Mergers and Acquisitions, Technological Change and Inequality

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*** PRELIMINARY ***

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This paper documents important shifts in the occupational composition of industries following high merger and acquisition (M&A) activity as well as accompanying increases in mean wages and wage inequality. We propose mergers and acquisitions act as a catalyst for skill-biased and routine-biased technological change (Autor, Levy, and Murnane, 2003). We argue that due to an increase in scale, improved efficiency or lower financial constraints, M&As facilitate technology adoption and automation, disproportionately increasing the productivity of high-skill workers and enabling the displacement of occupations involved in routine-tasks, typically mid-income occupations. An increase in M&A intensity of 10% is associated with a 29% reduction in industries' routine share intensity and an eight percentage point increase in the share of high skill workers relative to the mean. These results have important implications on wage inequality: An increase in M&A activity by 10% is associated with a 22% increase in the mean industry wage and an 18% increase in industry wage polarization. We also show evidence that human capital complementary investments increase following M&As, while investments unrelated to human capital do not change. We find no evidence that our results are driven by industry shocks that simultaneously lead to a merger wave and changes to labor and capital decisions.

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A number of studies have shown a substantial rise in wage inequality in the United States and other developed countries since the 1980s. The greater adoption of technology is often cited as one of the drivers behind this trend. Machines augment human and physical capital, and in particular, have a disproportionate effect on the productivity of high-skilled labor (Katz and Autor, 1999). Machines also enable firms to automate routine tasks replacing middle-skill workers (Autor, Levy, and Murnane, 2003; Acemoglu and Autor, 2011; Autor and Dorn, 2013), leading to an increase in the relative demand for non-routine and high-skill jobs. Given the importance of these trends, it is of great interest to understand the speed by which firms adopt such technologies. Recently, researchers have shown that shocks that lower adjustment costs, such as recessions, accelerate technology adoption, which in turn can contribute to increasing job polarization (Jaimovich and Siu, 2015; Hershbein and Kahn, 2016). In this paper, we propose and show evidence consistent with a new catalyst for routine-biased and skill-biased technological change: mergers and acquisitions (M&As).

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

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

All three mechanisms predict a pattern where investments in automation increase post-M&A, leading to a lower demand for routine tasks, greater demand for high-skilled labor, higher mean wages and greater overall wage inequality. Considering the large scale of M&A activity, with over 4 $trillion in activity in 2015 alone, it is plausible to expect M&A activity may be an economically important catalyst of routine-biased and skill-biased technological change.

To test our hypotheses, we collect data from Thomson's SDC on M&A activity, starting in 1980. We measure M&A intensity as the count of deals in an industry-decade, normalized by the count of total deals in the decade. Data on occupational employment is collected from the Integrated Public Use Microdata Service (IPUMS). Using the 5% extract from Census years 1980, 1990, 2000 and the American Community Survey (ACS) for 2010, we identify the fraction of employment in a given occupation and the share of employees with college education within each industry as well as industry wage distributions. To identify the routine-task content of each occupation, we replicate the approach in Autor and Dorn (2013) and construct time-varying shares of routine intensity using an employment-weighted mean to aggregate at the industry-level.

As the intensity of M&A activity increases, we observe a decline in the occupational share of routine intensive jobs within industries. In the time-series, we find that an increase in M&A intensity by 10% is associated with a 29% reduction in routine share intensity within a given industry. This trend is robust to using a first-difference estimation, adding additional controls such as the offshorability of occupations, and using alternative measures of routine intensive occupations and M&A activity.

Consistent with the view of skill-biased technological change, high M&A activity should also be accompanied with a relative increase in the demand for high-skill workers. Indeed, we find that the share of workers with college or graduate education increases with past M&A intensity. In the time-series, we find that an increase in M&A activity by 10% is associated with an increase in employees with graduate education by 8 percentage points relative to the mean within a given industry.

The documented shifts in occupational employment following mergers and acquisitions have implications on wages. Mean wages should increase following significant industry M&A activity as the relative fraction and productivity of high-skill workers within a given industry increases. Second, wages should become increasingly polarized and unequal as the labor shares within a given industry are increasingly represented by both the high- and low-skill tails of the skill distribution. Both results are confirmed in the data.

To further bolster our hypothesis, we parse the performance results into subgroups where we expect to find heterogeneous effects. Technology adoption and displacement of routine tasks should happen to a greater degree in industries with more routine occupations ex-ante. We follow Autor and Dorn (2013) and characterize industries by their initial share of routine-intensive occupations. We then look within industries and construct measures of "top-bottom" and "top-middle" inequality. We show that within-industry upper-tail wage disparity, defined as the ratio between wages at the 90^{th} and 10^{th} percentile distribution or between the $90^{\%}$ and 50^{th} percentile distribution, increases more following higher M&A activity for industries with higher routine shares one decade earlier.

To understand precisely how M&A activity can act as a catalyst for skill-biased and routine-biased technological change, we consider three non-mutually exclusive mechanisms. We show empirical support for all three. First, the increased scale associated with M&As can reduce the fixed costs of investing in new technology. To wit, if an investment in computer software can more efficiently perform a specific function in accounting, then it can displace one worker in a small firm but possibly several workers in a larger firm. Indeed, we show that the effect of lagged M&A activity is greater in industries where we observe larger contemporaneous changes in firm scale. We proxy for changes in scale by changes in median firm size (as measured by assets or employees) at a given industry over a decade.

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

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

Moreover, we show evidence of higher rates of investment in technology in a sample of manufacturing industries post M&A. Specifically, we show that following high M&A intensity, industry investment in equipment (measured as real capital invested in equipment normalized by employment) goes up. However, there is no simultaneous change in investment in buildings and structures (measured as real capital invested in structures normalized by employment).

To further support the view that our results are not driven by industry or technology shocks, we directly control for shocks that are known to trigger M&A waves, as identified in Harford (2005) and Ovtchinnikov (2013). Our coefficients of interest are effectively unchanged with this added control indicating that the largest and most well-known industry shocks do not explain our results. It is important to note also that the several cross-sectional heterogeneity results explained above are specific to our hypotheses and are not obviously explained by omitted variables. Moreover, in our regressions we control for industry fixed effects to control for any time-invariant industry characteristics and year fixed effects to capture changes in macroeconomic conditions. Although we cannot make a strong statement in terms of causality, all these tests taken together support a causal interpretation.

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

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

1. Data

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

1.1. M&A Data

We use Thomson's SDC to identify mergers and acquisitions. SDC provides information on the date the deal was announced and the date it became effective. The data also include the industry affiliation of the target and the acquirer and, for some observations, the transaction value. We use all completed M&As, announced between 1980 and 2010, of a US target and US acquirer, for which we can confirm the acquirer completed a purchase of a majority stake.[1]

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

1.2. IPUMs

Data on occupational employment is collected from the Integrated Public Use Microdata Service (IPUMs) 5 percent extract for 1980, 1990, 2000 and the 2010 American Community Survey (ACS).[2,3] IPUMs provides detailed surveys of the American population drawn from federal censuses and the

[1] Our sample begins in 1980 due to availability of M&A activity in SDC.
[2] ACS is the continuation of the decennial Census surveys post-2000.
[3] For more information, see Ruggles, Genadek, Goeken, Grover, and Sobek (2015).

American Community Surveys. IPUMs was created to facilitate time series analysis and, as such, has unique industry (IND1990) and occupational identifiers (OCC1990), which are calculated as to minimize changes in industry and occupation definitions over time. We map NAICS industries from SDC to IPUMs industries, using the cross-walk provided by IPUMs, as detailed in Appendix A1. We use the crosswalk defined by Autor and Dorn (2013), which is a slightly modified version of occupational identifiers (OCC1990) provided by IPUMs, to ensure time-consistent occupation categories. In our final sample, we have 132 industries and more than 300 occupations in each Census-year.[4]

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

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

[4] Farming occupations are excluded.

1.3. Data on routine employment share

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

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

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

[5] In the Appendix, we show robustness tests where we define occupations as routine task intensive if they are in the top employment-weighted third of routine task-intensity every Census year. Results are similar.

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

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

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

1.4. NBER-CES data

We draw information on industries' investment intensity from the NBER-CES Manufacturing Industry database provided by the National Bureau of Economic Research (NBER) and U.S. Census Bureau's Center for Economic Studies (CES).[6] The start year in our sample is 1980 as this is the first year of M&A data in our sample and the final year is 2007 to minimize the overlap with the financial crisis. The NBER-CES data is available annually at the 4-digit SIC level, which allows to directly link these data to SDC data (also provided at the 4-digit SIC level). We end up with a sample of 459 4-digit SIC manufacturing industries. Besides industries' investment intensity in equipment and structures, we also

[6] For more information, see documentation provided by Becker, Gray, Marvakov (2013).

define important controls used in the analysis, namely employee productivity, industries' skill intensities and labor shares. We define all variables in Appendix A2.

1.5. Summary Statistics

Table 1 reports summary statistics of several key variables used in the analysis. We report the mean value across all industries for a given year along with the standard deviation in parentheses. We observe that our measure of normalized merger intensity is relatively evenly distributed across the 132 sample industries. The average industry has about one half of a percent of the overall merger activity in the given decade.

Similar to Autor and Dorn (2013), we document that about one third of all occupations are routine-intensive. Likewise, we find that between 12% and 15% of all occupations in the average industry is offshorable.

We find that nearly 17% of workers in our average industry has a college degree in 1980, which we define as four or more years of post-secondary education. This fraction increases over time and is above 28% in 2010. The average hourly wage is $20.34 in 1980 and by 2010, the average hourly wage is $22.87. Moreover, we show a steady increase in the standard deviation of wages within a given industry over time.

Table 2 provides summary statistics of variables sourced from the NBER-CES dataset. It can be observed that average equipment and plant intensity increase over time by about 36% and 21% between the first and last decade of our sample. A similar trend is observed for employee productivity and skill intensity, while, on the contrary, labor share is following a declining trend.

2. Results

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

2.1 M&A and Occupational Changes

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

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

where i and t index industries and years. $X_{i,t}$ controls for industry offshorability, time-varying at the industry level. *Merger intensity* is our proxy of M&A activity as defined in Section 1 and log-transformed.[7] The IPUMs data is only available every 10 years for the period between 1980 and 2000. As such, M&A activity is measured over three decades in our sample: 1980-1989; 1990-1999; and, 2000-2009. *Δlog(rsh)* measures the change in the fraction of routine-based occupations within a given industry over a decade, namely 1980-1990, 1990-2000, 2000-2010. Standard errors are clustered at the industry level to take into account correlation in industries over time.

Columns 1-3 of Table 3, present the results. Column 1 does not include any controls. Column 2 includes time fixed effects to control for differences in computer costs, and hence uses, as well as other macro-level trends in occupational shares. In column 3, we control for the offshorability of tasks within an industry. Blinder and Krueger (2013) estimate that 25% of US jobs are offshorable and an increasing exposure to foreign competition from low-wage countries has led to large changes in domestic local labor markets and worker outcomes. In the context of our tests on routine intensity, this control is particularly

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

important as Goos, Manning and Salomons (2014) find a positive correlation between routine employment shares and offshorability.

We find that industries characterized by higher merger intensity over the past decade are associated with a more rapid decline in the share of routine-based occupations. The results are both statistically and economically significant. An increase in M&A intensity by 10% is associated with a 13% greater increase in the speed of change in the share of routine intensive occupations for a given industry (column 3).

In columns 4-9 of Table 3, we turn to a time-series estimation. We consider the following specification:

$$\log(rsh)_{i,t} = \alpha_t + \alpha_i + \gamma \log(merger\ intensity)_{i,(t-10,t-1)} + \beta X_{i,t} + \varepsilon_{i,t} \qquad (2)$$

where i and t index industries and years; α_t, α_i are time and industry fixed effects. All variables are defined as in Equation (1). Standard errors are clustered at the industry level to take into account correlation in industries over time.

Column 4 of Table 3, confirms that our intuition also holds in the time-series. An increase in M&A intensity by 10% is associated with a 29% decrease in routine intensity share in the industry. The result is statistically significant at the 1% level and robust to controlling for industry task-offshorability, as shown in column 5.

Columns 6-9 show this result is robust to different specifications. In column 6, we address the possibility that our results may be capturing mean-reversion, namely high M&A industries adjusting back to an industry-specific routine-intensity equilibrium level. To address this concern, we interact the value of the dependent variable for each industry defined in 1980 (the start of the sample) with a full set of time dummies. This test allows us to flexibly control for mean-reversion and for differential trends across industries that depend on industry characteristics (e.g. based on industries' labor supplies). The results are very similar, indicating that mean-reversion or differential trends based on start-of-the-sample routine intensity are not driving the results.

In column 7, we consider a first-difference specification where we take the first differences of both the merger intensity and routine share intensity. This specification also addresses concerns of mean-reversion and is a test on the strict exogeneity assumption necessary for consistency of the fixed-effects estimator (Wooldridge, 2002) and on the importance of measurement error (Griliches and Hausman 1986). The first-difference estimation yields results very similar to the baseline analysis.

Columns 8 and 9 consider two further robustness tests. In column 8, we use a measure of merger intensity calculated based on M&A transaction values. Given transaction values are often missing in SDC, we limit the sample by dropping those industry-decades in the 95th and above sample percentiles in terms of missing transaction values. In column 9, we redefine M&A activity using only mergers observed in the first half of the preceding decade. This allows for a greater time lag between the merger effective date and the year in which occupational shares are measured addressing concerns that occupational changes take time to materialize. The results are robust to both of these modifications.[8]

These results show a clear pattern that high M&A intensity at a given industry is associated with a subsequent decline in occupational shares of routine tasks, suggesting polarization of employment by reducing job opportunities in the middle-skill occupations which are most commonly associated with high routine-intensity. At the same time, this process of automation will also increase relative demand for high-skill employees as technology is complementary to skilled labor, leading to "upskilling" of affected industries. To round our argument, we look next at the share of high-skill workers within a given industry, following mergers and acquisitions.

We use two measures to proxy for high-skill employees. We define the share of employees with college education, namely employees with 4 or more years of post-high school education, in a given

[8] As detailed in section 1, in the above tests, we define the share of routine-based occupations following the approach in Autor and Dorn (2013) where occupations are classified as routine based on the 1980 Census. We also consider a variant where we instead define routine and non-routine occupations each Census year. Then, as in our baseline, we employee-weight this measure using the relative importance of each occupation in a given industry-year to calculate the industry share of routine occupations. We replicate Table 3 using this alternative measure and results remain robust. Results are shown in Appendix Table A2.

industry-year. We also define the share of employees with graduate education, which we define as workers with 5 or more years of post-high school education.[9]

Table 4 reports the results using a panel of industries. In columns 1 and 2, the dependent variable is the change in the share of workers with a college education within a given industry. We document a positive and statistically significant effect of M&As on the share of employees with a college education in a univariate setting (column 1) and with year fixed effects (column 2). Columns 3-5 repeat the estimation in the time-series using the share of workers with a college education as the dependent variable. Again, we show that an increase in lagged merger intensity is related to an increase in the relative share of college educated workers within a given industry. The results are economically important: an increase in M&A intensity by 10% is associated with an increase in the share of college-educated employees by 8 percentage points relative to the mean in a given industry. Column 4 further controls for the offshorability of jobs within a given industry as this may influence demand for skill: the coefficient of task offshorability is not statistically significant. Column 5 controls for time dummies interacted with the value of the dependent variable at the start of the sample and results are robust. In columns 6-10, we alternatively consider the fraction of workers with a graduate education. Our results are robust to using this alternative measure of skill.

Overall, these findings are consistent with the argument in Autor, Levy, and Murnane (2003) that industries with low routine task intensity employ relatively more high-skill workers. Thus, an increase in the share of college graduates can be interpreted as a decrease in the reliance of workers engaged in primarily routine-based activities. Moreover, these findings are also consistent with Autor and Dorn (2013) who argue the adoption of technology that replaces routine-based labor inputs will lead to an outsized increase in the share of high-skilled employees due to the complementarities between high-skilled employees and computer technologies.

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

2.2 M&A and Wages

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

We draw data on wages for full-time workers measured hourly, weekly and annually. Table 5 presents the results. The dependent variable in columns 1 and 2 is the change in the log mean hourly wage for a given industry. Column 1 shows univariate results and column 2 adds year fixed effects. Both regressions show a positive and statistically significant correlation between lagged M&A activity and the change in the average hourly wages by industry. The results are economically important. An increase in M&A activity by 10% in one industry is associated with a higher change in mean hourly wages in that industry by 17%.

In column 3, we use the log of the industry average hourly wage as the dependent variable and add industry fixed effects. We find similar results in the time-series: a 10% increase in M&A intensity within an industry is associated with a 23% increase in mean hourly wages in the industry. This result is robust to controlling for the offshorability of tasks of the industry (column 4) and to including interactions of time dummies with the dependent variable defined in 1980, the beginning of our sample (column 5). The latter specification addresses concerns of mean-reversion to a pre-M&A equilibrium level and of differential trends of wages across industries.

Columns 6 and 7, Table 5, repeat the specification in Column 5 using annual (column 6) or full-time workers' weekly (column 7) wages. The results are similar both in terms of statistical significance and economic magnitudes. Note wage trends for full-time, full-year weekly workers depicted with our measure of full-time workers' weekly wages may obscure wage developments lower in the wage distribution, where a larger part of the workforce is part-time or part-year (Acemoglu and Autor, 2011). Moreover, measures of annual income, like the one presented in Column 7, may be capturing changes in hours worked and related practices and not in wages. Therefore, we prefer to focus on hourly wages to follow changes in wage trends.

To test the effect of wages on wage polarization following M&A activity, we look at the standard deviation of wages, as in Barth, Bryson, Davis, and Freeman (2015). Table 6 presents results using hourly wages as our measure of wages. Columns 1 and 2 use the change in log standard deviation of industry wages as the dependent variable and shows a positive correlation between lagged M&A activity and wage disparity. An increase of lagged M&A activity by 10% in a sector is correlated with a 15% increase in the change in the standard deviation of wages. In columns 3-5, we use the log of the standard deviation of industry wages as the dependent variable and include industry fixed effects. The positive correlation also holds in the time-series. Within industries, an increase in M&A activity by 10% increases wage disparity by 18% (column 3). Column 4 controls for industry task offshorability, while column 5 additionally controls for differential trends in industries' wage inequality by interacting year dummies with the initial industry values of standard deviations of hourly wages. The coefficients are very similar across the different specifications.

In Table 7, we provide further evidence that M&As contribute to wage polarization by exploiting our sample heterogeneity. Autor and Dorn (2013) argue that the treatment effect of technology adoption on the share of routine intensive jobs should be magnified when the share of such workers is high in the first place. Following their intuition, we replicate the measures used in their analysis to test whether wage inequality increases more in cases where the initial share of routine intensive jobs was higher in the prior decade. To parallel the wage inequality literature (Autor, Levy and Murnane, 2003; Autor and Dorn, 2013), we look *within* the distribution of wages in a given industry. Thus, we construct log wage differentials between the 90^{th} and 10^{th}, the 90^{th} and 50^{th}, and the 50^{th} and 10^{th} percentiles of the hourly wage distribution.

Columns 1 and 2, 3 and 4, and 5 and 6 present results using the 90/10, 90/50, and 50/10 log wage differentials, respectively, as the dependent variable. The odd columns include year and industry fixed effects as controls. The even columns also include interactions of time dummies with the dependent variable defined in 1980. In all regressions, we control for industry and year fixed effects, industry task offshorability, and share of workers with some graduate education, our measure of the most skilled labor inputs. The coefficient of interest is the interaction term between lagged M&A activity and industry routine share intensity in the previous decade. The coefficient is positive and statistically significant when looking at top-bottom (90/10) inequality and at top-middle (90/50) inequality. However, results are different in columns 5 and 6 when we look at lower tail inequality. Inequality between the 50th and 10th percentiles of the hourly wage distribution is typically not interpreted as a skill premium. As such, we do not predict to find a significant interaction. These results are confirmed in the data.

In sum, these results show that industry-level M&A activity is followed by an increase in the industry-wide mean wages as well as an increase in wage inequality within industries. These findings are consistent with the argument that M&A activity acts as a catalyst for industry wage polarization.

3. Evidence concerning Mechanisms

In this section, we explore potential mechanisms driving the relationship between M&As and skill-biased and routine-biased technological change. We propose three non-mutually exclusive mechanisms: 1) an increase in scale; 2) adoption of best practices; and 3) lower financial constraints.

The increased scale associated with M&As can reduce the fixed costs of investing in new technologies, predicting greater treatment effects when industry firm size is most impacted. To test this mechanism, we measure the contemporaneous change in the median firm size, in a given industry, over the window during which we are estimating M&As.[10] As we are limited to observing firm size only for those firms in Compustat, we assume that changes in publicly listed firms parallel changes in the broader industry. We further assume that changes in median industry firm size can at least partially be assigned to M&A activity. The results are reported in Table 8. We measure median firm size as log assets in columns 1 to 4 and, alternatively, as log employment in columns 5 to 8. We report consistent results, using both

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

proxies, although not all coefficients of interest are significant.[11] When we observe greater increase in the median firm size in a given industry-decade following M&A activity, the treatment effect on routine occupations, high skill employees, average wages and wage polarization is stronger.

Alternatively, M&As may increase the technology adoption by facilitating the transfer of best practices from the acquirer to the target. We proxy for the quality of the acquirer by taking the acquirers' industry median market-to-book ratio, based on Compustat publicly listed firms.[12] We use market-to-book ratios as they are a measure of firm value which is comparable across industries and also reflects future expectations, potentially capturing expected gains from recently implemented technologies which are not yet reflected in other accounting ratios. The results are reported in Table 9, columns 1 to 4. As predicted, the treatment effect of M&A activity is more pronounced when acquirers are assumed to be more productive.

Finally, we consider the role of financing constraints. We assume targets are more likely to be financially constrained and acquirers select some target with the specific objective of easing these constraints, as in Erel, Jang, and Weisbach (2015). We assume targets are most likely to be financially constrained when credit spreads are high, as in Officer (2007). We compute credit spreads taking the difference between BAA and the effective federal funds rate at the time of the deal announcement. Then, we define a dummy variable which takes the value of 1 if the average credit spread at a given industry-decade is higher than the sample median.[13] The results are reported in column 5 to 8 of Table 9. As predicted, we find stronger treatment effects when credit spreads are relatively higher at the time of the M&A activity.

In sum, these results suggest three specific mechanisms by which M&As can act as a catalyst to skill-biased and routine-biased technological change. We observe a more pronounced relationship

[11] In some cases, the results are close to being significant. In column 3, the p-value on the interaction term is 0.12. In column 5, the p-value on the interaction term is 0.25.
[12] We use industry-year characteristics to avoid dropping M&A observations where the individual acquirer cannot be matched to Compustat.
[13] Since all regressions in Table 10 include year fixed effects, we are estimating this effect by using variation in the timing of M&A deals for a given industry *within* the decade and variations in the credit spread *within* this same window of time.

between ex-ante M&A activity and routine share intensity, the share of college-educated workers, and mean and standard deviation of industry wages when one of these mechanisms is more likely to be important.

4. Evidence concerning Investment in Automation

The results presented so far suggest an increase in labor-saving technology following greater M&A intensity. In this section, we explore changes in industry investment patterns using data provided by the NBER-CES Database. The NBER-CES Database provides industry level aggregates of investments in equipment capital, including investment in labor saving technology, as well as investment in plant capital for the manufacturing sector. Using this data, we define two new variables: equipment capital intensity (measured as real capital invested in equipment normalized by employment and log-transformed) and plant capital intensity (measured as real capital invested in structures normalized by employment and log-transformed).

We start our sample in 1980 due to availability of the M&A data, and end in 2007 to exclude the years of the financial crisis. To follow a similar estimation methodology with our previous analysis, we define M&A activity in the following time-periods: 1980-1998; 1989-1997; 1998-2006.[14] We then examine the effect of M&A intensity on industries' investment intensity in years 1999, 1998, and 2007. Our sample includes 459 4-digit SIC industries.

Table 10 reports the results. Columns 1 and 2 include 4-digit SIC industry and year fixed effects with standard errors clustered at the 4-digit SIC level. Column 1 shows that, following high M&A activity within an industry, equipment capital intensity, namely investments in non-structural physical assets normalized by employment, increases. The coefficient is positive and statistically significant at the 1% level. On the contrary, plant capital intensity, investment in new and modified structures normalized by

[14] In this analysis, we chose 8-year windows to define M&A activity in order to use 2007 as the end year of the sample and minimize the overlap with the financial crisis. We also run robustness, in unreported regressions, where we define time-windows of 4 years to measure M&A intensity. Results are similar.

employment, does not change (column 2). Moreover, the magnitudes of the effect are significantly different.

Columns 3 and 4 repeat these specifications after including time-varying industry-level controls. We control for industry productivity, measured as the logarithm of total value of shipments over employment, to control for differences in the productivity of capital. We add skill intensity, measured as the logarithm of the share of non-production employees in the industry, to proxy for complementarities between human capital skill and capital. Finally, we use the labor share, measured as total payroll over total cost of inputs, to account for differences in labor shares. As expected, skill intensity is positively correlated with both equipment and plant investment intensity and it is statistically significant. The other two control variables are not statistically significant. The coefficients of M&A intensity are similar to those in columns 1 and 2 after adding these controls. These results complement our earlier findings and suggest skill-biased and routine-biased technological change in industries following M&A activity.

5. Evidence regarding Causality

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

5.1 Cost-cutting by reducing employment and payroll

Shleifer and Summers (1988) argue that M&As can be used to break implicit contracts with employees at the target firm, resulting in a lower ex-post payroll. More recently, Dessaint, Golubov, and Volpin (2015) and John, Knyazeva, and Knyazeva, (2015) show that labor restructuring, in the form of layoffs or wage cuts, is a primary source of synergies for mergers and acquisitions. More broadly, M&As can be motivated to reduce agency costs present at the target firm. For example, a manager may be reluctant to fire employees who are no longer adding value to the firm due to the high social costs associated with such actions. Our results support these earlier findings by also showing evidence of post-

M&A labor restructuring. However, our story has unique predictions regarding which type of workers will be replaced (those involved in routine-intensive occupations). Moreover, predictions regarding average wage increases do not directly follow from a simple cost-cutting motivation.

5.2 Market power and the distribution of rents

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

5.3 Technological or regulatory shocks

Mergers may be motivated by unexpected changes within the industry. It is possible these same shocks then predict greater adoption of labor-saving technology also predict greater M&A intensity and as such we are capturing two concurrent trends driven by one omitted variable. To address this issue, we include dummy variables for both the technology and regulatory shocks identified in Harford (2005) and Ovtchinnikov (2013) and report the results in Table 11. In this table, we find that our coefficient of interest is effectively unchanged as compared to our baseline results. These results show that a set of the most important industry shocks known to be associated with merger waves explains none of our findings. Moreover, besides having an insignificant influence on our coefficient of interest, the industry shock variable cannot directly predict our dependent variable in the same direction as the impact of M&A activity. The industry shock variable is a significant predictor of mean hourly wages, but in the opposite direction of our hypothesis. In the other three regressions, the shock variable is not significant.

5.4 IV Evidence

As additional evidence in support of a causal interpretation of our results, we instrument for merger activity in a given industry with merger activity in upstream or downstream industries. Ahern and Harford (2014) show that merger activity in a given industry can lead to merger activity in related industries, as identified by the BEA input-output (I-O) table, due to the fact that related industries respond to the changes in concentration at their customers or suppliers. Following Ahern and Harford (2014), we use the 1997 I-O table to map our industries into the BEA industries.

We map BEA industries to NAICS1997 using a crosswalk provided by BEA. We map NAICS 1997 to our data, in two steps: first, we map NAICS1997 to NAICS2007, and second, we map NAICS 2007 to our sample meta-NAICS industries. We identify connected industries if there is a non-zero transfer between industries. Since one industry can be connected to multiple industries, we sum up the merger activity of all connected industries and normalize by total M&A activity for that decade. We preserve two separate variables, *lgUseMA* and *lgMakeMA* which are the normalized count of M&A activity in the contemporaneous decade for upstream and downstream related industries (in logs). We present the results Table 11, column 5. Given the weak power of the instruments, we are cautious to not over-interpret the results. However, the results are suggestive that mergers motivated in response to a change in concentration up or down the supply chain are associated with a decrease in routine intensity.

5 Conclusion

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

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

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

Finally, while we do not have one specific test which allows us to make a strong causal interpretation, we argue that the wealth of the presented evidence is consistent with a causal relationship. Our next step is to provide firm-level evidence consistent with our findings at the industry level. Such data will allow the comparison of realized and failed mergers, an empirical strategy used by many papers in the literature to causally link M&A activity to various outcomes.

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Figure 1, Panel A. Mean Annual Wage by Occupation and Year.

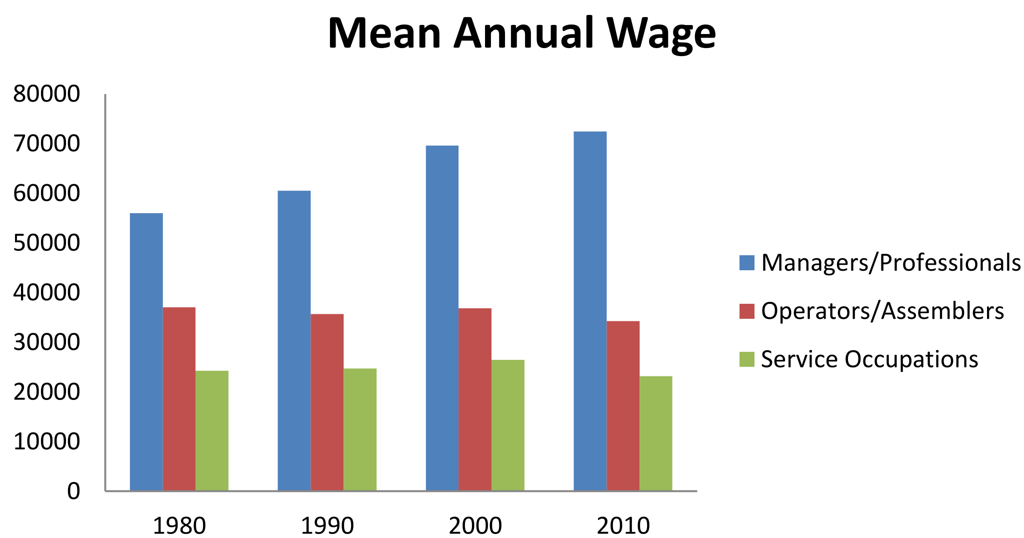

Figure 1, Panel B. Mean Routine Intensity by Occupation and Year.

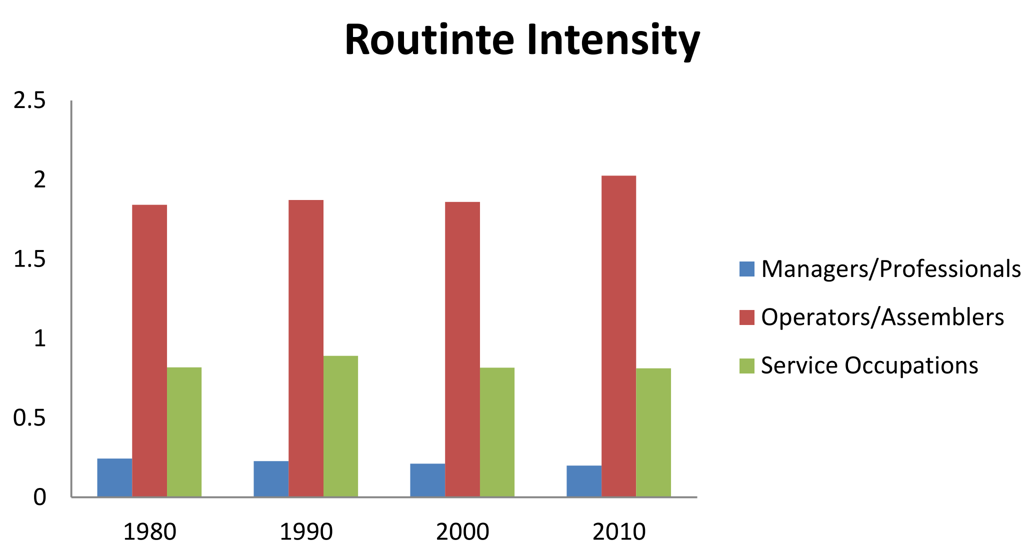

Figure 1, Panel C. Mean Employment Share by Occupation and Year.

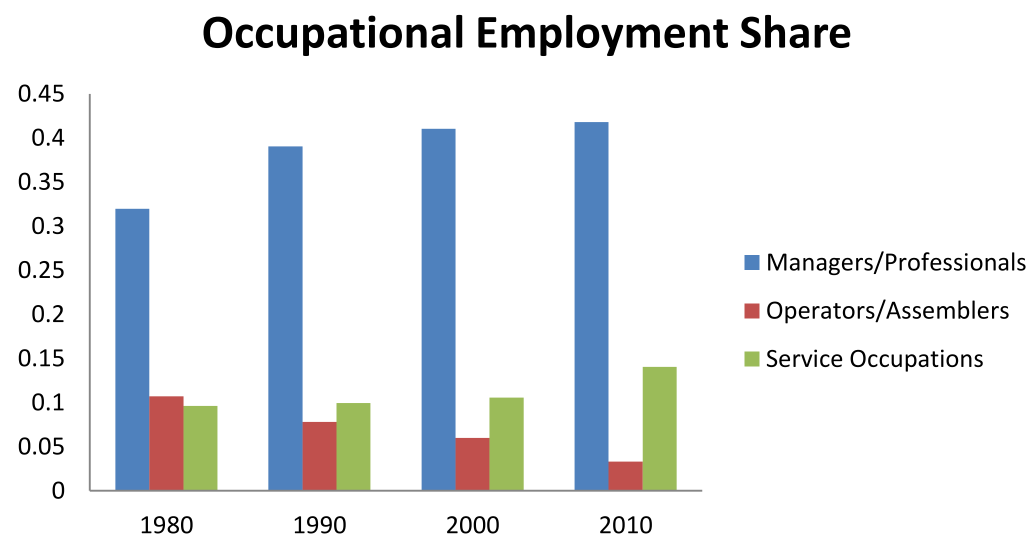

Table 1. Summary Statistics of Merger Intensity and Worker Variables. Table 1 reports mean and standard deviation of key variables from SDC and IPUMs for the years identified in the column header. Each observation is an industry-year, measured once per decade, with the exception of *merger intensity*, which is measured over years *t-10* to *t-1*, and *Δlg(RSH)* which is the change in log RSH from the previous decade. All variable definitions are provided in Appendix A2.

	1980	1990	2000	2010
Merger intensity (%)	.	0.49%	0.51%	0.57%
	[.]	[.0064]	[.008]	[.0134]
Routine employment share (RSH) (%)	34.75%	32.75%	33.28%	33.82%
	[0.16]	[0.16]	[0.15]	[0.16]
Δlg(RSH)	.	-0.0596	0.0151	0.0072
	[.]	[0.10]	[0.15]	[0.16]
Offshorability (%)	12.26%	11.82%	12.91%	15.49%
	[0.43]	[0.44]	[0.45]	[0.45]
College workers labor share (%)	16.74%	20.75%	24.39%	28.27%
	[.1247]	[.1387]	[.1561]	[.1717]
Graduate workers labor share (%)	6.72%	5.91%	7.21%	8.62%
	[0.08]	[0.07]	[0.08]	[0.098]
Average hourly income ($)	20.34	20.71	22.35	22.87
	[4.27]	[4.61]	[5.35]	[6.68]
Standard deviation of hourly income	10.8241	10.9368	11.1045	11.085
	[.2252]	[.243]	[.2679]	[.3194]

Table 2. Summary Statistics of Manufacturing Variables. Table 2 reports mean and standard deviation of key variables from the NBER-CES Manufacturing Industry Dataset for the years identified in the column headers. Each observation is an industry-year. All variable definitions are provided in Appendix A2.

	1980	1989	1998	2007
Equipment Intensity	3.0575	3.3642	3.6602	4.1689
	[.9024]	[.9456]	[.9356]	[.814]
Plant Intensity	2.9229	3.0868	3.1484	3.5406
	[.779]	[.7879]	[.7588]	[.7678]
Employee Productivity	10.0021	11.0819	11.7818	14.6112
	[9.386]	[8.9114]	[8.6398]	[12.8997]
Labor Share	0.2845	0.2762	0.2656	0.2407
	[.1182]	[.1153]	[.1084]	[.1079]
Skill Intensity	0.2616	0.2767	0.2713	0.2894
	[.1114]	[.1215]	[.1129]	[.1144]

Table 3. The Relation between Past Merger Activity and Routine Employment Share. The dependent variable in columns 1-3 and 7 is Δlg(RSH). The dependent variable in columns 4-6 and 8-9 is lg(RSH). With the exception of column 7, the timeline starts in 1980 and ends in 2010 with one observation per decade for each industry. In column 7, the timeline starts in 1990 to measure first differences. Each observation is an industry-year, with the exception of the merger intensity variables which are measured over the period *t-10* to *t-1* or over the period *t-10* to *t-5* in the case of merger intensity_alt2. All variables are defined in Appendix A2. Robust standard errors are clustered at the industry-level. *** indicates p< 0.01, ** indicates p< 0.05, and * indicates p< 0.1.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Dependent Variable	Δlg(RSH)	Δlg(RSH)	Δlg(RSH)	lg(RSH)	lg(RSH)	lg(RSH)	Δlg(RSH)	lg(RSH)	lg(RSH)
Merger intensity	-0.907**	-0.992**	-1.374***	-2.877***	-2.639***	-2.849***			
	(0.446)	(0.428)	(0.434)	(0.595)	(0.798)	(0.570)			
ΔMerger intensity							-1.999***		
							(0.626)		
Merger intensity_alt1								-2.751**	
								(1.167)	
Merger intensity_alt2									-3.193***
									(0.901)
Offshorability			0.029*		0.360				
			(0.017)		(0.315)				
Year FE		Yes	Yes	Yes	Yes		Yes	Yes	Yes
Industry FE				Yes	Yes	Yes		Yes	Yes
Year FE*lgRSH80$_i$						Yes			
Observations	396	396	396	396	396	396	264	376	396
R-squared	0.004	0.060	0.068	0.952	0.956	0.953	0.008	0.952	0.952

Table 4. The Relation between Past Merger Activity and High-Skill Workers. Columns 1-5 explore the fraction of workers in a given industry with a college degree (4+ years of post-secondary education). Columns 6-10 explore the fraction of workers in a given industry with graduate degrees (5+ years of post-secondary education). The dependent variable in columns 1-2 and 6-7 is the change in the share of workers with post-secondary education. The dependent variables in columns 3-5 and 8-10 is the share (%) of workers with post-secondary education. The timeline starts in 1980 and ends in 2010 with one observation per decade for each industry. Each observation is an industry-year, with the exception of the merger intensity variables which are measured over the period *t-10* to *t-1*. All variables are defined in Appendix A2. Robust standard errors are clustered at the industry-level. *** indicates p< 0.01, ** indicates p< 0.05, and * indicates p< 0.1.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Workers with College Education					Workers with Graduate Education				
	ΔShare	ΔShare	Share (%)	Share (%)	Share (%)	ΔShare	ΔShare	Share (%)	Share (%)	Share (%)
Merger intensity	0.968***	0.970***	0.842**	0.870**	0.637	0.504***	0.476***	0.771***	0.780***	0.505**
	(0.229)	(0.227)	(0.400)	(0.364)	(0.436)	(0.113)	(0.112)	(0.175)	(0.167)	(0.246)
Offshorability				0.042	0.046				0.014	0.017
				(0.045)	(0.045)				(0.023)	(0.022)
Year FE		Yes	Yes	Yes	Yes		Yes	Yes	Yes	Yes
Industry FE			Yes	Yes	Yes			Yes	Yes	Yes
Year FE*share80$_i$					Yes					Yes
Observations	396	396	396	396	396	396	396	396	396	396
R-squared	0.055	0.057	0.967	0.968	0.969	0.039	0.217	0.963	0.964	0.964

Table 5. The Relation between Past Merger Activity and Mean Wages. Columns 1-5 measure wages using hourly wages. Column 6 measures wages as annual wages. Column 7 measures wages as weekly wages for full time workers. The dependent variable in columns 1-2 is the change in the log mean wage. The dependent variable in columns 3-7 is log wages. The timeline starts in 1980 and ends in 2010 with one observation per decade for each industry. Each observation is an industry-year, with the exception of the merger intensity variables which are measured over the period *t-10* to *t-1*. All variables are defined in Appendix A2. Robust standard errors are clustered at the industry-level. *** indicates p< 0.01, ** indicates p< 0.05, and * indicates p< 0.1.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dependent Variable			Hourly Wages			Annual Wages	Weekly Wages
	ΔlgWages	ΔlgWages	lgWages	lgWages	lgWages	lgWages	lgWages
Merger intensity	1.678***	1.708***	2.250***	2.237***	2.029***	2.060***	1.882***
	(0.435)	(0.420)	(0.549)	(0.528)	(0.494)	(0.515)	(0.481)
Offshorability				-0.020	-0.028	-0.053	-0.045
				(0.083)	(0.082)	(0.101)	(0.093)
Year FE		Yes	Yes	Yes			
Industry FE			Yes	Yes	Yes	Yes	Yes
Year FE*lgwages80$_i$					Yes	Yes	Yes
Observations	396	396	396	396	396	396	396
R-squared	0.035	0.155	0.959	0.959	0.961	0.961	0.955

Table 6. The Relation between Past Merger Activity and Wage Dispersion. The dependent variable in columns 1-2 is the change in the log of the standard deviation of hourly wages. The dependent variable in columns 3-5 is the log of the standard deviation of hourly wages. The timeline starts in 1980 and ends in 2010 with one observation per decade for each industry. Each observation is an industry-year, with the exception of the merger intensity variables which are measured over the period *t-10* to *t-1*. All variables are defined in Appendix A2. Robust standard errors are clustered at the industry-level. *** indicates p< 0.01, ** indicates p< 0.05, and * indicates p< 0.1.

	(1)	(2)	(3)	(4)	(5)
Dependent Variable	Δlg_StdWages	Δlg_StdWages	lg_StdWages	lg_StdWages	lg_StdWages
Merger intensity	1.465**	1.702***	1.822***	1.802***	1.500***
	(0.710)	(0.556)	(0.544)	(0.536)	(0.520)
Offshorability				-0.029	-0.050
				(0.128)	(0.125)
Year FE		Yes	Yes	Yes	
Industry FE			Yes	Yes	Yes
Year FE*lgstddev80$_i$					Yes
Observations	396	396	396	396	396
R-squared	0.012	0.402	0.947	0.947	0.949

Table 7. The Relation between Past Merger Activity, Past Routine Share Intensity and Wage Dispersion. The dependent variable in columns 1-2 is the log of the ratio of the 90th percentile of the wage distribution to the 10th percentile of the wage distribution, using hourly wages. The dependent variable in columns 3-4 is the log of the ratio of the 90th percentile of the wage distribution to the 50th percentile of the wage distribution, using hourly wages. The dependent variable in columns 5-6 is the log of the ratio of the 50th percentile of the wage distribution to the 10th percentile of the wage distribution, using hourly wages. The timeline starts in 1980 and ends in 2010 with one observation per decade for each industry. Each observation is an industry-year, with the exception of the merger intensity variables which are measured over the period *t-10* to *t-1*. All variables are defined in Appendix A2. Robust standard errors are clustered at the industry-level. *** indicates p< 0.01, ** indicates p< 0.05, and * indicates p< 0.1.

Dependent Variable	(1) lg(wage90/ wage10)	(2) lg(wage90/ wage10)	(3) lg(wage90/ wage50)	(4) lg(wage90/ wage50)	(5) lg(wage50/ wage10)	(6) lg(wage50/ wage10)
Merger intensity	4.396	5.098*	2.434	3.189	1.962	1.847
	(2.890)	(2.733)	(2.150)	(2.519)	(2.372)	(2.383)
lg(RSH)	-0.071	-0.068	-0.013	-0.007	-0.059	-0.054
	(0.051)	(0.052)	(0.038)	(0.035)	(0.037)	(0.035)
Merger intensity * lg(RSH)	4.006**	4.335***	2.396**	2.729*	1.610	1.540
	(1.646)	(1.561)	(1.186)	(1.384)	(1.335)	(1.339)
Offshorability	0.068	0.066	0.081	0.083	-0.013	-0.016
	(0.055)	(0.055)	(0.053)	(0.054)	(0.038)	(0.037)
Graduate workers share (%)	1.881***	1.886***	0.781**	0.835***	1.100***	1.111***
	(0.367)	(0.363)	(0.299)	(0.305)	(0.211)	(0.213)
Year FE	Yes		Yes		Yes	
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE* lgwageratio80$_i$		Yes		Yes		Yes
Observations	396	396	396	396	396	396
R-squared	0.912	0.914	0.909	0.912	0.863	0.864

Table 8. The Relation between Past Merger Activity and Routine Share Intensity, High-Skill Workers, Mean Wages and Standard Deviation of Wages: Interactions with median industry firm size. Columns 1-4 measure median industry firm size using log assets. Columns 5-8 measure median industry firm size using log employment. The dependent variable in columns 1 and 5 is lg(RSH). The dependent variable in columns 2 and 6 is the share (%) of workers with college degrees (4+ years of post-secondary education). The dependent variable in columns 3 and 7 is log hourly wages. The dependent variable in columns 4 and 8 is the log of the standard deviation of hourly wages. The timeline starts in 1980 and ends in 2010 with one observation per decade for each industry. Each observation is an industry-year, with the exception of the merger intensity variables which are measured over the period *t-10* to *t-1*. All variables are defined in Appendix A2. Robust standard errors are clustered at the industry-level. *** indicates p< 0.01, ** indicates p< 0.05, and * indicates p< 0.1.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Size measurement			Log assets				Log employment	
Dependent Variable	lg(RSH)	Share (%)	lgWages	lg_StdWages	lg(RSH)	Share (%)	lgWages	lg_StdWages
Merger intensity	-1.475	0.461	1.526**	0.753	-1.896	-0.025	0.963	0.0578
	(1.000)	(0.484)	(0.747)	(0.729)	(1.459)	(0.465)	(0.848)	(0.890)
Median industry firm size	0.013	0.005	0.006	0.008	0.012	0.001	0.004	0.000
	(0.012)	(0.003)	(0.005)	(0.006)	(0.012)	(0.003)	(0.004)	(0.006)
Merger intensity * median industry firm size	-2.025**	0.641	1.017	1.339*	-1.767	1.445**	1.948**	2.535***
	(1.042)	(0.431)	(0.682)	(0.756)	(1.532)	(0.582)	(0.830)	(0.932)
Offshorability	0.219	0.025	-0.062	-0.096	0.193	0.0234	-0.062	-0.098
	(0.377)	(0.049)	(0.093)	(0.145)	(0.395)	(0.052)	(0.098)	(0.154)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	318	318	318	318	313	313	313	313
R-squared	0.963	0.972	0.962	0.951	0.961	0.973	0.962	0.949

Table 9. The Relation between Past Merger Activity and Routine Share Intensity, High-Skill Workers, Mean Wages and Standard Deviation of Wages: Interactions with acquirer quality and financing availability. The dependent variable in columns 1 and 5 is lg(RSH). The dependent variable in columns 2 and 6 is the share (%) of workers with college degrees (4+ years of post-secondary education). The dependent variable in columns 3 and 7 is log hourly wages. The dependent variable in columns 4 and 8 is the log of the standard deviation of hourly wages. The timeline starts in 1980 and ends in 2010 with one observation per decade for each industry. Each observation is an industry-year, with the exception of the merger intensity variables which are measured over the period *t-10* to *t-1*. Acquirer median MB is the log transformed median of the market to book of all acquirers in Compustat within a given industry, as measured over the previous decade. Market to book is measured as (total long term debt + debt in current liabilities + market capitalization at fiscal year end + preferred stock liquidating value – deferred taxes and investment tax credit) divided by total assets. Credit spread is the average of the difference in the yield on BAA bonds and the effective federal funds rate, as measured at the time of the deal announcement, for all M&As in a given industry-decade. Credit spread_high is an indicator variable if the value is above the sample median. All other variables are defined in Appendix A2. Robust standard errors are clustered at the industry-level. *** indicates p< 0.01, ** indicates p< 0.05, and * indicates p< 0.1.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent Variable	lg(RSH)	Share (%)	lgWages	lg_StdWages	lg(RSH)	Share (%)	lgWages	Lg_StdWages
Merger intensity	-1.239	-1.705	-1.117	-2.652	-0.487	-0.853	-0.106	-1.030
	(3.573)	(1.208)	(1.805)	(1.965)	(2.980)	(0.995)	(1.322)	(1.677)
Acquirer median MB	0.140	0.019	0.032	0.092				
	(0.150)	(0.030)	(0.041)	(0.061)				
Merger intensity * acquirer median MB	-3.748	6.427**	8.360**	11.020**				
	(8.081)	(3.011)	(4.217)	(4.584)				
Credit spread_high					0.048*	-0.003	-0.008	-0.009
					(0.028)	(0.008)	(0.014)	(0.019)
Merger intensity * credit spread_high					-2.138	1.676*	2.283*	2.760
					(2.540)	(0.874)	(1.395)	(1.736)
Offshorability	0.377	0.043	-0.018	-0.022	0.363	0.0348	-0.0406	-0.0289
	(0.285)	(0.036)	(0.076)	(0.104)	(0.316)	(0.0428)	(0.127)	(0.0812)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	396	396	396	396	396	396	396	396
R-squared	0.957	0.970	0.961	0.951	0.957	0.969	0.960	0.948

Table 10. The Relation between Past Merger Activity and Investments in Equipment and Plants. The dependent variable in columns 1 and 3 is the log of real capital invested in equipment normalized by industry employment for a given 4-digit SIC industry-year. The dependent variable in columns 2 and 4 is the log of real capital invested in buildings and structures normalized by industry employment for a given 4-digit SIC industry-year. The timeline starts in 1980 and ends in 2007. All variables are defined in Appendix A2. Robust standard errors are clustered at the industry-level. *** indicates p< 0.01, ** indicates p< 0.05, and * indicates p< 0.1.

Dependent Variable	(1) Equipment intensity	(2) Plant intensity	(3) Equipment intensity	(4) Plant intensity
Merger intensity	10.620**	3.927	11.410**	4.923
	(5.184)	(7.945)	(5.113)	(8.450)
Employee productivity			0.002	0.004
			(0.003)	(0.005)
Skill intensity			0.663***	0.762***
			(0.104)	(0.115)
Labor share			-0.751	-0.491
			(0.541)	(0.659)
Industry FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	1,361	1,361	1,359	1,359
R-squared	0.94	0.895	0.948	0.909

Table 11. The Relation between Past Merger Activity and Routine Share Intensity, College Degree Workers, Mean Wages and Standard Deviation of Wages: Controlling for Industry Shocks. The dependent variable in column 1 is lg(RSH). The dependent variable in column 2 is the share (%) of workers with college degrees (4+ years of post-secondary education). The dependent variable in column 3 is log hourly wages. The dependent variable in column 4 is the log of the standard deviation of hourly wages. The dependent variable in column 5 is the change in lg(RSH). Columns 1-4 are OLS regressions. Column 5 reports the 2[nd] stage of a 2SLS regression. Merger intensity is instrumented with lgUseMA and lgMakeMA. The timeline starts in 1980 and ends in 2010 with one observation per decade for each industry. Each observation is an industry-year, with the exception of the merger intensity variables which are measured over the period t-10 to t-1. Industry shock is an indicator variable which takes the value of 1 if the industry is identified as having a shock over the relevant decade as described in Harford (2005) or Ovtchinnikov (2013). All other variables are defined in Appendix A2. Robust standard errors are clustered at the industry-level. *** indicates p< 0.01, ** indicates p< 0.05, and * indicates p< 0.1.

	(1)	(2)	(3)	(4)	(5)
Dependent Variable	lg(RSH)	Share (%)	lgWages	lg_StdWages	Δlg(RSH)
Merger intensity	-2.673***	0.852**	2.155***	1.719***	-13.80*
	(0.802)	(0.371)	(0.530)	(0.543)	(0.802)
Offshorability	0.356	0.040	-0.030	-0.040	0.031
	(0.316)	(0.045)	(0.080)	(0.127)	(0.035)
Industry Shock	-0.013	-0.007	-0.033*	-0.033	0.006
	(0.034)	(0.011)	(0.018)	(0.022)	(0.030)
Year FE	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	
Observations	396	396	396	396	396
R-squared	0.956	0.968	0.960	0.948	0.956
F-test					5.566

Appendix

A1. Industry mapping between IPUMs and SDC data.

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

In the first step, we map the variable INDNAICS from ACS 2008-2014 samples to NAICS 2007 using a crosswalk provided by IPUMs.[15] Unfortunately, about 4% percentage of the unique IND1990 industry classifications are not mapped to an INDNAICS. We drop these IND1990 classifications. We also standardize NAICS codes by limiting all NAICS to 4 digits. This crosswalk provides a one-to-one mapping between INDNAICS and IND1990.

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

For example, IND1990 industry 0190 maps to NAICS 2213 and to NAICS 2212. NAICS 2213 and NAICS 2212 only map to IND1990 industry 0190. In this case, we combine NAICS 2213 and NAICS 2212 into one meta-industry and identify a clean link between IND1990 industry 0190 and NAICS industry 2213-2212. We follow an iterative approach to identify all possible such matches. Industries which cannot be assigned to a clean match are dropped.

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

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

A2. Variable Definitions

M&A Variables

Merger intensity captures the intensity of M&A activities in an industry-decade. It is the count of deals in a given industry-decade normalized by all deals in the decade.

Merger intensity_alt1 is the sum of M&A transaction values in an industry-decade over the sum of transaction values in the decade.

Merger intensity_alt2 is the count of M&A transaction values in the first half of an industry-decade, normalized by all deals over the same period.

Autor and Dorn (2013)

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

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

IPUMs Dataset

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

Graduate workers labor share is defined as the employment share of high skill workers in each industry and year. Graduate workers are workers who have attained at least 5 years college education.

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

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

Average annual wage is the employment weighted average of annual income and salary income of workers in that industry and year. All wages are inflated to year 2009 following the instruction provided by IPUMs: https://cps.ipums.org/cps/cpi99.shtml.

Standard deviation of annual wage is the employment weighted standard deviation of annual wages in each industry and year.

Average full-time weekly wage is the employment weighted average of weekly income and salary income of workers in that industry and year who are employed full time. All wages are inflated to year 2009 following IPUMs: https://cps.ipums.org/cps/cpi99.shtml.

Standard deviation of full-time weekly wage is the employment weighted standard deviation of weekly wages for full time employees in each industry and year.

90-percentile hourly wage/10-percentile hourly wage is the logarithmic difference of the hourly wage at 90^{th} percentile and the hourly wage at 10^{th} percentile of the industrial hourly wage distribution.

90-percentile hourly wage/50-percentile hourly wage is the logarithmic difference of the hourly wage at 90^{th} percentile and the hourly wage at 50^{th} percentile of the industrial hourly wage distribution.

50-percentile hourly wage/10-percentile hourly wage is the logarithmic difference of the hourly wage at 50^{th} percentile and the hourly wage at 10^{th} percentile of the industrial hourly wage distribution.

NBER-CES Manufacturing Industry Dataset

Equipment intensity is defined as the logarithm of real capital invested in equipment normalized by industry employment for a given 4-digit SIC industry-year.

Plant intensity is measured as the real capital invested in buildings and structures normalized by industry employment for a given 4-digit SIC industry-year.

Skill intensity measures the share of non-production employees in each 4-digit SIC industry-year.

Labor share is cost for labor input divided by total input cost.

Employee productivity is the ratio of total shipments to production worker wages for a given 4-digit SIC industry-year.

Appendix Tables

Table A1. Industries Ranked by Level of Routine Share Intensity. Panel A of the table ranks the industries with the highest RSH by decade (in descending order). Panel B of the table ranks the industries with the lowest RSH by decade (in ascending order). 4-digit 2007 NAICS are included in parentheses.

1980	1990	2000	2010
Panel A. Industries with highest RSH			
legal services(5411)	legal services(5411)	legal services(5411)	legal services(5411)
veterinary services_miscellaneous personal services_beauty shops_barber shops	accounting, auditing, and bookkeeping services(5412)	accounting, auditing, and bookkeeping services(5412)	accounting, auditing, and bookkeeping services(5412)
newspaper publishing and printing_printing, publishing, and allied industries, except newspapers(5111_3231)	newspaper publishing and printing_printing, publishing, and allied industries, except newspapers(5111_3231)	grocery stores(4451)	drug stores(4461)
advertising (5418)	metalworking machinery(3335)	liquor stores(4453)	grocery stores(4451)
metalworking machinery (3335)	advertising(5418)	newspaper publishing and printing_printing, publishing, and allied industries, except newspapers(5111_3231)	metalworking machinery(3335)
Panel B. Industries with lowest RSH			
taxicab service (4853)	retail florists (4531)	retail florists(4531)	taxicab service (4853)
alcoholic beverages (4248)	logging (1133)	taxicab service (4853)	nonmetallic mining and quarrying, except fuels(2123)
metal mining (2122)	alcoholic beverages (4248)	logging (1133)	metal mining(2122)
nonmetallic mining and quarrying, except fuels (2123)	metal mining (2122)	metal mining (2122)	shoe stores(4482)
vending machine operators (4542)	miscellaneous vehicle dealers (4412)	auto and home supply stores (4413)	retail florists (4531)

Table A2. The Relation between past Merger Activity and Routine Employment Share: Alternate definition of routine employment share. The dependent variable in columns 1-3 and 7 is Δlg(RSH). The dependent variable in columns 4-6 and 8-9 is lg(RSH). In this table we define routine and non-routine occupations each Census year. Then, as in our baseline, we employee-weight this measure using the relative importance of each occupation in a given industry-year to calculate the industry share of routine occupations. With the exception of column 7, the timeline starts in 1980 and ends in 2010 with one observation per decade for each industry. In column 7, the timeline starts in 1990 to measure first differences. Each observation is an industry-year, with the exception of the merger intensity variables which are measured over the period *t-10* to *t-1* or over the period *t-10* to *t-5 in the case of* merger intensity_alt2. All variables are defined in Appendix A2. Robust standard errors are clustered at the industry-level. *** indicates p< 0.01, ** indicates p< 0.05, and * indicates p< 0.1.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(9)	(9)
Dependent Variable	Δlg(RSH)	Δlg(RSH)	Δlg(RSH)	lg(RSH)	lg(RSH)	lg(RSH)	Δlg(RSH)	lg(RSH)	lg(RSH)
Merger intensity	-2.338***	-2.387***	-2.518***	-3.775***	-3.438***	-3.785***			
	(0.543)	(0.526)	(0.601)	(0.722)	(1.200)	(0.642)			
ΔMerger intensity							-2.631***		
							(0.645)		
Merger intensity_alt1								-1.794	
								(1.236)	
Merger intensity_alt2									
									-3.905***
Offshorability			0.010		0.512***				(0.988)
			(0.032)		(0.115)				
Year FE		Yes	Yes	Yes	Yes		Yes	Yes	Yes
Industry FE				Yes	Yes	Yes		Yes	Yes
Year*lgRSH80_i FE						Yes			
Observations	396	396	396	396	396	396	264	376	396
R-squared	0.016	0.023	0.024	0.944	0.951	0.946	0.011	0.943	0.944