(0.0076)	(0.0080)
Offshorability		-0.0015	-0.0034	-0.0001
		(0.0077)	(0.0080)	(0.0080)
Observations	25,588	25,588	25,040	25,007
R^2	0.862	0.862	0.889	0.896
Year FE	YES	YES		
Establishment FE	YES	YES	YES	YES
Industry · Year FE			YES	YES
State · Year FE				YES

	Panel B			
	(1)	(2)	(3)	(4)
	StdWages	StdWages	StdWages	StdWages
$Post_t \cdot M\&A_i$	0.0331**	0.0341**	0.0316**	0.0310*
	(0.0165)	(0.0165)	(0.0158)	(0.0166)
Offshorability		0.0271*	0.0240	0.0314**
		(0.0143)	(0.0152)	(0.0151)
Observations	25,225	25,225	24,660	24,632
R^2	0.758	0.758	0.802	0.815
Year FE	YES	YES		
Establishment FE	YES	YES	YES	YES
Industry · Year FE			YES	YES
State · Year FE				YES

Appendix A.

Table A.1
Variable definitions

This table describes establishment-level variables. Panel A includes those constructed using OEWS and SDC. Panel B includes those constructed using CiTDB and SDC.

Panel A. Establishment-level variables from OEWS and SDC	
Variable Name	Definition
Total Employment	The number of employees in a given establishment year.
Routine Employment Share (RSH)	The share of employment in routine occupations. An occupation is routine if it is in the top employment-weighted quartile of routine task intensity within the 2000 American Community Survey (ACS). The ACS is available at https://usa.ipums.org/usa/.
Routine Task Intensity (RTI)	The 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 o is defined as $RTI_o = lnR_{o,1980} - lnA_{o,1980} - lnM_{o,1980}$, where $R_{o,1980}$, $A_{occ,1980}$ and $M_{o,1980}$ are the routine, abstract, and manual inputs, respectively, by occupation, indexed by o, in 1980. Then, RTI_o is merged with OEWS data using the SOC occupation codes. The occupational routine, abstract, and manual input data are available at https://www.ddorn.net/data/occ1990dd_task_alm.zip.
Routine Employment	The employment in routine occupations at the establishment level. An occupation is routine if it is in the top employment-weighted quartile of RTI within the American Community Survey (ACS) 2000 sample. The ACS is available at https://usa.ipums.org/usa/.
$Offshorability$	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 with 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.
Tech-oriented Employment	The number of tech-oriented workers in a given establishment-year. Tech-oriented occupations are classified following Hecker (2005) and include scientific, engineering, and technician occupations: computer and information systems managers, SOC 11-3020; engineering managers, SOC 11-9040; and natural sciences managers, SOC 11-9120; computer and mathematical scientists, 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.
Engineering Employment	The number of employees within the following occupational groups: engineering managers, SOC 11–9040; engineers, SOC 17–2000; drafters, engineering, and mapping technicians, SOC 17–3000.

Panel A. Establishment-level variables from OEWS and SDC (cont.)	
Variable Name	Definition
Routine-manual Employment	The number of employees within routine-manual occupations in a given establishment year. An occupation ($occ1990dd$) is classified as routine-manual if its RTI and routine manual tasks score are within the top quartile of the employment-weighted distribution, where employment comes from the 2000 ACS. Occupational task scores can be downloaded from Daron Acemoglu's website, https://www.dropbox.com/s/835jzwyo0o0x0xn/task-construct(1).zip?e=1&dl=0. The ACS is available at https://usa.ipums.org/usa/
Routine-cognitive Employment	The number of employees within routine-cognitive occupations in a given establishment year. An occupation ($occ1990dd$) is classified as routine-cognitive if its RTI and routine cognitive tasks score are within the top quartile of the employment-weighted distribution, where employment comes from the 2000 ACS. Occupational task scores can be downloaded from Daron Acemoglu's website, https://www.dropbox.com/s/835jzwyo0o0x0xn/task-construct(1).zip?e=1&dl=0. The ACS is available at https://usa.ipums.org/usa/
Average Hourly Wages ($Wages$)	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 for 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 the year 2001.
Std. Dev. of Hourly Wages ($StdWages$)	The occupational employment-weighted standard deviation of hourly wages in each establishment and year.
$M\&A_i$	An indicator equal to one if the establishment belongs to an M&A target, zero otherwise.
$Post_t$	An indicator equal to one for years post-M&A, zero otherwise.
(Non-) Routine Employment Percentile	The percentile ranks of establishment employment within (non-) routine occupations in the sample distribution for a given year. An occupation is routine if it is in the top employment-weighted quartile of RTI within the American Community Survey (ACS) 2000 sample. The ACS is available at https://usa.ipums.org/usa/.
Total Employment Percentile	The percentile ranks of establishment employment in the sample distribution each year.
Routine-manual (-cognitive) Employment Percentile	The percentile ranks of establishment employment forroutine-manual (cognitive) occupations defined based on the sample distribution each year. An occupation ($occ1990dd$) is classified as routine-manual (-cognitive) if its RTI and routine-manual (-cognitive) tasks score are within the top quartile of the employment-weighted distribution, where employment comes from 2000 ACS. Occupational task scores can be downloaded from Daron Acemoglu's website, https://www.dropbox.com/s/835jzwyo0o0x0xn/task-construct(1).zip?e=1&dl=0. The ACS is available at https://usa.ipums.org/usa/

Panel A. Establishment-level variables from OEWS and SDC (cont.)	
Variable Name	Definition
Tech-oriented (Engineering, or Non-engineering) Employment Percentile	The percentile ranks of establishment employment for tech-oriented (engineering, or non-engineering) occupations defined based on the sample distribution each year. Tech-oriented occupations are classified following Hecker (2005) and include scientific, engineering, and technician occupations: computer and information systems managers, SOC 11-3020; engineering managers, SOC 11-9040; and natural sciences managers, SOC 11-9120; 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. Among tech-oriented occupations, the following groups are classified as engineering: engineering managers, SOC 11–9040; engineers, SOC 17–2000; drafters, engineering, and mapping technicians, SOC 17–3000. Non-engineering occupations include the rest of the tech-oriented occupations.
Pre_n	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, zero otherwise.
$Post_n$	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 *plus*, zero otherwise.
$\mathbb{1}_{TargetRSH>AcquirerRSH}$	An indicator equal to one if the target firm's employment share of routine occupations exceeds that of its acquirer firm in the first observed year before the M&A, and zero for the rest of treated establishments and all control establishments.
$\mathbb{1}_{AcquirerWage>TargetWage}$	An indicator equal to one if the acquirer firm's average wages exceed that of its target firm in the first observed year before the M&A, and zero for the rest of treated establishments and all control establishments.
$\mathbb{1}_{AcquirerTechWage>TargetTechWage}$	An indicator equal to one if the acquirer firm's average wages of high-technology workers exceed that of its target firm in the first observed year before the M&A, and zero for the rest of treated establishments and all control establishments.
$\mathbb{1}_{TargetOffshor>AcquirerOffshor}$	An indicator equal to one if the target firm's $Offshorability$ exceeds that of its acquirer firm in the first observed year before the M&A, and zero for the rest of treated establishments and all control establishments.
$\mathbb{1}_{HighOccOverlap}$	An indicator equal to one if the share of target employment in occupations that exist in both the target and its acquirer exceeds the sample median in the first observed year before the M&A, and zero for the rest of treated establishments and all control establishments.

Panel A. Establishment-level variables from OEWS and SDC (cont.)	
Variable Name	Definition
$\mathbb{1}_{HighOccSimilarity}$	An indicator equal to one if the occupational similarity between the target and its acquirer exceeds the sample median, and zero for the rest of treated establishments and all control establishments. We take the following steps to construct the cosine-similarity score between a target firm and its acquirer firm. 1) We construct pairwise occupation cosine similarity scores based on vectors of text descriptions of SOC occupations ($Simi_{a,b}$, where a and b are 6-digit SOC codes). 2) For each occupation a at the target, we calculate the acquirer occupational employment weighted average of cosine-similarity score ($OccSimi_a = \sum_b \omega_b \times Simi_{a,b}$, where ω_b represents employment share of occupation b at the acquirer firm). 3) For a given target i, the cosine-similarity score is the target employment weighted average of similarity scores of occupations at targets and its acquirer ($OccSimilarity_i = \sum_a \omega_a OccSimi_a$, where ω_a represents employment share of occupation a at the target firm).

Panel B. Establishment-level variables from CITDB and SDC	
Variable Name	Definition
Total Employment	The number of employees at a CITDB establishment.
IT Budget (Hardware, Software, Service, Storage, or Communication) Percentile	The percentile rank of an establishment's budget for IT (hardware, software, IT services, storage, or communications service) within the sample distribution of a given year.
IT Budget (Hardware, Software, Service, Storage, or Communication)/Emp Percentile	The percentile rank of an establishment's budget for IT (hardware, software, IT services, storage, or communications service) normalized by its employment within the sample distribution of a given year.
$M\&A_i$	An indicator equal to one if the establishment belongs to a M&A target, zero otherwise.
$Post_t$	An indicator equal to one for years post-M&A, zero otherwise.
$\mathbb{1}_{AcquirerIT>TargetIT}$	An indicator equal to one if the acquirer's ex-ante average IT budget per worker exceeds its target's average IT budget per worker, zero for the rest of treated establishments and all control establishments.

Mergers and Acquisitions, Technological Change, and Inequality

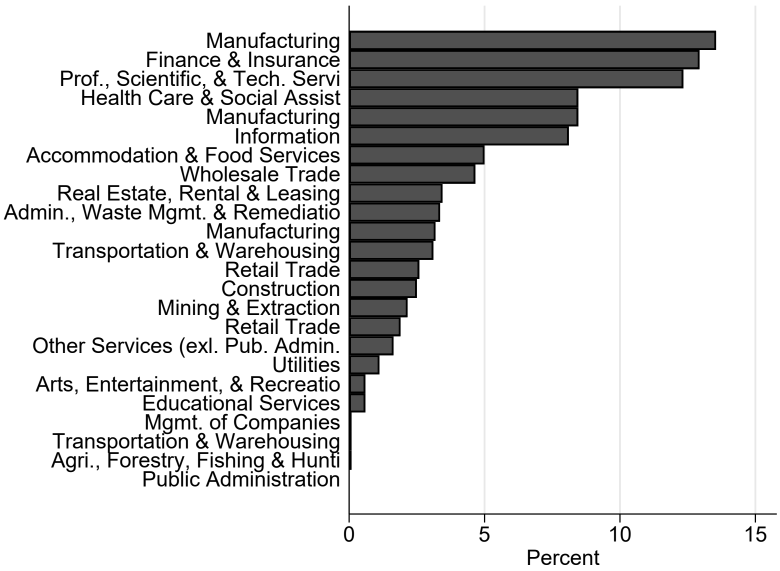
Wenting Ma, Paige Ouimet, and Elena Simintzi

INTERNET APPENDIX

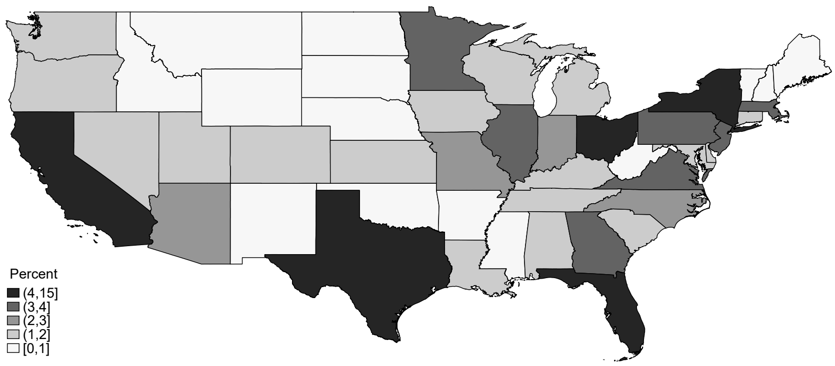
Internet Appendix A. Figures and Tables

Figure IA. A.1. Industry and geographic distributions of in-sample M&As

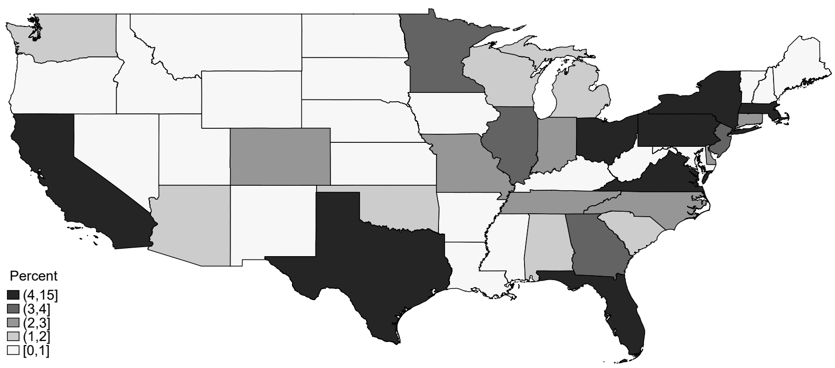
This figure presents the distributions of horizontal M&A deals by industry and geography in our sample. Panel A presents the distribution of 2-digit NAICS sectors of targets and acquirers, who are in the same sector in horizontal deals. Panel B and Panel C show the geographical distribution of the states where the target and acquirer firms, respectively, are headquartered.



Panel A. Distribution of sectors



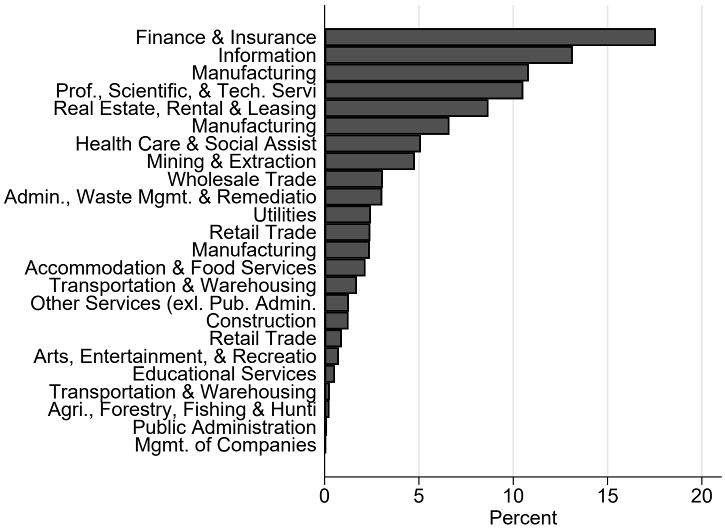
Panel B. Distribution of target headquarters states



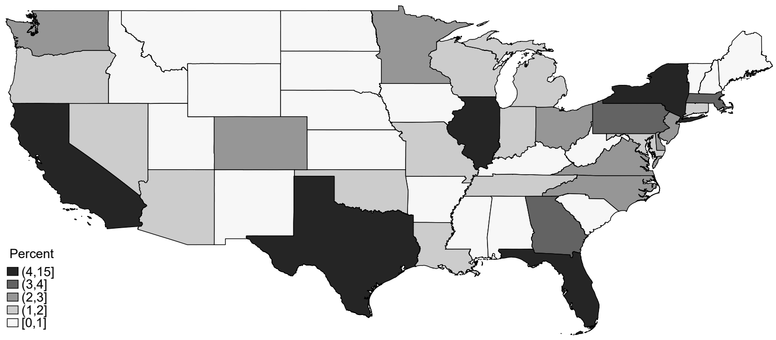
Panel C. Distribution of acquirer headquarters states

Figure IA. A.2. Industry and geographic distributions of unmatched M&As

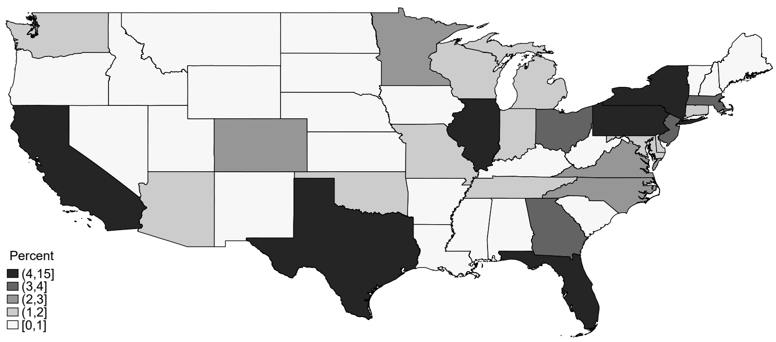
This figure presents the distributions of horizontal M&A deals that are *not* included in our sample. Panel A presents the distribution of 2-digit NAICS sectors of targets and acquirers. Panel B and Panel C show the geographical distribution of the states where the target and acquirer firms, respectively, are headquartered.



Panel A. Distribution of sectors



Panel B. Distribution of target headquarters states

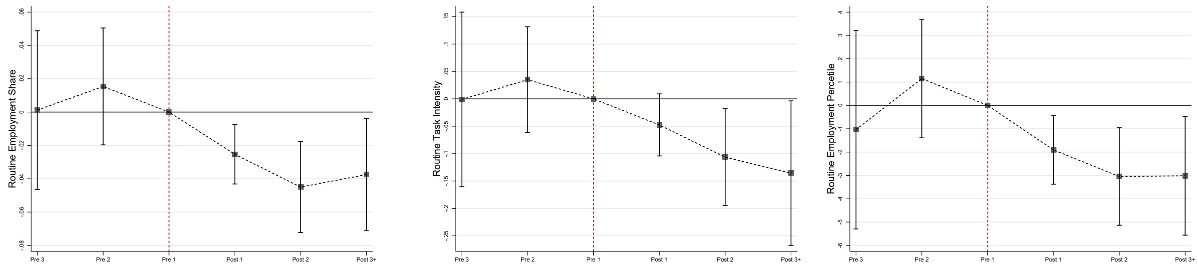


Panel C. Distribution of acquirer headquarters states

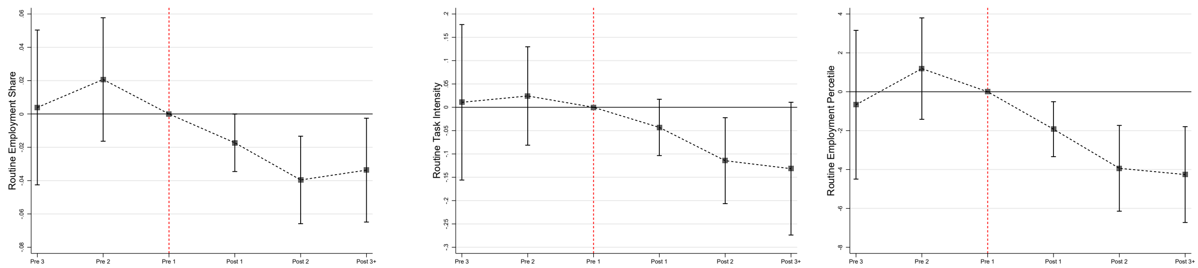
Figure IA. A.3. Dynamic effects of M&A on target routine occupation composition: Keeping the nearest matches

These figures plot the dynamic effects of M&A on routine occupation composition at target establishments compared to control establishments. This sample is drawn from a subset of treated and control pairs with the nearest match in a given outcome variable ex-ante. The effects are estimated using the equation described in Figure 1. In Panel A (B, C), the sample keeps pairs in which a given treated establishment's average *RTI* (*RSH*, *Routine Employment Percentile*) observed in years prior to the M&A is within the 25% range of its matched control establishments. In each panel, the dependent variables are routine employment share (*RSH*), routine task intensity (*RTI*), and percentile rank of routine employment (*Routine Employment Percentile*) in the left, middle, and right plot, respectively. On the x-axis, Pre_n is an indicator equal to one for the n^{th} observation of the establishment observed in OEWS *before* the M&A, 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, zero otherwise. The first observation prior to/at the M&A ($Pre1$) is the omitted coefficient, depending on which one is covered by OEWS. The vertical bands represent the associated 95% confidence intervals. The sample consists of establishments 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. All variable definitions are provided in Appendix Table A.1.

Panel A. Nearest pre-RTI



Panel B. Nearest pre-RSH



Panel C. Nearest pre-routine employment percentile

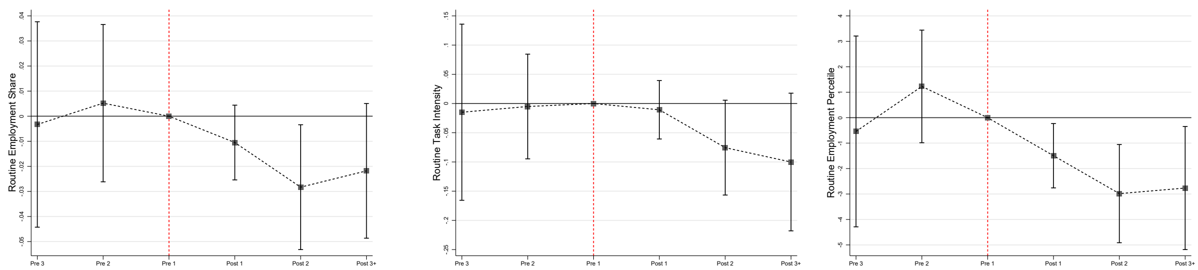


Table IA. A.1
OEWS sample observation distribution across periods

This table presents the observation count distribution across periods in our OEWS sample.

Period	Observations	Percent	Cumulative Percent
Pre_3	674	2.63	2.63
Pre_2	1934	7.56	10.19
Pre_1	7239	28.29	38.48
$Post_1$	7239	28.29	66.77
$Post_2$	4341	16.96	83.74
$Post_{3\ plus}$	4161	16.26	100

Table IA. A.2
M&A and target RSH: Robustness

This table presents estimates of changes in the employment share of routine occupations (RSH) at M&A target establishments compared to control establishments. An occupation is routine if it is in the top employment-weighted quartile of RTI in the 2000 ACS sample distribution. $M\&A_i$ is absorbed by fixed effects. $Post_t$ is estimated but not reported for brevity. Column 1 reports baseline estimates with standard errors double clustered at the firm and year level. In column 2, the sample includes all pre and first post-M&A observations. In column 3, the sample includes all pre and up to two post-M&A observations. In column 4 (5 and 6), the sample includes observations observed within 4 (5 and 6) calendar years before and after effective years of M&As. In column 7, we interact $Post$ with two dummy variables, $M\&A\_pre2008$ and $M\&A\_post2008$, indicating acquisitions made in the 2001-2008 period and the 2009-2017 period, respectively. In column 8, we further interact $Post_t \cdot M\&A_i$ with $M\&A\_pre2008$ to examine marginal differences in effects of deals made in the early period. Standard errors are clustered at the firm level in columns 2-8. Standard errors are reported in parentheses. Industries are classified by 4-digit NAICS. Significance levels are indicated by *, ** and *** and correspond to 10%, 5%, and 1% significance levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Firm and year clustering	1 post obs. only	Up to 2 post obs.	[-4 year, 4 year]	[-5 year, 5 year]	[-6 year, 6 year]	Early and late year M&As	
	RSH	RSH	RSH	RSH	RSH	RSH	RSH	RSH
$Post_t \cdot M\&A_i$	-0.0189***	-0.0136*	-0.0181***	-0.0135*	-0.0146*	-0.0174**		-0.0231*
	(0.0058)	(0.0076)	(0.0070)	(0.0081)	(0.0076)	(0.0072)		(0.0131)
$Post_t \cdot M\&A_{pre2008}$							-0.0179**	
							(0.0073)	
$Post_t \cdot M\&A_{post2008}$							-0.0231*	
							(0.0131)	
$Post_t \cdot M\&A_i \cdot M\&A_{pre2008}$								0.0052
								(0.0142)
Offshorability	0.1615***	0.1605***	0.1613***	0.1671***	0.1661***	0.1640***	0.1615***	0.1615***
	(0.0097)	(0.0104)	(0.0088)	(0.0115)	(0.0105)	(0.0093)	(0.0082)	(0.0082)
Observations	25,040	16,620	20,890	14,894	17,090	18,801	25,040	25,040
R^2	0.813	0.861	0.835	0.869	0.854	0.845	0.813	0.813
Establishment FE	YES	YES	YES	YES	YES	YES	YES	YES
Industry · Year FE	YES	YES	YES	YES	YES	YES	YES	YES

Table IA. A.3
Probability of being targets

This table presents conditional logit estimates on the log odds of being a target establishment in horizontal M&As. This sample includes all target establishments in the OEWS and their alternative peers in the same 4-digit NAICS industry. For each target establishment, only the last observation observed before the M&A is included. Their alternative industry peers are matched on the year of the observation. Standard errors are reported in parentheses and clustered at the 4-digit NAICS industry level. Significance levels are indicated by *, ** and *** and correspond to 10%, 5%, and 1% significance levels, respectively.

	(1)	(2)	(3)	(4)
	Target	Target	Target	Target
Routine Employment	0.226***	0.224***	0.227***	0.225***
	(0.0295)	(0.0305)	(0.0365)	(0.0378)
Offshorability			-0.00495	-0.00573
			(0.115)	(0.116)
Observations	4,112,738	4,112,738	4,112,738	4,112,738
State FE		Yes		Yes

Table IA. A.4
Summary statistics: CiTDB sample

This table reports the mean and standard deviation of key variables from the Ci Technology Database (CiTDB). Each observation is measured at the establishment level. Columns 1-3 present summary statistics for all establishments. Columns 4-6 and 7-9 present summary statistics for establishments with M&A (treated) and without M&A (controls), respectively, in the years before an M&A. Column 10 reports the p-value of the differences in means (clustered by firm) between treated and control groups pre-treatment and the level of significance. The last column reports the mean of all establishments' key variables in the pre-treatment period. The sample consists of CiTDB establishments targeted in horizontal M&As from 2009 through 2015, along with matched control establishments, used in the tests reported in Table 4.

				Establishments before M&A						
	All Establishments			With M&A			Without 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
Establishment Employment	15,990	110.1	292.9	3,126	114.0	309.3	4,869	107.9	283.6	0.81
IT Budget ($)	15,990	496,371	1,628,919	3,126	373,785	1,029,378	4,869	403,565	1,483,173	0.78
IT Budget Per Employee ($)	15,990	8,455	32,518	3,126	8,002	14,830	4,869	9,698	56,658	0.56
Hardware Budget ($)	15,990	70,761	200,205	3,126	64,102	144,568	4,869	68,337	166,160	0.66
Software Budget ($)	15,990	153,152	596,708	3,126	88,469	239,594	4,869	99,830	373,990	0.54
Storage Budget ($)	15,990	12,009	46,396	3,126	17,918	61,862	4,869	18,482	63,411	0.87
Services Budget ($)	15,990	177,974	609,628	3,126	87,661	244,154	4,869	98,935	403,666	0.57
Communication Budget ($)	15,990	75,549	512,275	3,126	94,865	530,514	4,869	99,247	785,059	0.95

Table IA. A.5
External Validation for CiTDB IT data

This table presents correlations between IT investment at the firm level over 2009-2015, normalized by employment from CiTDB and patenting activities from the United States Patent and Trademark Office (USPTO) and Bena and Simintzi (Forthcoming) in columns 1-2, and by capital intensity at the 4-digit NAICS level from the NBER-CES Manufacturing Industry Database in columns 3-6. In columns 1-2, CiTDB establishment-level data are aggregated to the firm-year level and matched with patenting data. Due to the presence of zeros in firm-level observations, we transform patent count and IT measures into percentiles by measuring the rank of each observation within its relevant sample each year. The independent variable reported is the percentile rank of a given firm's IT investment per employee in a given year's distribution. In column 1, the dependent variable is the percentile rank of the total number of patents filed by an assignee in a given year and eventually granted by the USPTO. In column 2, the dependent variable is the ratio of the number of process innovation claims over the total number of claims filed (%) by an assignee in a given year. In columns 3-6, CiTDB establishment-level data are aggregated to 4-digit NAICS-level and matched with the NBER-CES Manufacturing Industry Database. At the industry level, there are no observed zeros in our variables, allowing us to apply the log transformation to correct for data skewness. The independent variable reported is the logarithm of IT investment per employee at the 4-digit NAICS-year level. The dependent variables are the logarithm of investment per worker, the logarithm of capital stock per worker, the logarithm of equipment per worker, and the employment share of production workers at the 4-digit NAICS-year level, respectively. Standard errors are reported in parentheses and clustered at the firm level in columns 1-2 and at the 4-digit NAICS level in columns 3-6. Significance levels are indicated by *, ** and *** and correspond to 10%, 5%, and 1% significance levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
	Patent Counts Percentile	Process Claim Share	Investment/Emp	Capital/Emp	Equipment/Emp	Production Emp Share
IT budget/Emp Percentile	0.038***	0.122***				
	(0.004)	(0.007)				
IT budget/Emp			-0.092***	0.401**	0.417***	0.488***
			(0.0158)	(0.179)	(0.121)	(0.126)
Observations	249,422	46,828	602	602	602	602
R^2	0.001	0.012	0.240	0.080	0.112	0.125
Year FE	Yes	Yes	Yes	Yes	Yes	Yes

Table IA. A.6
Mechanism: Heterogeneity analysis with continuous measures

This table presents estimates of changes in routine employment share (RSH) at M&A target establishments compared to controls, further interacting $Post_t \cdot M\&A_i$ with $Gap_{TargetRSH-AcquirerRSH}$ in column 1, $Gap_{AcquirerWage-TargetWage}$ in column 2, and $Gap_{AcquirerTechWage-TargetTechWage}$ in column 3. $Gap_{TargetRSH-AcquirerRSH}$ represents the difference between target and acquirer firms in routine employment share before M&As. $Gap_{AcquirerWage-TargetWage}$ and $Gap_{AcquirerTechWage-TargetTechWage}$ represent the differences between acquirer and target firms in average hourly wages of all workers and average hourly wages of tech workers before M&As, respectively. The dependent variable in columns 1-3 is the employment share of routine occupations, where an occupation is routine if it is in the top employment-weighted quartile of RTI in the 2000 ACS sample distribution. Columns 4-5 present estimates of changes in percentile ranks of IT spending and IT spending per employee at target establishments compared to control establishments, further interacting $Post_t \cdot M\&A_i$ with $Gap_{AcquirerIT-TargetIT}$, which represents the difference in average IT budget per worker between the acquirer and target in the first year prior to the M&A. $Gap_{TargetRSH-AcquirerRSH}$ $Gap_{AcquirerWage-TargetWage}$, $Gap_{AcquirerTechWage-TargetTechWage}$, and $Gap_{AcquirerIT-TargetIT}$ are standardized with a mean of 0 and a standard deviation of 1. Before standardization, the average RSH gap between the target and acquirer is -1%, with a standard deviation of 13.3%. The mean hourly wage gap between the acquirer and target is -32 cents, with a standard deviation of $5. For tech jobs, the average wage gap between acquirer and target is also -32 cents, with a standard deviation of $4.9. The mean IT intensity gap between the acquirer and target is -$0.5 million, with a standard deviation of $3 million. The sample used in columns 1-3 consists of establishments targeted in horizontal M&As from 2001 through 2017 and those of matched control establishments in the OEWS sample. The sample used in columns 4-5 consists of establishments targeted in horizontal M&As from 2009 through 2015 and those of matched control establishments in the CiTDB sample. The estimates are generated by Equation 2. $M\&A_i$ and its interaction with $Gap_{TargetRSH-AcquirerRSH}$ ($Gap_{AcquirerWage-TargetWage}$, $Gap_{AcquirerTechWage-TargetTechWage}$, or $Gap_{AcquirerIT-TargetIT}$) is absorbed by establishment fixed effects. The interaction between $Post_t$ and $Gap_{TargetRSH-AcquirerRSH}$ ($Gap_{AcquirerWage-TargetWage}$, $Gap_{AcquirerTechWage-TargetTechWage}$, or $Gap_{AcquirerIT-TargetIT}$) is absorbed by $Post_t \cdot M\&A_i$. $Post_t$ is estimated but not reported for brevity. *Offshorability* is not included in the estimation in columns 4-5 because we do not observe occupational offshorability data in the CiTDB sample. Industries follow the 4-digit NAICS classification. Standard errors are reported in parentheses and clustered at the firm level. Significance levels are indicated by *, ** and *** and correspond to 10%, 5%, and 1% significance levels, respectively.

	(1)	(2)	(3)	(4)	(5)
	RSH	RSH	RSH	IT Budget Percentile	IT Budget/Emp Percentile
$Post_t \cdot M\&A_i$	-0.0119	-0.0112	-0.00450	0.644	-0.288
	(0.0114)	(0.0115)	(0.0177)	(0.675)	(0.787)
$Post_t \cdot M\&A_i \cdot Gap_{TargetRSH-AcquirerRSH}$	-0.0350***				
	(0.0125)				
$Post_t \cdot M\&A_i \cdot Gap_{AcquirerWage-TargetWage}$		-0.00443			
		(0.0107)			
$Post_t \cdot M\&A_i \cdot Gap_{AcquirerTechWage-TargetTechWage}$			-0.0274*		
			(0.0164)		
$Post_t \cdot M\&A_i \cdot Gap_{AcquirerIT-TargetIT}$				0.703	1.647**
				(0.604)	(0.698)
Offshorability	0.1636***	0.1640***	0.1279***		
	(0.0178)	(0.0177)	(0.0274)		
Observations	6,468	6,468	3,063	15,983	15,983
R^2	0.835	0.835	0.810	0.871	0.840
Establishment FE	YES	YES	YES	YES	YES
Industry · Year FE	YES	YES	YES	YES	YES

Table IA. A.7
M&As and target investment in IT subcategories

This table presents estimates of investment changes in IT subcategories at M&A target establishments compared to control establishments, interacting $Post_t \cdot M\&A_i$ with $\mathbb{1}_{AcquirerIT>TargetIT}$ estimated using Equation 2. $\mathbb{1}_{AcquirerIT>TargetIT}$ equals one if the average IT budget per worker of the acquirer exceeds that of its target in the first year prior to the M&A, zero otherwise. In the odd-numbered columns, the dependent variables are the percentile ranks of establishment budget for hardware, software, services, storage, and communication services within the relevant sample distribution each year. In the even-numbered columns, the dependent variables are the percentile ranks of establishment budget for hardware, software, services, storage, and communication services normalized by the number of employees in the establishment within the relevant sample distribution each year. $M\&A_i$ and its interaction with $\mathbb{1}_{AcquirerIT>TargetIT}$ is absorbed by fixed effects. $Post_t$ and its interaction with $\mathbb{1}_{AcquirerIT>TargetIT}$ is estimated but not reported for brevity. The sample consists of establishments in the CiTDB data targeted in horizontal M&As from 2009 through 2015 and those of matched control establishments. All variable definitions are provided in Appendix Table A.1. Standard errors are reported in parentheses and clustered at the firm level. Significance levels are indicated by *, ** and *** and correspond to 10%, 5%, and 1% significance levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Hardware Percentile	Hardware/Emp Percentile	Software Percentile	Software/Emp Percentile	Service Percentile	Service/Emp Percentile	Storage Percentile	Storage/Emp Percentile	Communication Percentile	Communication/Emp Percentile
$Post_t \cdot M\&A_i$	-0.0471	-1.567*	0.0420	-0.992	0.438	-1.025	-1.166	-2.291	-0.594	-2.420*
	(0.866)	(0.865)	(0.878)	(1.095)	(0.755)	(0.918)	(2.573)	(1.474)	(1.107)	(1.234)
$Post_t \cdot M\&A_i \cdot \mathbb{1}_{AcquirerIT>TargetIT}$	2.019*	3.426***	1.928*	3.221**	2.161**	4.201***	4.196	3.152*	2.786**	4.523***
	(1.032)	(1.178)	(1.022)	(1.464)	(0.958)	(1.132)	(2.669)	(1.731)	(1.355)	(1.613)
Observations	15,983	15,983	15,983	15,983	15,983	15,983	15,983	15,983	15,983	15,983
R^2	0.875	0.852	0.877	0.838	0.866	0.820	0.829	0.816	0.865	0.833
Establishment FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Industry · Year FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES

Table IA. A.8
Robustness: Controlling for offshorability-by-year fixed effects

This table presents estimated changes in routine occupation composition at M&A target establishments compared to control establishments with different sets of controls. Dependent variables in columns 1-3 are establishment-level routine employment share, average routine task intensity, and percentile ranks of routine employment, respectively. This table repeats the specification in Table 2, column 3, but instead controls for *Offshorability*-by-year fixed effects. $M\&A_i$ is absorbed by fixed effects. $Post_t$ is estimated but not reported for brevity. The sample consists of establishments in OEWS data that are targeted in horizontal M&As from 2001 through 2017 and those of matched control establishments. Industries are classified by 4-digit NAICS. All variable definitions are provided in Appendix Table A.1. Standard errors are reported in parentheses and clustered at the firm level. Significance levels are indicated by *, ** and *** and correspond to 10%, 5%, and 1% significance levels, respectively.

	(1)	(2)	(3)
	RSH	RTI	Routine Employment Percentile
$Post_t \cdot M\&A_i$	-0.0190***	-0.0635***	-2.277***
	(0.0067)	(0.0211)	(0.598)
Observations	25,040	25,040	25,040
R^2	0.928	0.958	0.869
Establishment FE	YES	YES	YES
Industry · Year FE	YES	YES	YES
Offshorability · Year FE	YES	YES	YES

Table IA. A.9
Testing alternative explanations with continuous measures

This table presents estimated changes in routine employment share (RSH) at M&A target establishments compared to control establishments, interacting $Post_t \cdot M\&A_i$ with $Gap_{TargetRSH-AcquirerRSH}$ in each column and further augmenting the specification by interacting $Post_t \cdot M\&A_i$ with $Gap_{TargetOffshor-AcquirerOffshor}$, $OccOverlap$, and $OccSimilarity$ in columns 1-3, respectively. $Gap_{TargetOffshor-AcquirerOffshor}$ represents the difference between target and acquirer firms' offshorability prior to M&As. $OccOverlap$ presents the target employment share of occupations overlapping with those at acquirers prior to M&As. $OccSimilarity$ represents the cosine-similarity in target and acquirer occupation profiles before M&As. $Gap_{TargetRSH-AcquirerRSH}$ $Gap_{TargetOffshor-AcquirerOffshor}$, $OccOverlap$ and $OccSimilarity$ are standardized with a mean of 0 and a standard deviation of 1. Before standardization, the average RSH gap between the target and acquirer is -1%, with a standard deviation of 13.3%. The target's average employment share in overlapping occupations with the acquirer is 25.9%, with a standard deviation of 39.4%. Occupational similarity scores have a mean of 0.05 and a standard deviation of 0.1. The average offshorability gap between the target and acquirer is 0.029, with a standard deviation of 0.33. The dependent variable is the employment share of routine occupations at target establishments, where an occupation is routine if it is in the top employment-weighted quartile of RTI in the 2000 ACS sample distribution. $M\&A_i$ and its interaction with $Gap_{TargetRSH-AcquirerRSH}$ ($Gap_{TargetOffshor-AcquirerOffshor}$, $OccOverlap$, and $OccSimilarity$) is absorbed by establishment fixed effects. The interaction between $Post_t$ and $Gap_{TargetRSH-AcquirerRSH}$ ($Gap_{TargetOffshor-AcquirerOffshor}$, $OccOverlap$, and $OccSimilarity$) is absorbed by $Post_t \cdot M\&A_i$. $Post_t$ is estimated but not reported for brevity. The sample consists of establishments in OEWS data that are targeted in horizontal M&As from 2001 through 2017 and those of matched control establishments. Industries follow the 4-digit NAICS classification. Standard errors are reported in parentheses and clustered at the firm level. Significance levels are indicated by *, ** and *** and correspond to 10%, 5%, and 1% significance levels, respectively.

	(1)	(2)	(3)
	RSH	RSH	RSH
$Post_t \cdot M\&A_i$	-0.0119	-0.0108	-0.0121
	(0.0114)	(0.0192)	(0.0110)
$Post_t \cdot M\&A_i \cdot Gap_{TargetRSH-AcquirerRSH}$	-0.0350***	-0.0349***	-0.0351***
	(0.0136)	(0.0125)	(0.0123)
$Post_t \cdot M\&A_i \cdot Gap_{TargetOffshor-AcquirerOffshor}$	0.0001		
	(0.0124)		
$Post_t \cdot M\&A_i \cdot OccOverlap$		-0.0008	
		(0.0111)	
$Post_t \cdot M\&A_i \cdot OccSimilarity$			0.0130
			(0.0114)
Offshorability	0.1630***	0.1624***	0.1629***
	(0.0177)	(0.0177)	(0.0180)
Observations	6,468	6,468	6,468
R^2	0.835	0.836	0.835
Establishment FE	YES	YES	YES
Industry · Year FE	YES	YES	YES

Table IA. A.10
Robustness: Cancelled M&As

This table presents estimated changes in routine occupations at announced and subsequently withdrawn M&A target establishments 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 effects of cancelled M&As are estimated using Equation 1. The dependent variable is the employment share of routine occupations in column 1, the average routine task intensity at the establishment in column 2, and percentile ranks of establishment employment for routine occupations in column 3. $M\&A_i$ is absorbed by fixed effects. $Post_t$ 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. Industries are classified by 4-digit NAICS. All variable definitions are provided in Appendix Table A.1. Standard errors are reported in parentheses and clustered at the firm level. Significance levels are indicated by *, ** and *** and correspond to 10%, 5%, and 1% significance levels, respectively.

	(1)	(2)	(3)
	RSH	RTI	Routine Employment Percentile
$Post_t \cdot pseudo\ M\&A_i$	0.0524	0.0754	10.3475*
	(0.0389)	(0.2108)	(5.8236)
Offshorability	0.0961**	0.4412**	1.8528
	(0.0408)	(0.1647)	(6.4727)
Observations	212	212	212
R^2	0.723	0.640	0.752
Establishment FE	YES	YES	YES
Industry · Year FE	YES	YES	YES

Table IA. A.11
Robustness: Mean reversion

This table presents estimated changes in routine occupation composition at M&A target establishments compared to control establishments. This table repeats the specification in Table 2, column 3, but additionally controls for the ex-ante dependent variable-by-year fixed effects. Dependent variables in columns 1-3 are establishment-level routine employment share, average routine task intensity, and percentile ranks of routine employment, respectively. $M\&A_i$ is absorbed by fixed effects. $Post_t$ is estimated but not reported for brevity. The sample consists of establishments in OEWS data that are targeted in horizontal M&As from 2001 through 2017 and those of matched control establishments. Industries are classified by 4-digit NAICS. All variable definitions are provided in Appendix Table A.1. Standard errors are reported in parentheses and clustered at the firm level. Significance levels are indicated by *, ** and *** and correspond to 10%, 5%, and 1% significance levels, respectively.

	(1)	(2)	(3)
	RSH	RTI	Routine Employment Percentile
$Post_t \cdot M\&A_i$	-0.0165***	-0.0436**	-2.0885***
	(0.0054)	(0.0182)	(0.5477)
Offshorability	0.1373***	0.5524***	9.6083***
	(0.0077)	(0.0263)	(0.5854)
Observations	25,040	25,040	25,040
R^2	0.939	0.965	0.881
Establishment FE	YES	YES	YES
Industry · Year FE	YES	YES	YES
Pre-Y · Year FE	YES	YES	YES

Table IA. A.12
Robustness: Survival

This table presents estimates of changes in routine occupation composition at M&A target establishments compared to control establishments from a subsample of treated-control pairs that can be observed the same number of times in OEWS. Dependent variables in columns 1-3 are establishment-level routine employment share, average routine task intensity, and percentile ranks of routine employment, respectively. $M\&A_i$ is absorbed by fixed effects. $Post_t$ is estimated but not reported for brevity. Standard errors are reported in parentheses and clustered at the firm level. Industries are classified by 4-digit NAICS. All variable definitions are provided in Appendix Table A.1. Significance levels are indicated by *, ** and *** and correspond to 10%, 5%, and 1% significance levels, respectively.

	(1)	(2)	(3)
	RSH	RTI	Routine Employment Percentile
$Post_t \cdot M\&A_i$	-0.0225**	-0.0860**	-2.7308***
	(0.0104)	(0.0340)	(0.8758)
Offshorability	0.1551***	0.5616***	10.7426***
	(0.0117)	(0.0392)	(1.1008)
Observations	7,332	7,332	7,332
R^2	0.858	0.909	0.892
Establishment FE	YES	YES	YES
Industry · Year FE	YES	YES	YES

Table IA. A.13
Occupation groups and corresponding *occ1990dd* occupations

This table lists titles of 23 occupation groups defined by Autor and Dorn (2013). The last column provides the codes of *occ*1990*dd* occupations classified under each occupation group. Appendix Table 2 in Dorn (2009) provides detailed titles for occupation groups and *occ*1990*dd* occupations.

Occupation Group	Occupation Group Title	occ1990dd list
beauty	Personal appearance occupations	occ1990dd⩾457 & occ1990dd⩽458
child	Child care workers	occ1990dd=468
clean	Housekeeping, cleaning, laundry	occ1990dd⩾405 & occ1990dd⩽408
cleric	Administrative support occupations	occ1990dd⩾303 & occ1990dd⩽389
constr	Construction trades	occ1990dd⩾558 & occ1990dd⩽599
exec	Executive, administrative and managerial occupations	occ1990dd⩾3 & occ1990dd⩽22
finsales	Financial sales and related occupations	occ1990dd⩾243 & occ1990dd⩽258
food	Food preparation and service occupations	occ1990dd⩾433 & occ1990dd⩽444
guard	Supervisors of guards; guards	occ1990dd=415 or occ1990dd⩾425 & occ1990dd⩽427
janitor	Building and grounds cleaning and maintenance occupations	occ1990dd⩾448 & occ1990dd⩽455
mechanic	Mechanics and repairers	occ1990dd⩾503 & occ1990dd⩽549
mgmtrel	Management related occupations	occ1990dd⩾23 & occ1990dd⩽37
mining	Extractive occupations	occ1990dd⩾614 & occ1990dd⩽617
operator	Machine operators, assemblers, and inspectors	occ1990dd⩾703 & occ1990dd⩽799
othpers	Miscellaneous personal care and service occupations	occ1990dd⩾469 & occ1990dd⩽472
product	Precision production occupations	occ1990dd⩾628 & occ1990dd⩽699
prof	Professional specialty occupations	occ1990dd⩾43 & occ1990dd⩽200
protect	All protective service	occ1990dd⩾415 & occ1990dd⩽427
recreation	Recreation and hospitality occupations	occ1990dd⩾459 & occ1990dd⩽467
retsales	Retail sales occupations	occ1990dd⩾274 & occ1990dd⩽283
shealth	Health service occupations (dental ass., health/nursing aides)	occ1990dd⩾445 & occ1990dd⩽447
tech	Technicians and related support occupations	occ1990dd⩾203 & occ1990dd⩽235
transp	Transportation and material moving occupations	occ1990dd⩾803 & occ1990dd⩽889

Table IA. A.14
Target employment changes around M&As and occupational characteristics

This table presents correlations between the changes in the employment percentile ranks post M&As and occupational characteristics, including routine task intensity (RTI), share of union members ($Union\ Share$), managerial occupations (*Executive, Admin, and Managerial Occs*), and scalable task intensity (*Scalability*). RTI (*Scalability*) captures the degree to which the tasks performed by a given occupation (*occ*1990*dd*) are routine intensive (scalable). RTI is defined following Autor and Dorn (2013). $Union\ Share$ is the percentage of union membership in a given occupation based on the 2000 Current Population Survey (CPS). *Executive, Admin, and Managerial* include occupations (*occ*1990*dd* 3-22 defined by Dorn (2009) and Autor and Dorn (2013)) that manage other people's work. *Scalability* is defined as the intensity of the cosine similarity between the 2000 O*NET job task descriptions of a given occupation and the predefined templates of scalable tasks, which are developed through a natural language processing (NLP) method and suggest the potential for centralization, automation and reaching economies of scale. Internet Appendix B2 describes the construction of scalability. All specifications control for occupational offshorability, but estimates are not reported for brevity. Bootstrap standard errors are reported in parentheses. Significance levels are indicated by *, ** and *** and correspond to 10%, 5%, and 1% significance levels, respectively.

	(1)	(2)	(3)	(4)	(5)
	Employment Percentile	Employment Percentile	Employment Percentile	Employment Percentile	Employment Percentile
RTI	-0.0372**				-0.0372**
	(0.0178)				(0.0187)
Union Share		0.0207			-0.0344
		(0.108)			(0.113)
Executive, Admin, and Managerial Occs			0.0164		-0.0325
			(0.138)		(0.147)
Scalability				0.335	0.268
				(0.282)	(0.268)
Observations	320	306	320	320	306
R^2	0.028	0.011	0.021	0.019	0.033

Internet Appendix B. Data

B1. 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 (*UDB-Num*) 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 OEWS, we take the following steps. First, we get firms' EINs from Compustat and match them to acquirer and target companies in SDC using CUSIP codes. For companies that get more than one match, we manually check each match and keep only those corresponding to company names.

Second, we link M&A deals to the establishments in OEWS using target EINs. By taking this step, approximately 15% of the M&A deals are matched to 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, and 2) multiunit firms may have multiple EINs, but only one EIN is reported in OEWS or Compustat. The inconsistency in EINs reported in different databases reduces the match rate.[2]

To improve the matching between the SDC and OEWS data and to match private targets, 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

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

[2] See more details about linking firms with establishments in BLS microdata in Handwerker and Mason (2018).

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 OEWS before and after the M&A deal is completed and if we are able to observe a suitable control establishment. In the end, we identify a total of 1,159 horizontal M&A deals in the OEWS survey covering 2,946 establishments from 2001 through 2017.

B2. Construction of scalable task intensity scores for occupations

We construct scalable task intensity scores (*Scalability*) based on occupational task descriptions by using Natural Language Processing (NLP) techniques to compare task descriptions to predefined keyword templates.

Step 1: Data Preprocessing: We begin with occupational task descriptions for occupations classified by the 2000 SOC from the U.S. Department of Labor's Occupational Information Network database (O*NET), which provides detailed information about job roles.[3] To ensure consistency, we clean and standardize the text by converting all text to lowercase, removing non-word characters (e.g., symbols and punctuation), concatenating job titles and task descriptions into a single clean description.

Step 2: Defining Scalable and Non-Scalable Templates: We manually define two sets of keyword templates based on theoretical distinctions. Scalable tasks are those that benefit from economies of scale, automation, and centralization (e.g., "standardizes", "analyzes data", and "streamlines").[4] Non-scalable tasks require manual labor, physical presence, or customization (e.g., "manual labor", "face-to-face service", "cook, and repair").[5] These templates act as reference points for classification.

Step 3: Computing Task Similarity Scores: We use a sentence-transformer model to convert both the task descriptions and the predefined templates into vector embeddings—numerical representations capturing semantic meaning as Reimers and Gurevych

[3] The O*NET-SOC 2000 occupation descriptions are provided by the U.S. Department of Labor, Employment and Training Administration (USDOL/ETA) and can be found at `https://www.onetcenter.org/taxonomy/2000/list.html`

[4] Scalable template includes "standardizes", "analyzes data", "performs centralized processing", "coordinates", "streamlines", "inventory management", "centralized IT support", "standardized reporting", "financial records", "manage operations", "develop programs", "negotiate", and "design".

[5] Non-Scalable template includes "face-to-face customer service", "register guests", "assign rooms", "issue room keys", "make reservations", "confirm reservations", "handle payments", "transmit messages", "receive messages", "assist patrons", "interact with customers", "payroll processing", "data entry", "maintains local relationships", "provides direct assistance", "requires on-site engagement", "manual labor", "on-site tasks", "prepare items for shipping", "stock shelves", "repair equipment", "cook", "serve food", "clean dishes", "janitorial services", "operate cash register", "process credit card transactions", "receive orders", "sell merchandise", "sell goods", "hotel desk clerk", "assigning rooms", "registering guests", "make reservations", "confirm reservations", "attach price to merchandise", "laundry", "dry-cleaning", "press articles", "sew garments", "tailor garments", "iron clothes", "interview", "cleaning", "wash", "cleaning agents", "timekeeping", "compile", "payroll data", "compute post wages", "deductions", "prepare paychecks", "compile records", "accounting", "payroll and timekeeping clerks", "low-level clerical jobs", "prepare paychecks", "compute employees time worked", "compute employees time commission", "compute employees production", and "compute employees deduction".

(2019). Using cosine similarity, we compute the scalable (non-scalable) similarity score which measures how closely the task descriptions match the scalable (non-scalable) template.

Step 4: Aggregation to Occupation Level: As each *occ*1990*dd* occupation is mapped to at least one SOC code, we aggregate SOC codes to *occ*1990*dd* codes.[6]

Step 5: Normalization to Adjust for Task Length Bias: Longer task descriptions tend to have higher similarity scores simply because they contain more words. To correct this, we normalize the scalable (non-scalable) similarity score of each *occ*1990*dd* occupation by the sum of its scalable and non-scalable similarity scores. The normalized scalable (non-scalable) similarity score is named the scalable (non-scalable) task intensity score. Each occupation's scalable and non-scalable task intensity scores sum to 1, allowing fair comparisons across occupations. In our sample, the scalable task intensity score has a mean of 0.52 and a standard deviation of 0.11.

Step 6: Define Highly Scalable Occupations: Among 320 *occ*1990*dd* occupations in our OEWS sample, we define an occupation as highly scalable if it is in the top employment-weighted quartile of scalable task intensity score within the 2000 American Community Survey (ACS).[7] In Table IA. B.1, we present a list of highly scalable occupations. For example, Management Analysts on the list conduct organizational studies and evaluations, design systems and procedures, conduct work simplifications and measurement studies, and prepare operations and procedures manuals to assist management in operating more efficiently and effectively. These tasks are classified as scalable since efforts, such as organizational studies, can apply to operations at both the target and the acquirer. Likewise, Accountants and Auditors determine tax liability or collect taxes from business firms according to prescribed laws and regulations, examine, analyze, and interpret accounting records for the purpose of giving advice or preparing statements, install or advise on systems of recording costs or other financial and budgetary data, analyze financial information and prepare financial reports to determine or maintain a record

[6] The crosswalks between SOC codes and *occ*1990*dd* are available at David Dorn's website, `https://www.ddorn.net/data.htm`

[7] The ACS is available at `https://usa.ipums.org/usa/`

of assets, liabilities, profit and loss, tax liability, or other financial activities within an organization, and examine and analyze accounting records to determine the financial status of the establishment and prepare financial reports concerning operating procedures. Both the target and acquirer can use these tasks, which are also highly scalable.

Table IA. B.1
Examples of highly scalable occupations

This table presents examples of occupations (*occ*1990*dd*) that perform tasks that are highly scalable. An occupation's scalable task intensity score (*Scalability*) is defined as the intensity of the cosine similarity between the 2000 O*NET job task descriptions of a given occupation and the predefined templates of scalable tasks, which are developed through a natural language processing (NLP) method and indicate the potential for centralization, automation and reaching economies of scale.

Occupation Codes	Occupation Title	Scalability
229	Computer software developers	0.737
26	Management analysts	0.679
55	Electrical engineers	0.672
64	Computer systems analysts and computer scientists	0.663
699	Other plant and system operators	0.652
25	Other financial specialists	0.628
178	Lawyers and judges	0.617
56	Industrial engineers	0.614
59	Engineers and other professionals, n.e.c.	0.593
37	Management support occupations	0.589
13	Managers and specialists in marketing, advert., PR	0.583
206	Radiologic technologists and technicians	0.580
7	Financial managers	0.576
22	Managers and administrators, n.e.c.	0.576
23	Accountants and auditors	0.574

References

Autor, D. H., Dorn, D., 2013. The growth of low-skill service jobs and the polarization of the US labor market. American Economic Review 103, 1553–97.

Bena, J., Simintzi, E., Forthcoming. Machines could not compete with Chinese labor: Evidence from U.S. firms' innovation. Review of Finance.

Dorn, D., 2009. Essays on inequality, spatial interaction, and the demand for skills. Dissertation, University of St. Gallen.

Handwerker, E. W., Mason, L., 2018. What happens to the employers involved in mass layoffs? Southern Economic Journal 85, 485–507.

Reimers, N., Gurevych, I., 2019. Sentence-bert: Sentence embeddings using siamese bert-networks. CoRR abs/1908.10084.

Wasi, N., Flaaen, A., 2015. Record linkage using stata: Preprocessing, linking, and reviewing utilities. The Stata Journal 15, 672–697.

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