Mergers and Acquisitions, Technological Change and Inequality

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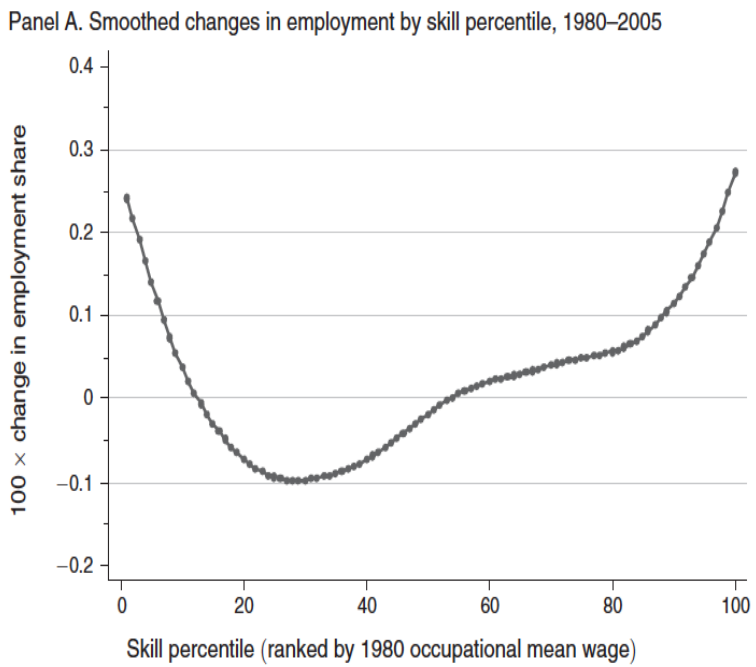
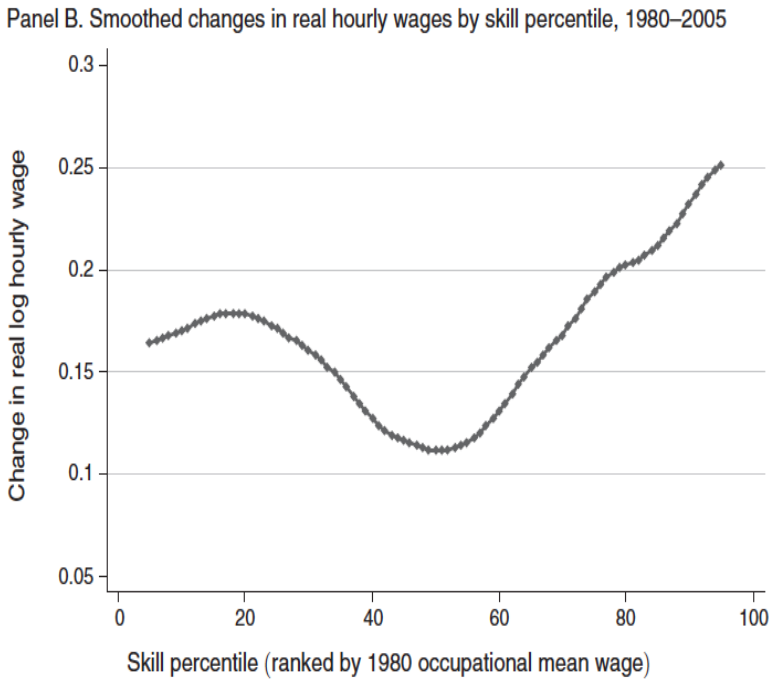
US Labor Market: Job Polarization

Employment growth is concentrated at the tails of occupational skill distribution, in relatively high-skill, high-wage jobs, and low-skill, low-wage jobs.

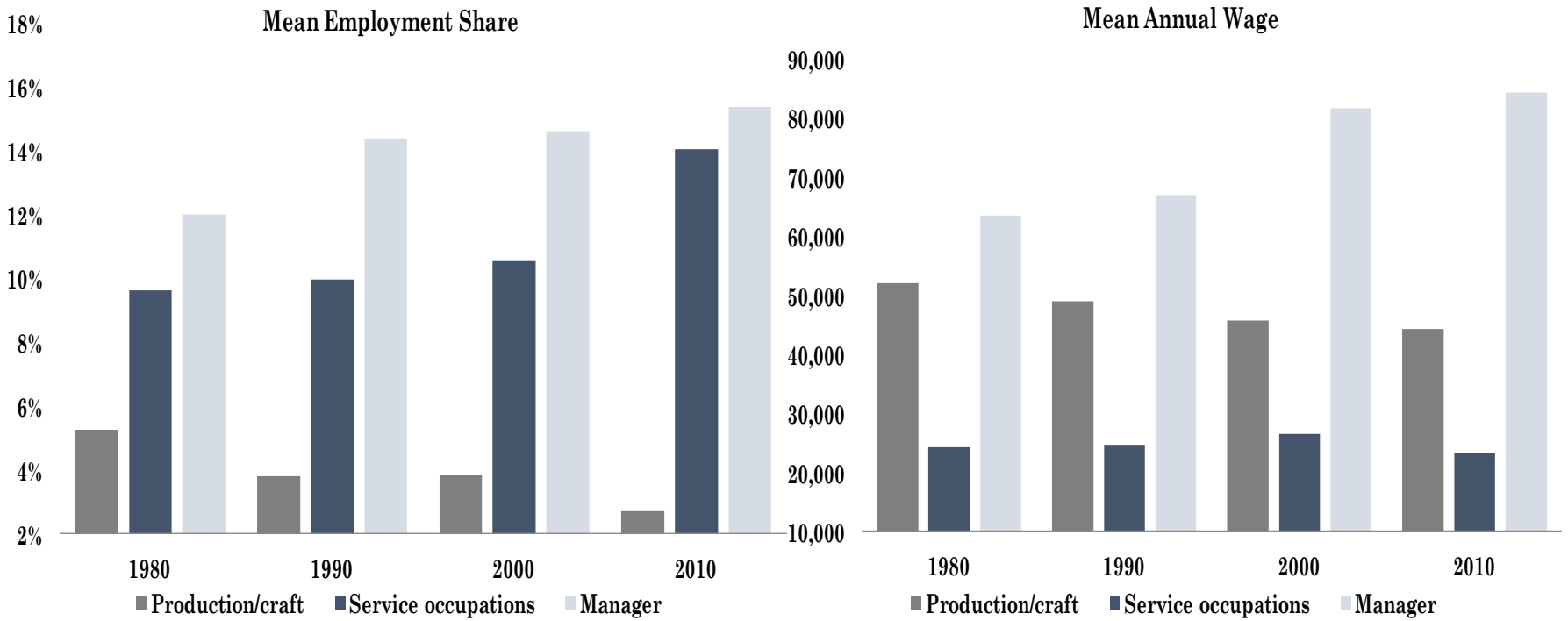




Source: Autor and Dorn (2013)

"Hollowing-out" of middle-skill jobs...

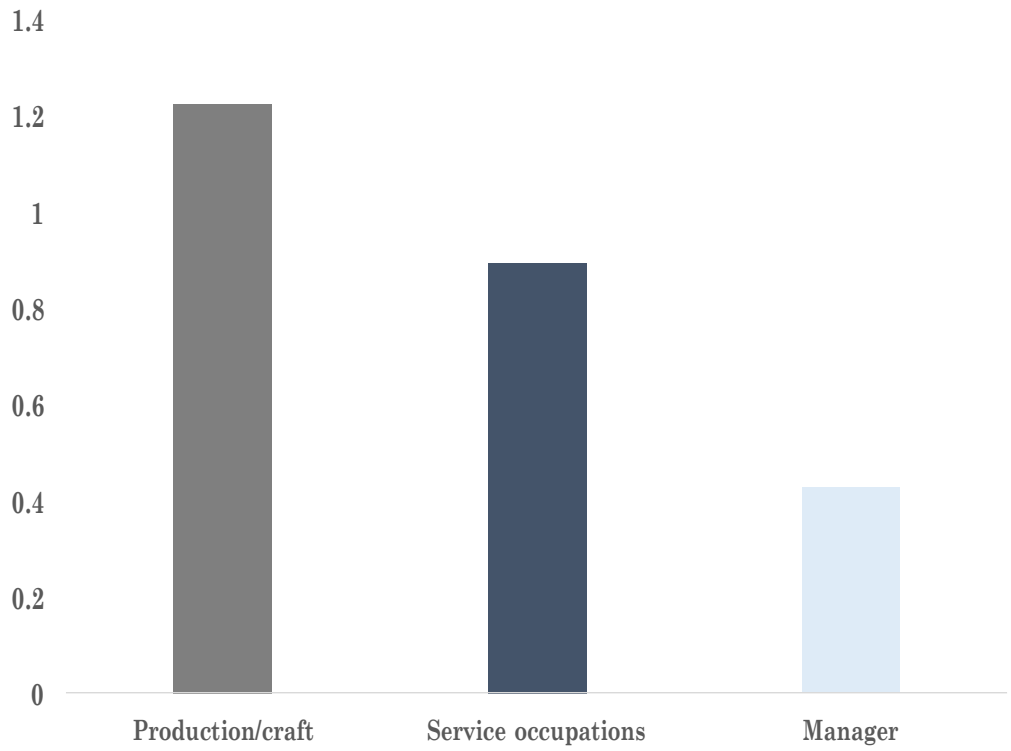
Declining demand for middle-skilled jobs relative to high skill jobs.



Source: IPUMS

...which are more likely to be routine

Middle-skilled jobs are relatively more likely to have a large routine component. Autor and Dorn, 2013: **RTI= ln(Routine) - ln(Abstract) - ln(Manual)**



Source: IPUMS

Key explanation for increasing wage inequality

Technological change:

1. Routine-biased (RBTC):
   - Technology is best at doing routine tasks. Jobs with high routine-task intensity tend to be middle-wage jobs. Replacing these jobs with machines hollows out the wage distribution, leading to an increase in wage inequality. (Autor, Levey and Murnane, 2003; Acemoglu and Autor, 2011; Autor and Dorn, 2013)
2. Skill-biased (SBTC):
   - New technology disproportionately increases productivity of high-skill employees. This leads to an increased demand for highly skilled workers and a rise in wages for high-wage workers. (Bound and Johnson 1992; Berman, Bound, and Griliches 1994; Autor and Katz, 1999)

What drives technology adoption?

- Adjustments to technological change may not be necessarily gradual:
  - Frictions (e.g. adjustment costs) may disrupt optimal reallocation of resources in the face of technological change (Hershbein and Kahn, 2016).

- We argue that firm reorganization, in the form of **M&As**, acts as a **catalyst** for the adoption of technology leading to increased income inequality and other changes in labor demand.
  - M&As can reduce frictions, thereby lowering the opportunity cost of investing in new technologies, and make investment in such technologies more profitable.

M&As and Technology Adoption

A reduction of technology adjustment costs is possible due to:

1. an increase in scale
2. an increase in efficiency
3. lower financial constraints

Predictions

Following the predictions by the job polarization literature, we examine the effect of M&As on occupation changes and wages. We study the effect of M&As on:

- Share of routine employment
- Share of high-skill employment
- Wages

Literature Review

- Literature on technological change and inequality
  - Katz and Autor 1999; Goldin and Katz 2008, 2009; Acemoglu and Autor 2011; Autor, Levy, and Murnane 2003; Autor and Dorn, 2013; Goos, Manning, and Salomons, 2014.

- **This literature talks about how changes in technology and technology adoption leads to changes in the labor market. A discussion of when and which firms are more likely to implement such changes has been missing from the debate.**
  - Barth et al., 2016; Hershbein and Kahn, 2016; Jaimovich and Siu, 2016; Mueller, Ouimet, and Simintzi, 2016; Song at al., 2016.

- Literature on M&As and employment outcomes
  - Ouimet and Zarutskie (2015); Tate and Yang (2015); Dessaint, Gobulov, and Volpin (2015); John, Knyazeva, and Knyazeva (2015); Agrawal and Tambe (2016); Olsson and Tåg (2016).

Data

- M&A deals: Thomson's SDC deals between 1980 and 2010.
  - We focus on **horizontal** deals as these are the type of deals where we can more naturally argue that our proposed mechanisms directly apply.
- Employment data from IPUMs available every 10 years (1980-2010).
  - Anonymous 5% extract of Census data
  - Information on population employment, wages and education by industry (IND1990), geography, and occupation (OCC1990).
  - 300 occupations in each Census-year.
- Autor and Dorn (2013) to define routine occupations.
  - We define the frequency of "routine" tasks typically performed by employees assigned to a given occupation as of 1980.
  - e.g. secretaries and stenographers, bank tellers, bookkeepers and accounting and auditing clerks.

Samples

- We perform two independent analyses:
  - At the industry-level (132 industries×3 decades)
  - At the local labor labor market level, approximated by commuting zones (722 commuting zones×3 decades)

1. **Match IPUMS to SDC by Industry:**
   - IPUMS includes unique industry identifiers (IND1990), consistent over time.
   - IPUMS offers a crosswalk that allows matching IND1990 to NAICS 2007.
   - To identify only cases that cleanly match between IND1990 and NAICS 2007, we consider only cases (after possibly aggregating IND1990 industries to one meta-industry) of industries that map to one and only one NAICS 2007, or aggregation of NAICS 2007 codes.
   - 132 industries which include 79.5% of the unique IND1990 industries in IPUMs and 209 unique 4-digit NAICS 2007.

Samples (cont.)

- We perform two independent analyses:
  - At the industry-level (132 industries×3 decades)
  - At the local labor labor market level, approximated by commuting zones (722 commuting zones×3 decades)

2. **Match IPUMS and SDC by Commuting Zones:**
   - We map the target's city name in SDC to commuting zones.
   - We drop M&A deals in cities that are mapped to multiple commuting zones.
   - We map IPUMs data with commuting zones using a crosswalk by Autor and Dorn (2013).

Key Variables

- **Merger intensity** is the count of horizontal mergers in a given industry (commuting-zone) decade, normalized by total count of horizontal mergers in the decade. It is measured over three decades: 1980-1989; 1990-1999; and, 2000-2009.
- **RSH** is share of employment in high routine intensive occupations in each industry (commuting zone) year.
- **College workers labor share (Share %)** is defined as the employment share of high skill workers in each industry (commuting zone) and year.
- **Average and Standard Deviation of hourly wage** is employment-weighted average and standard deviation of hourly wages in each industry or commuting zones.
- **Offshorability** is the degree to which the tasks performed by an industry (commuting zone) are offshorable. It is defined as the employment-weighted average of occupational offshorability, available by Autor and Dorn (2013).

Summary Statistics

	Industry		Commuting Zones	
	1990	2010	1990	2010
Merger intensity(%)	0.52%	0.66%	0.14%	0.14%
	[.008]	[.014]	[.005]	[.005]
Routine employment share (RSH) (%)	32.75%	33.82%	30.53%	30.63%
	[.156]	[.161]	[.029]	[.034]
College workers labor share(%)	20.75%	28.27%	19.25%	25.45%
	[.139]	[.172]	[.050]	[.069]
Hourly wage at 90 percentile ($)	34.37	39.74	29.75	32.48
	[7.73]	[13.29]	[3.75]	[5.19]
Hourly wage at 10 percentile ($)	8.73	8.74	6.79	6.92
	[2.10]	[2.29]	[.903]	[.757]
Average hourly income ($)	20.71	22.87	17.15	18.59
	[4.61]	[6.68]	[2.25]	[2.55]
Standard deviation of hourly income	10.94	11.09	10.73	10.88
	[.243]	[.319]	[.132]	[.161]

Empirical Methodology

- **In the cross-section:**

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

- **In the time-series:**

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

- **Controls:**
  - α_t=year fixed effects
  - α_i=industry (commuting zone) fixed effects
  - $X_{i,t}$= offshorability to captures the degree to which the tasks performed by an industry (commuting zone) are offshorable.

Consistent with RBTC...

We find a **decline in routine share intensity** in affected industries and local labor markets.

	(1) Δlg(RSH)	(2) lg(RSH)	(3) lg(RSH)	(4) Δlg(RSH)	(5) lg(RSH)	(6) lg(RSH)
Merger Intensity_ind	-1.477***	-2.380***	-2.293***			
	(0.422)	(0.834)	(0.795)			
Merger Intensity_cz				-1.894***	-2.695**	-2.199**
				(0.357)	(1.279)	(1.032)
Offshorability	0.030*	0.364	0.392	0.072***	0.581***	0.590***
	(0.017)	(0.313)	(0.300)	(0.019)	(0.054)	(0.054)
Year FE	Yes	Yes		Yes	Yes	
Industry FE		Yes	Yes			
Commuting Zone FE					Yes	Yes
Year FE*lgRSH80			Yes			Yes
Observations	396	396	396	2,166	2,166	2,166
R-squared	0.07	0.96	0.96	0.02	0.82	0.83

Consistent with RBTC...

In the cross-section, a 10% increase in M&A intensity is associated with a 15% (19%) greater increase in change of share of routine intensive occupations for a given industry (commuting zone).

In the time-series, a 10% increase in M&A intensity is associated with a 24% (27%) decrease in routine intensity share in the industry (commuting zone).

	(1)	(2)	(3)	(4)	(5)	(6)
	ΔlgRSH	lgRSH	lgRSH	ΔlgRSH	lgRSH	lgRSH
Merger Intensity_ind	**-1.477*** **	**-2.380*** **	-2.293***			
	(0.422)	**(0.834)**	(0.795)			
Merger Intensity_cz				**-1.894*** **	**-2.695** **	-2.199**
				(0.357)	**(1.279)**	(1.032)
Offshorability	0.030*	0.364	0.392	0.072***	0.581***	0.590***
	(0.017)	(0.313)	(0.300)	(0.019)	(0.054)	(0.054)
Year FE	Yes	Yes		Yes	Yes	
Industry FE		Yes	Yes			
Commuting Zone FE					Yes	Yes
Year FE*lgRSH80			Yes			Yes
Observations	396	396	396	2,166	2,166	2,166
R-squared	0.07	0.96	0.96	0.02	0.82	0.83

Consistent with SBTC...

We find a relative **increase in the demand for high-skill workers** (4+years college education) in affected industries and local labor markets.

	(1) ΔShare	(2) Share(%)	(3) Share(%)	(4) ΔShare	(5) Share(%)	(6) Share(%)
Merger Intensity_ind	0.675***	0.771*	0.563			
	(0.171)	(0.430)	(0.479)			
Merger Intensity_cz				0.452***	1.597*	1.197*
				(0.157)	(0.829)	(0.738)
Offshorability	0.027***	0.041	0.045	0.058***	0.038*	0.021
	(0.006)	(0.045)	(0.045)	(0.006)	(0.023)	(0.023)
Year FE	Yes	Yes		Yes	Yes	
Industry FE		Yes	Yes			
Commuting Zone FE					Yes	Yes
Year FE*Share80			Yes			Yes
Observations	396	396	396	2,166	2,166	2,166
R-squared	0.16	0.97	0.97	0.09	0.92	0.92

Consistent with SBTC...

In the time-series, a 10% increase in M&A intensity is associated with an increase in the share of college-educated employees by 8 percentage points within industries and 16 percentage points within commuting zones.

	(1) ΔShare	(2) Share(%)	(3) Share(%)	(4) ΔShare	(5) Share(%)	(6) Share(%)
Merger Intensity_ind	0.675***	**0.771***	0.563			
	(0.171)	**(0.430)**	(0.479)			
Merger Intensity_cz				0.452***	**1.597***	1.197*
				(0.157)	**(0.829)**	(0.738)
Offshorability	0.027***	0.041	0.045	0.058***	0.038*	0.021
	(0.006)	(0.045)	(0.045)	(0.006)	(0.023)	(0.023)
Year FE	Yes	Yes		Yes	Yes	
Industry FE		Yes	Yes			
Commuting Zone FE					Yes	Yes
Year FE*Share80			Yes			Yes
Observations	396	396	396	2,166	2,166	2,166
R-squared	0.16	0.97	0.97	0.09	0.92	0.92

Occupational changes have implications on wages...

We find a relative **increase in average hourly wages** in affected industries and local labor markets.

	(1) ΔlgWages	(2) lgWages	(3) lgWages	(4) ΔlgWages	(5) lgWages	(6) lgWages
Merger Intensity_ind	1.294***	2.363***	2.145***			
	(0.338)	(0.753)	(0.724)			
Merger Intensity_cz				0.799***	4.344***	4.637***
				(0.303)	(1.267)	(1.472)
Offshorability	0.026**	-0.023	-0.030	0.073***	-0.026	0.008
	(0.012)	(0.082)	(0.081)	(0.013)	(0.035)	(0.035)
Year FE	Yes	Yes		Yes	Yes	
Industry FE		Yes	Yes			
Commuting Zone FE					Yes	Yes
Year FE*lgWages80			Yes			Yes
Observations	396	396	396	2,166	2,166	2,166
R-squared	0.18	0.96	0.96	0.45	0.94	0.94

Occupational changes have implications on wages...

In the time-series, a 10% increase in M&A intensity is associated with a 24% (43%) increase in average wages in the industry (commuting zone).

	(1) ΔlgWages	(2) lgWages	(3) lgWages	(4) ΔlgWages	(5) lgWages	(6) lgWages
Merger Intensity_ind	1.294***	**2.363*** **	2.145***			
	(0.338)	**(0.753)**	(0.724)			
Merger Intensity_cz				0.799***	**4.344*** **	4.637***
				(0.303)	**(1.267)**	(1.472)
Offshorability	0.026**	-0.023	-0.030	0.073***	-0.026	0.008
	(0.012)	(0.082)	(0.081)	(0.013)	(0.035)	(0.035)
Year FE	Yes	Yes		Yes	Yes	
Industry FE		Yes	Yes			
Commuting Zone FE					Yes	Yes
Year FE*lgWages80			Yes			Yes
Observations	396	396	396	2,166	2,166	2,166
R-squared	0.18	0.96	0.96	0.45	0.94	0.94

...and wage disparity

We find a relative **increase in wage dispersion** in affected industries and local labor markets, based on (i) wage percentiles at the top- and bottom-end of the (hourly) wage distribution and (ii) the standard deviation of hourly wages.

	(1) lgWages90th	(2) lgWages10th	(3) Wages90th/10th	(4) lgStdWages	(5) lgWages90th	(6) lgWages10th	(7) Wages90th/10th	(8) lgStdWages
Merger Intensity_ind	1.948**	1.558***	0.389	2.033**				
	(0.830)	(0.440)	(0.799)	(0.850)				
Merger Intensity_cz					3.975**	-0.449	8.389*	4.874*
					(1.943)	(2.683)	(4.494)	(2.596)
Offshorability	0.027	-0.052	0.080	-0.031	0.023	0.016	0.009	-0.106*
	(0.076)	(0.068)	(0.061)	(0.129)	(0.038)	(0.045)	(0.057)	(0.056)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes				
Commuting Zone FE					Yes	Yes	Yes	Yes
Observations	396	396	396	396	2,166	2,166	2,166	2,166
R-squared	0.95	0.97	0.89	0.95	0.92	0.85	0.76	0.90

Mechanisms

- An increase in scale
  - The increased scale associated with M&As can reduce the fixed costs of investing in new technology.
  - May be size (e.g. count of employees) or specialized size (e.g. count of employees in specific occupation)
  - *"median industry firm size"*
- An increase in efficiency
  - Acquirer may transplant best practices, including automation.
  - *"st. dev. of within industry productivity (profits per employee)"*
- Lower financial constraints
  - Targets may have been unable to implement otherwise cost-effective automation due to financial constraints
  - *"credit spreads high (at the time of deal announcement)"*

Mechanisms: Coefficients on interactions with merger intensity

	(1) lg(RSH)	(2) Share (%)	(3) lgWages	(4) lg_StdWages
Median industry firm size high	-2.443**	1.134***	2.411***	2.385***
	(1.230)	(0.375)	(0.718)	(0.797)
Acquirer industry profitability variance	-0.809	0.844***	1.013*	0.916*
	(1.006)	(0.271)	(0.609)	(0.483)
Credit_spread high	-0.932	1.500***	1.761**	2.149**
	(1.590)	(0.462)	(0.733)	(0.911)

Causality

1. Controlling for industry shocks
   - Technology and regulatory shocks at the industry level identified by Harford (2005) and Ovtchinnikov (2013).
   - *Industry shock*, a dummy variable, takes the value of one if the relevant industry experienced either a technology or regulatory shock over a decade.

Industry Shocks

	(1)	(2)	(3)	(4)
	lg(RSH)	Share (%)	lgWages	lg_StdWages
		Panel A		
Industry shock	-0.008	-0.020**	-0.049**	-0.044***
	(0.027)	(0.009)	(0.019)	(0.016)
Offshorability	0.262	0.068	0.033	0.017
	(0.250)	(0.042)	(0.098)	(0.065)
		Panel B		
Merger Intensity_ind	**-2.405*** **	**0.757***	**1.970** **	**2.301*** **
	(0.850)	**(0.431)**	**(0.842)**	**(0.746)**
Offshorability	0.360	0.039	-0.042	-0.033
	(0.315)	(0.044)	(0.127)	(0.080)
Industry shock	-0.013	-0.007	-0.033	-0.032*
	(0.034)	(0.011)	(0.022)	(0.018)
Year FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes

Causality

2. IV Analysis
   - Use merger activity in upstream or downstream industries as an instrument.
   - Concentration in upstream/ downstream industries may lead to higher bargaining power for suppliers/customers. As a result, connected firms downstream or upstream may decide to merge to counter any change in market power of their suppliers/customers (Ahern and Harford 2014).
   - **Assumption:** Such merger waves propagate for reasons *quasi-exogenous* to changes in labor demand in the own industry.
   - We identify customer-supplier relationship using BEA input-output tables.

IV Analysis

Merger wave in a given industry: count of horizontal mergers in that industry exceeds the 90th percentile of the distribution for that industry, measured from 1980 to 2014.

dummy_hor_wave takes the value of one if any connected industry (defined as having a significant supplier or customer linkage) had a merger wave in the preceding decade.

	(1)	(2)	(3)	(4)	(5)
	First Stage	Second Stage			
	Merger Intensity_ind	lg(RSH)	Share (%)	lgWages	lg_StdWages
dummy_hor_wave	0.005**				
	(0.003)				
Merger Intensity_ind		-17.11*	5.61*	10.21*	10.45*
		(8.968)	(3.285)	(5.764)	(5.436)
Year FE	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes
F-stat	13.5				

We find similar evidence after controlling for deregulatory and product-market shocks in a given industry.

Causality

3. Laws governing firms ability to fire workers
   - State laws, set by court precedence.
   - Good-faith exception: Limits ability of firms to fire workers for what the court deems to be "bad" cause and to impose penalties beyond what is required to provide restitution to the injured employee as a deterrent to future wrong-doing by the firm.
   - These laws have been shown to matter for employment outcomes (Kugler and Saint-Paul, 2004; Autor et al. 2006).
   - Such laws create **exogenous variation** in labor market rigidities which should mitigate the effect of M&As on changes to employment and wages.

State Laws

Good-faith exception applies is 1 if a particular legal precedent has been set at a given state-decade, indicating that this exception will apply to termination decisions of employees located in a given state.

	(1) lg(RSH)	(2) Share (%)	(3) lgWages	(4) lg_StdWages
Merger Intensity_cz	-0.943	3.40***	11.72***	8.52***
	(0.585)	(0.704)	(1.580)	(1.260)
Merger Intensity_cz * good-faith exception applies	-0.846	-2.10**	-6.14***	-4.90**
	(1.308)	(1.052)	(2.317)	(1.933)
Good-faith exception applies	0.008	0.001	0.015	0.015
	(0.010)	(0.004)	(0.011)	(0.009)
Offshorability	0.683***	0.259***	0.463***	0.392***
	(0.026)	(0.019)	(0.045)	(0.035)
Year FE	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes
Observations	2,166	2,166	2,166	2,166
R-squared	0.65	0.62	0.65	0.70

Alternative Explanations

1. Cost-cutting by reducing employment and payroll
   - 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 M&As.
   - **But** this explanation does not have specific predictions regarding the type of workers that will be replaced (e.g. routine), or an increase in average wage.
2. Market power and the distribution of rents
   - These rents are more likely to be captured by high skill employees within the firm leading to higher wage disparity.
   - **But** this explanation does not have specific predictions about the decline in share of routine intensive occupations, namely occupations in the middle of the skill distribution.

Conclusion

- We document the link between firm reorganizations and the impact of income inequality and labor demand.
- The large scale of **M&A activity**, with over 4 $trillion in activity in 2015 alone, makes it an economically important **catalyst** of routine-biased and skill-biased technological change.
- Results robust using two different independent analyses: (i) at the industry level, (ii) at the local labor market level.
- Caveat: our results are specific to the employees who remain employed in the industry or local labor market, and do not take into account unemployed or under-employed workers.