Online Appendix for How does worker mobility affect business adoption of a new technology? The case of machine learning

Appendix A. Construction of the dependent variable—ML adoption

Our process of identifying ML adoption in 2018 includes the following steps:

- *Match product name from CI data to vendor website:* Our first step was to match the product name in the CI database with that which appears in the vendor's website. Our goal was to identify whether the identified products incorporated ML functionality, according to the vendor's product description on its website. There were several special cases that we needed to consider. In particular, the names of some products in the CI database did not exactly match the product name listed on the website (for example, in some cases the product in the CI database was listed as "BI"). In these cases, we identified the product from the vendor for which the primary functionality was business intelligence or data analytics and used that product. Some other products experienced name or version changes over time from the time when the CI data were created (2018) to when we identified the product details on the web (2019). These name changes could be due to product upgrades or mergers and acquisitions of vendors. We thus assumed that products with older names were upgraded by vendors to the latest versions, since tech vendors regularly end premier support of their older version products to promote upgrades to the latest version[1]. After these adjustments for each vendor-product, we were able to identify the associated product description during our web search in 2019.
- *Identifying products with ML functionality*: We searched product functionality from descriptions and product manuals on the vendor's website and conducted string matching using ML keywords. Our keywords were motivated by a similar procedure to identify ML in other settings such as patents (see, e.g., Cockburn, Henderson, & Stern, 2019) and included the words ML, neural networks, reinforcement learning, unsupervised learning, and machine intelligence. We also confirmed that the keywords were used to describe product features and were not used as context in the product description or manual (e.g., an example of using keywords as context would be noting that new technologies like ML were changing business but not describing a specific functionality of the product).

[1] For example, IBM provides support to their commercial firm users to upgrade the Cognos product to the latest version (https://www.ibm.com/docs/en/cognos-analytics/11.0.0?topic=configuring-upgrade-cognos-analytics, https://www.ibm.com/support/pages/how-upgrade-your-version-cognos-analytics, retrieved Dec 2021). If the users fail to upgrade, over time their support from IBM is likely to end.

TABLE A1 List of 31 business analytic packages driven by ML

	Product vendor	Product name from CI data	Product name on the vendor website if different from CI name	Product description from vendor website, user manual, and/or third party tutorial website	Source of information
1	Angoss	KnwldgSTUDIO		Altair supports an open, flexible end-to-end platform for data analytics including Machine Learning and AI. Its collaborative approach enables the organization to create curated datasets that follow lineage and governance protocols.	https://www.datawatch.com/resource-center/literature/altair-knowledge-studio-overview-quad-chart/
2	BIRST	BI	Smart Analytics/Networked BI	Birst's networked analytics empowers business people with easy-to-use tools to make fast and confident decisions on top of centrally governed data, accelerating the delivery of trusted analytics across the enterprise, and reducing many manual tasks with AI-powered automation.	https://www.birst.com/blog/birst-smart-analytics-using-ai-to-operationalize-bi/, https://www.birst.com/tutorials/
3	COGNOS[2]	BI	Cognos analytics	Automate the traditional steps in the business intelligence with machine learning (ML), natural language processing (NLP), ontologies and other cognitive capabilities to improve the user experience in Cognos Analytics.	https://www.ibm.com/support/knowledgecenter/en/SSEP7J_10.2.2/com.ibm.swg.ba.cognos.wig_cr.10.2.2.doc/c_gtstd_c8_bi.html https://techd.com/data-solutions/ibm-business-intelligence-and-analytics/cognos-analytics/
4	Crimson Hex	CrimsonHex	Brandwatch Analytics/Crimson Hex ForSights	With Crimson Hex's strength in machine learning and Brandwatch's in scale and UI, the CEO says, the newly integrated platform will reach out beyond social listening.	https://martechtoday.com/brandwatch-crimson-hexagon-merger-gives-rise-to-social-based-market-intelligence-226313
5	Dassault	EXALEAD		The unique 3D CAD Similarity and Machine Learning technologies enable cross-linking of engineering and purchasing data to quickly reveal similar or identical parts with different reference numbers and prices, facilitating quantity discounts and optimizing the selection of preferred suppliers.	https://www.3ds.com/products-services/exalead/
6	Domo	BI-SOFTWARE	BI analytics	Domo provides fast business insights using alerts, machine learning algorithms, natural language processing, predictive analytics, and other AI technologies; it also text bot function that offers an instant response to questions asked in natural language.	https://www.domo.com/roles/bi
7	GoodData	BI-SOFTWARE	Embedded analytics	To help its multi-location customers optimize their businesses, ServiceChannel partnered with GoodData to develop an offering that would deliver insights at the point of work and accelerate—and ultimately automate—decision making through machine learning.	https://www.gooddata.com/embedded-analytics
8	HYPERION	BI	Oracle Hyperion Workspace[3]	The cloud-based EPM solution provides access features and functionality including AI, machine learning, chatbots, process automation to gain greater efficiencies and improve the quality of decision-making.	https://www.oracle.com/assets/reimagine-financial-process-cloud-4505248.pdf
9	IBM	Cognos ENT		IBM Cognos Analytics is a cloud and on-premise-based business intelligence solution that offers the essential analytics functions, including advanced dashboarding, data integration, reporting, exploration and data modeling, create beautiful dashboards and reports with AI recommendations, and unearth insights in your data using plain language, visual exploration and machine learning.	https://www.ibm.com/products/cognos-analytics
10	IBM	CgnsImprmptu		Create beautiful dashboards and reports with AI recommendations, and unearth insights in your data using plain language, visual exploration and machine learning.	https://www.ibm.com/products/cognos-analytics
11	IBM	Cognos 9		Create beautiful dashboards and reports with AI recommendations, and unearth insights in your data using plain language, visual exploration and machine learning.	https://www.ibm.com/products/cognos-analytics
12	IBM	Cognos 10		Create beautiful dashboards and reports with AI recommendations, and unearth insights in your data using plain language, visual exploration and machine learning.	https://www.ibm.com/products/cognos-analytics
13	IBM	Cognos		Create beautiful dashboards and reports with AI recommendations, and unearth insights in your data using plain language, visual exploration and machine learning.	https://www.ibm.com/products/cognos-analytics
14	IBM	Cognos 8		Create beautiful dashboards and reports with AI recommendations, and unearth insights in your data using plain language, visual exploration and machine learning.	https://www.ibm.com/products/cognos-analytics
15	IBM	BI	Cognos analytics	AI drives IBM Cognos Analytics from data prep and discovery to data visualization and collaboration. Leverage the AI Assistant to ask questions about your data and receive easy-to-understand responses in natural language.	https://www.ibm.com/support/knowledgecenter/en/SSEP7J_10.2.2/com.ibm.swg.ba.cognos.wig_cr.10.2.2.doc/c_gtstd_c8_bi.html

[2] COGNOS was a business intelligence producing company acquired by IBM on January 31, 2008. The Cognos name continues to be applied. (https://en.wikipedia.org/wiki/IBM_Cognos_Analytics. Retrieved Dec 2021)
[3] Hyperion Solutions Corporation was acquired by Oracle Corporation in 2007. (https://en.wikipedia.org/wiki/Oracle_Hyperion. Retrieved Jan 2022)

					https://techd.com/data-solutions/ibm-business-intelligence-and-analytics/cognos-analytics/
16	INFO-BUILD	WebFOCUS		WebFOCUS RStat is a powerful user interface that integrates machine learning with WebFOCUS. This toolset addresses the main requirements of predictive analytics: data access and preparation, predictive model training, testing and evaluation, and model deployment.	https://www.informationbuilders.com/product/webfocus-architecture#webfocus-infographic
17	Informatica	MstrDataMgmt		Informatica MDM leverages AI and machine learning to help locate, access, and utilize trusted data exactly when and where it's needed.	https://www.informatica.com/products/master-data-management.html#fbid=_qda1_Mn75G
18	INFORMATICA	BI	Informatica Operational Insights	Operational Insights is a machine learning–based operational monitoring and analytics tool that provides deep insight into all PowerCenter and Big Data Management installations.	https://www.informatica.com/products/data-integration/powercenter.html#fbid=_qda1_Mn75G
19	InsghtSqrd	BI-SOFTWARE		InsightSquared's AI-powered revenue intelligence software shortens the distance between data and informed decisions for every business leader involved in generating revenue for your company	https://www.insightsquared.com/
20	LogiAnlytcs	LogiXML	Logi Analytics	Machine-learning augments intelligence across the entire workflow – from data to insight to action.	https://www.logianalytics.com/thankyou/maturity-model-for-analytics-capabilities/clkn/http/go.logianalytics.com/ebook-evaluating-business-intelligence-software.html
21	MICRO-STRAT	MicroStrat	Advanced Analytics	MicroStrategy delivers open-source R and Python packages that let data scientists surface powerful machine learning algorithms, empowering analysts and developers to rapidly build sophisticated intelligence applications.	https://microstrat.com/solutions/data-analytics/
22	MICRO-STRAT	BI	Advanced Analytics	MicroStrategy delivers open-source R and Python packages that let data scientists surface powerful machine learning algorithms, empowering analysts and developers to rapidly build sophisticated intelligence applications.	https://www.microstrat.com/solutions/data-analytics/advanced-analytics/ https://www.microstrategy.com/us/product/analytics/machine-learning
23	Oracle	BusIntelENT	Oracle Analytics	Oracle Analytics uses embedded machine learning and artificial intelligence to analyze data from across your organization so you can make smarter predictions and better decisions.	https://www.oracle.com/business-analytics/
24	ORACLE	BI		Oracle Analytics uses embedded machine learning and artificial intelligence to analyze data from across your organization so you can make smarter predictions and better decisions.	https://www.oracle.com/business-analytics/
25	RapidMiner	BI-SOFTWARE	RapidMiner Studio, RapidMiner Auto Model Web	It creates robust machine learning models without writing code from a rich library of over 1500 machine learning algorithms and functions to build the best model for common use cases including customer churn, predictive maintenance, fraud detection, and many more.	https://rapidminer.com/get-started/
26	SAS	Bus Intel	SAS Analytics	It offers quick insights using automated analysis backed by machine learning, with easy-to-understand natural language explanations.	https://www.sas.com/en_us/solutions/business-intelligence.html#visual-data-exploration
27	SAS	BI		It offers quick insights using automated analysis backed by machine learning, with easy-to-understand natural language explanations.	https://www.sas.com/en_us/solutions/business-intelligence.html#visual-data-exploration
28	SiSense	BI-SOFTWARE	Sisense Pulse	Sisense Pulse augmented intelligence leverages machine learning to monitor KPIs to let you know when important changes occur.	https://www.sisense.com/product/impact/pulse/
29	SnapLogic	BI-SOFTWARE		SnapLogic offers a visual drag-and-drop approach to collecting and preparing data, developing ML models, and deploying those models.	https://www.snaplogic.com/solutions/data-analytics
30	Tibco	Spotfire		Using search and recommendations powered by a built-in artificial intelligence engine, Spotfire helps to create simple dashboard metrics, predictive applications, and dynamic real-time analytics applications.	https://www.tibco.com/products/tibco-spotfire
31	Verint Sys	Verint	Situational Intelligence/ Social Intelligence	Verint offers a wide range of analytics engines, including machine learning, profiling, speech analytics, anomaly detection, behavioral analysis, and predictive analytics	https://cis.verint.com

Appendix B: Supplementary Tables

TABLE B1. Sample Construction

Calculation	*Change in observations*	*Remaining sample size*
Matched 2010 & 2018 sample	NA	1,046,523
Exclude government sectors, government-owned firms, military, and nonprofit organizations (elementary education, high education, and libraries), and agriculture sectors	-176,110	870,413
Exclude establishments affiliated with a county, city, or state-level government	-1,658	868,755
Exclude establishments that are located in different states in 2010 and 2018	-25,621	843,134
Exclude other outliers	-8673	834,461
Exclude establishments with below 50 employees	- 681,357	153,104
Exclude singleton observations in the regressions	-14	153,090
Our sample		153,090

Numbers in table reflect number of observations in 2018. First row of table reflects number of observations in 2018 that can be matched with a 2010 establishment. Second and third rows reflect changes in sample size from dropping some industries. The observations we excluded are: Public administration (SIC 90-99); Agriculture, forest, and fishing (SIC 01-09), Elementary and secondary schools (SIC 8211); Colleges and universities (8221), Junior Colleges and Technical Institutes (8222); Libraries (8231); and some establishments affiliated with a county, city, or state-level government (based on establishment names). Consistent with prior studies of IT adoption and productivity, we focus on non-farm business because the relationship between mobility and adoption may differ for establishments in these industries. We excluded outliers when abnormal values are observed, for example, if the value exceeds the threshold of the 99th percentile plus three standard deviations. Singleton observations refer to those that are dropped from our baseline regressions due to perfect collinearity with our dummy variable controls (which include dummies for 4 digit SIC industry, a dummy for having public policy exceptions to at-will employment, a dummy for having implied contract exceptions to at-will employment, and a dummy for having good-faith exceptions to at-will employment and right-to-work laws).

TABLE B2 Distributions of CI data vs. the U.S. Census County Business Patterns data, 2010

	CI 2010 full	CBP 2010 full	CI 2010>100	CBP 2010 >100
Number of establishments	4,370,901	7,403,197	273,072	171,632
% MSA	85.2	93.8	91.8	95.2
% > 100 employees / % > 500 employees given have 100 employees	6.2	2.3	16.2	13.9
% Northeast	18.2	19.4	14.7	19.6
% Midwest	21.4	21.9	24.3	23.9
% South	37.7	35.2	23.9	35.6
% West	22.7	23.5	37.0	20.9
% Agriculture, Forestry, Fishing, and Hunting (NAICS = 11)	0.7	0.3	0.4	0.1
% Mining (NAICS = 21)	0.4	0.4	1.8	0.6
% Utilities (NAICS = 22)	0.5	0.2	0.6	0.8
% Construction (NAICS = 23)	4.5	9.2	2.7	3.7
% Manufacturing (NAICS = 31, 32, 33)	6.7	4.1	12.9	13.8
% Wholesale Trade (NAICS = 42)	4.1	5.6	3.7	4.6
% Retail Trade (NAICS = 44, 45)	7.7	14.4	25.3	15.2
% Transportation & Warehousing (NAICS = 48, 49)	3.3	2.8	2.8	4.1
% Media, Telecommunications, and Data Processing (NAICS = 51)	3.0	1.8	2.9	3.4
% Finance and Insurance (NAICS = 52)	7.5	6.4	3.0	4.7
% Real Estate and Rental and Leasing (NAICS = 53)	2.7	4.7	0.9	1.0
% Professional, Scientific, and Technical Services (NAICS = 54)	10.0	11.5	8.3	5.9
% Management of Companies and Enterprises (NAICS = 55)	0.8	0.7	0.2	3.3
% Administrative and Support and Waste Management and Remediation Services (NAICS = 56)	5.3	5.2	3.0	9.3
% Educational Services (NAICS = 61)	6.1	1.2	8.0	2.8
% Health Care and Social Assistance (NAICS = 62)	23.8	11.0	10.0	17.0
% Arts, Entertainment, and Recreation (NAICS = 71)	1.0	1.7	1.1	2.1
% Accommodation and Food Services (NAICS = 72)	1.7	8.7	2.0	5.4
% Other Services (except Public Administration) (NAICS = 81)	4.1	9.8	4.7	2.2
% Government (NAICS = 92)	6.0	0.3	5.9	0.0

TABLE B3 Descriptive statistics – local control variables

Variable	Obs.	Mean	SD	Min	Max
Top quartile county high-tech employment fraction	153,090	0.751	0.433	0.000	1.000
Dummy for having public policy exceptions to at-will employment	153,090	0.824	0.381	0.000	1.000
Dummy for having implied contract exceptions to at-will employment	153,090	0.784	0.412	0.000	1.000
Dummy for having good-faith exceptions to at-will employment	153,090	0.244	0.429	0.000	1.000
Right-to-work law	153,090	0.374	0.484	0.000	1.000
Top corporate tax rate	153,090	6.755	2.719	0.000	12.000
State log total employment in private sectors	153,090	15.145	0.860	12.510	16.484
State log # of establishments in private sectors	153,090	12.473	0.903	9.964	14.103
State log total wages in private sectors	153,090	25.882	0.942	23.155	27.367
State log GDP	153,090	13.022	0.937	10.244	14.537
State log population	153,090	16.021	0.897	13.244	17.435
State percent 65+	153,090	0.131	0.017	0.077	0.173
State percent 15-64	153,090	0.671	0.012	0.641	0.746
State percent Black	153,090	0.129	0.082	0.004	0.516
State percent female	153,090	0.509	0.005	0.480	0.528
State log medium household income	153,090	10.825	0.142	10.515	11.140
State percent 18-24 enrolled in college	153,090	0.433	0.043	0.275	0.573

Unless otherwise indicated, all values are from 2010.

TABLE B4 Mean comparison by NCA group

Variable	NCA change favoring employers (-1)	No NCA change (0)	NCA change favoring workers (1)
Machine learning adoption in 2018 (percent)	0.109	0.096	0.089
Log number of site employees	4.724	4.713	4.740
Log number of sites in the enterprise	2.320	2.163	2.117
Top quartile county high-tech employment fraction	0.739	0.757	0.739
Dummy for having public policy exceptions to at-will employment	0.843	0.863	0.647
Dummy for having implied contract exceptions to at-will employment	0.843	0.786	0.714
Dummy for having good-faith exceptions to at-will employment	0.046	0.355	0.016
Right-to-work law	0.759	0.333	0.130
Top corporate tax rate	3.717	7.345	7.642
State log total employment in private sectors	15.381	15.084	15.137
State log # of establishments in private sectors	12.613	12.443	12.447
State log total wages in private sectors	26.101	25.816	25.914
State log GDP	13.248	12.959	13.032
State log population	16.257	15.964	16.000
State percent 65+	0.114	0.134	0.139
State percent 15-64	0.674	0.670	0.673
State percent Black	0.148	0.125	0.125
State percent female	0.506	0.509	0.511
State log medium household income	10.817	10.828	10.821
State percent 18-24 enrolled in college	0.399	0.438	0.450
Number of establishments	26,959	100,658	25,473

Unless otherwise indicated, all values are from 2010. We conducted one-way analysis of variance to compare the means across the three NCA groups, and all variables listed in the table are significantly different across the three groups.

TABLE B5 Baseline results of NCA effects on ML adoption – allowing for asymmetric effects of NCA enforceability

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
NCA favoring employers	0.009	0.009	0.003	0.004	0.002	0.005
	(0.006)	(0.006)	(0.004)	(0.004)	(0.003)	(0.003)
NCA favoring workers	-0.007	-0.008	-0.005	-0.004	-0.005	-0.006
	(0.004)	(0.004)	(0.002)	(0.002)	(0.002)	(0.003)
Log number of site employees in 2010		0.020	0.010	0.010	0.010	0.010
		(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Log number of sites in the enterprise in 2010			0.025	0.025	0.025	0.025
			(0.000)	(0.000)	(0.000)	(0.000)
Top quartile county high-tech employment fraction				0.008	0.008	0.008
				(0.001)	(0.001)	(0.001)
Establishments	153,090	153,090	153,090	153,090	153,090	153,090
R^2	0.131	0.141	0.237	0.237	0.237	0.237
Other laws	N	N	N	N	Y	Y
Demographic controls	N	N	N	N	N	Y
Economic controls	N	N	N	N	N	Y

This table replicates Table 3 of the main text, allowing for asymmetric effects of NCA enforceability increases and decreases. Robust standard errors clustered by state are in parentheses.

TABLE B6 Effects of NCA enforceability on ML adoption by establishment employment size – allowing for asymmetric effects of NCA enforceability

VARIABLES	(1) 50–99 employees	(2) 100+ employees	Test of differences (SUR) Chi-square	*p*-value
NCA favoring employers	-0.002	0.011	8.113	.004
	(0.003)	(0.004)		
NCA favoring workers	-0.005	-0.007	0.235	.627
	(0.002)	(0.005)		
Log number of site employees in 2010	0.004	0.014	14.760	.000
	(0.002)	(0.001)		
Log number of sites in the enterprise in 2010	0.025	0.024	0.946	.330
	(0.000)	(0.001)		
Top quartile county high-tech employment fraction	0.007	0.009	2.239	.134
	(0.001)	(0.001)		
Establishments	78,082	74,974		
R^2	0.245	0.240		
Mean adoption rate in 2018	0.0745	0.1210		

This table replicates Table 4 of the main text, allowing for asymmetric effects of NCA enforceability increases and decreases. Robust standard errors clustered by state are in parentheses.

TABLE B7 Heterogeneous effects of NCA enforceability on ML adoption by industry predictive analytics (PA) adoption intensity – allowing for asymmetric effects of NCA enforceability

VARIABLES	(1) Industry PA adoption rate ≥ 0.75	(2) Industry PA adoption rate < 0.75	Test of differences (SUR) Chi-square	*p*-value
NCA favoring employers	0.015	0.003	Warning: variance matrix is nonsymmetric or highly singular	
	(0.007)	(0.005)		
NCA favoring workers	-0.005	0.008		
	(0.006)	(0.004)		
Log number of site employees in 2010	0.009	0.008		
	(0.002)	(0.001)		
Log number of sites in the enterprise in 2010	0.028	0.014		
	(0.001)	(0.001)		
Top quartile county high-tech employment fraction	0.005	0.001		
	(0.002)	(0.001)		
Establishments	18,420	16,958		
R^2	0.220	0.160		
Mean adoption rate in 2018	0.1102	0.0403		

This table replicates Table 5 of the main text, allowing for asymmetric effects of NCA enforceability increases and decreases. Robust standard errors clustered by state are in parentheses.

TABLE B8 Heterogeneous effects of NCA enforceability on ML adoption by geographical location size – allowing for asymmetric effects of NCA enforceability

VARIABLES	(1) Sizable MSA (with over 1m population)	(2) Other locations	Test of differences (SUR) Chi-square	*p*-value
NCA changes favoring employers	0.010	-0.003	6.049	.014
	(0.004)	(0.003)		
NCA changes favoring workers	-0.006	-0.003	0.738	.390
	(0.004)	(0.003)		
Log number of site employees in 2010	0.013	0.007	15.812	.000
	(0.001)	(0.001)		
Log number of sites in the enterprise in 2010	0.026	0.023	20.735	.000
	(0.000)	(0.001)		
Top quartile county high-tech employment fraction	0.007	0.006	0.147	.701
	(0.001)	(0.001)		
Establishments	88,175	64,873		
R^2	0.238	0.253		
Mean adoption rate in 2018	0.1093	0.0812		

This table replicates Table 6 of the main text, allowing for asymmetric effects of NCA enforceability increases and decreases. Robust standard errors clustered by state are in parentheses.

TABLE B9 Heterogeneous effects of NCA on adoption by industry-location size – allowing for asymmetric effects of NCA enforceability

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
NCA changes favoring employers	0.001	0.004	-0.001	0.003	0.003	0.002	0.002	0.005	0.003
	(0.003)	(0.003)	(0.004)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.004)
NCA changes favoring workers	-0.005	-0.005	-0.001	-0.005	-0.005	-0.004	-0.004	-0.006	-0.005
	(0.003)	(0.004)	(0.005)	(0.004)	(0.004)	(0.003)	(0.003)	(0.004)	(0.005)
Sizable MSA	0.003		0.002						0.003
	(0.001)		(0.001)						(0.001)
Log number of establishments by MSA-SIC4 industry		0.000	0.000						
		(0.000)	(0.000)						
NCA changes favoring employers X Sizable MSA (with over 1m population)	0.007								0.007
	(0.007)								(0.007)
NCA changes favoring workers X Sizable MSA (with over 1m population)	0.000								0.001
	(0.006)								(0.006)
NCA changes favoring employers x Log number of establishment*s* by MSA-SIC4 industry		0.000							
		(0.001)							
NCA changes favoring workers x Log number of establishment*s* by MSA-SIC4 industry		-0.000							
		(0.001)							
NCA changes favoring employers x Log number of *small* establishment*s* by MSA-SIC4 industry				0.000	0.000			-0.001	-0.002
				(0.001)	(0.001)			(0.001)	(0.001)
NCA changes favoring workers x Log number of *small* establishment*s* by MSA-SIC4 industry				-0.000	-0.000			0.001	0.001
				(0.001)	(0.001)			(0.001)	(0.001)
Log number of small establishments by MSA-SIC4 industry				0.000	0.000			0.001	0.001
				(0.000)	(0.000)			(0.001)	(0.001)
NCA changes favoring employers x Log number of *large* establishment*s* by MSA-SIC4 industry						**0.002**	**0.002**	**0.003**	**0.003**
						(0.002)	**(0.002)**	**(0.002)**	**(0.002)**
NCA changes favoring workers x Log number of *large* establishment*s* by MSA-SIC4 industry						**-0.001**	**-0.001**	**-0.002**	**-0.002**
						(0.001)	**(0.001)**	**(0.002)**	**(0.002)**
Log number of large establishments by MSA-SIC4 industry						0.000	0.000	-0.000	-0.001
						(0.000)	(0.000)	(0.001)	(0.001)
Observations	153,090	153,090	153,090	153,090	153,090	153,090	153,090	153,090	153,090
R-squared	0.237	0.237	0.237	0.237	0.237	0.237	0.237	0.237	0.237

This table replicates Table 7 of the main text, allowing for asymmetric effects of NCA enforceability increases and decreases. Robust standard errors clustered by state are in parentheses.

TABLE B10 Alternative NCA measures

NCA Measures	(1) Original measures	(2) AL = -1, (baseline =0)	(3) AL =1, (baseline =0)	(4) ID=-1, (baseline =0)
NCA	-0.006	-0.005	-0.006	-0.005
	(0.002)	(0.002)	(0.002)	(0.002)
Log number of site employees in 2010	0.021	0.021	0.021	0.021
	(0.002)	(0.002)	(0.002)	(0.002)
Log number of sites in the enterprise in 2010	0.049	0.049	0.049	0.049
	(0.001)	(0.001)	(0.001)	(0.001)
Top quartile county high-tech employment fraction	0.016	0.016	0.016	0.016
	(0.001)	(0.001)	(0.001)	(0.001)
Establishments	153,090	153,090	153,090	153,090
R^2	0.237	0.238	0.238	0.238

NCA Measures	(5) IL=1, (baseline =0)	(6) NV=1, (baseline =0)	(7) NY=0, (baseline =1)	(8) IL=-1, (baseline =0)
NCA	-0.005	-0.006	-0.004	-0.005
	(0.002)	(0.002)	(0.002)	(0.002)
Log number of site employees in 2010	0.021	0.021	0.021	0.021
	(0.002)	(0.002)	(0.002)	(0.002)
Log number of sites in the enterprise in 2010	0.049	0.049	0.049	0.049
	(0.001)	(0.001)	(0.001)	(0.001)
Top quartile county high-tech employment fraction	0.016	0.016	0.016	0.015
	(0.001)	(0.001)	(0.001)	(0.001)
Establishments	153,090	153,090	153,090	153,090
R^2	0.238	0.238	0.238	0.238

This table reports the effects of NCA changes using alternative NCA measures (descriptions are available in Appendix C). All regressions include controls listed for column (6) of Table 3. Robust standard errors clustered by state are in parentheses.

TABLE B11 Effects by Strength of NCA Enforceability Changes

VARIABLES	(1) Legislative changes strong	(2) Legislative changes weak
Strong NCA changes	-0.010	-0.010
	(0.003)	(0.003)
Weak NCA changes	-0.002	-0.004
	(0.002)	(0.002)
Log number of site employees in 2010	0.021	0.021
	(0.002)	(0.002)
Log number of sites in the enterprise in 2010	0.049	0.049
	(0.001)	(0.001)
top quantile county high-tech employment fraction in 2010	0.015	0.015
	(0.001)	(0.001)
Observations	153,090	153,090
R-squared	0.237	0.237

This table re-estimates Column 6 of Table 3 in the main text, dividing NCA changes into "strong" and "weak" depending on the change they relate to. To classify changes, we rely on Bishara (2011), who identifies 8 questions that can be used to characterize the strength of NCA changes. For each such question Bishara creates a weight based upon the impact of that question on overall NCA enforceability. We similarly classify each of our sample NCA changes into one of Bishara's 8 questions and use this classification and the weight used by Bishara (2011) for that question to determine the strength of the change (a weight of 10 is classified as a strong change while a lower weight is considered as a weak change). Our classification is based upon our own analysis of the changes and associated coverage by legal analysts. While this classification is reasonably straightforward for changes to case law, it becomes more complicated for legislative changes to NCA enforcement during our sample: such legislative changes often involve multiple changes to NCA enforcement simultaneously, and so could be classified according to multiple questions. Hence, in column 1 of this table, we present results with legislative changes classified as strong changes; in column 2, legislative changes are classified as weak changes. Robust standard errors clustered by state are in parentheses.

TABLE B12: Regression results including IT controls

	(1) IT employees	(2) Servers	(3) PCs	(4) All IT measures	(5) IT developers	(6) All IT measures
NCA(-1,0,1) x Post	-0.005	-0.006	-0.005	-0.004	-0.009	-0.007
	(0.002)	(0.002)	(0.002)	(0.003)	(0.002)	(0.003)
Log number of site employees in 2010	0.017	0.021	0.018	0.018	0.029	0.024
	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)
Log number of sites in the enterprise in 2010	0.049	0.050	0.051	0.053	0.046	0.050
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Top quantile county high-tech employment fraction in 2010	0.016	0.015	0.017	0.016	0.013	0.014
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)
Fraction of IT employees in total employment in 2010	-0.244			-0.168		-0.227
	(0.033)			(0.027)		(0.051)
Number of servers per worker in 2010		0.096		0.531		0.493
		(0.046)		(0.046)		(0.064)
Number of PCs per worker in 2010			-0.120	-0.146		-0.147
			(0.009)	(0.008)		(0.012)
Number of IT developers per worker in 2010					0.102	0.115
					(0.018)	(0.018)
Constant	-0.093	-0.135	-0.072	-0.097	-0.164	-0.117
	(0.017)	(0.018)	(0.018)	(0.019)	(0.020)	(0.023)
Observations	153,090	153,090	153,090	153,090	87,811	87,811
R-squared	0.238	0.237	0.240	0.242	0.228	0.233

All regressions include controls listed for column (6) of Table 3. Some observations do not include information on number of IT developers, treating these as missing results in a decline in the number of observations in columns 5 and 6. Robust standard errors clustered by state are in parentheses.

TABLE B13 Predicting changes in NCA enforceability

VARIABLES	(1)	(2) NCA Enf. Up NCA changes favoring employers (NCAPost = –1)	(3)	(4)	(5) NCA Enf. Down NCA changes favoring employers (NCAPost = 1)	(6)
State Republicans to Democrats ratio		-0.040	-0.036		0.045	0.054
		(0.084)	(0.085)		(0.100)	(0.100)
State Labor Force (rate)	0.015	0.021	0.022	-0.036	-0.038	-0.035
	(0.018)	(0.019)	(0.020)	(0.021)	(0.023)	(0.023)
State Unemployment (rate)	-0.017	-0.027	-0.020	-0.057	-0.071	-0.057
	(0.036)	(0.038)	(0.040)	(0.043)	(0.046)	(0.048)
Uniform Trade Secrets Act (UTSA)			-0.130			-0.287
			(0.238)			(0.281)
State log median household income	-0.248	-0.148	-0.112	0.913	1.349	1.429
	(0.454)	(0.569)	(0.577)	(0.542)	(0.679)	(0.683)
State log population	0.131	0.417	0.479	0.374	0.844	0.980
	(0.243)	(0.448)	(0.465)	(0.290)	(0.534)	(0.550)
State log GDP	-0.012	-0.283	-0.359	-0.400	-0.852	-1.021
	(0.251)	(0.441)	(0.467)	(0.299)	(0.527)	(0.552)
Observations	51	49	49	51	49	49
R^2	0.116	0.140	0.146	0.100	0.123	0.144

Dependent variable NCA Enf. Up (Down) is an indicator variable equal to 1 if state experienced an increase (decrease) in NCA enforceability between 2010 and 2018. Washington, DC, and Nebraska are excluded when including controls of Republicans to Democrats ratio.

TABLE B14 Alternative technology and (log of) number of IT workers

	(1)	(2)
VARIABLES	Adoption of tablets	(Log of) Number of IT workers
NCA(-1,0,1)	-0.003	-0.041
	(0.003)	(0.017)
Log number of site employees in 2010	0.258	0.006
	(0.003)	(0.004)
Log number of sites in the enterprise in 2010	0.001	0.013
	(0.001)	(0.001)
Top quartile county high-tech employment fraction	0.010	-0.003
	(0.003)	(0.004)
Establishments	153,090	153,090
R^2	0.287	0.141
Mean adoption rate in 2018	0.420	N/A

All regressions include controls listed for column (6) of Table 3. Robust standard errors clustered by state are in parentheses.

TABLE B15 Effects of NCA enforceability by employment size

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Employment size:	All	1-9	10-24	25-49	50-99	100-249	250-499	500+
NCA (-1,0,1)	-0.010	-0.027	-0.002	-0.005	-0.002	-0.005	-0.008	-0.022
	(0.002)	(0.006)	(0.003)	(0.001)	(0.002)	(0.003)	(0.007)	(0.008)
Log number of site employees in 2010	0.006	0.025	-0.005	-0.004	0.008	0.015	0.051	0.031
	(0.002)	(0.013)	(0.002)	(0.003)	(0.004)	(0.005)	(0.017)	(0.006)
Log number of sites in the enterprise in 2010	0.066	0.066	0.074	0.059	0.050	0.048	0.049	0.045
	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.002)	(0.003)
Top quartile county high-tech employment fraction	0.017	0.027	0.012	0.012	0.013	0.018	0.014	0.023
	(0.001)	(0.003)	(0.001)	(0.002)	(0.001)	(0.002)	(0.007)	(0.008)
Observations	834,426	212,586	312,099	156,265	78,082	52,232	13,236	9,251
R-squared	0.303	0.259	0.373	0.249	0.245	0.234	0.273	0.295

This table re-estimates Column 6 of Table 3 in the main text for alternative size bins. Columns 5–8 comprise our baseline sample of firms with at least 50 employees. Robust standard errors clustered by state in parentheses.

TABLE B16 Effects of NCA enforceability in largest firms

VARIABLES	(1) 50+ employees	(2) 100+ employees	(3) 200+ employees	(4) 400+ employees	(5) 800+ employees
NCA(-1,0,1)	-0.006	-0.009	-0.011	-0.023	-0.036
	(0.002)	(0.004)	(0.006)	(0.009)	(0.017)
Log number of site employees in 2010	0.021	0.028	0.030	0.027	0.035
	(0.002)	(0.003)	(0.004)	(0.006)	(0.011)
Log number of sites in the enterprise in 2010	0.049	0.049	0.048	0.048	0.044
	(0.001)	(0.001)	(0.002)	(0.003)	(0.004)
Top quartile county high-tech employment fraction	0.016	0.017	0.017	0.022	0.042
	(0.001)	(0.002)	(0.004)	(0.007)	(0.011)
Establishments	153,090	74,974	31,719	12,267	4,895
R^2	0.237	0.240	0.249	0.285	0.329
Mean adoption rate in 2018	0.097	0.121	0.155	0.202	0.221

This table re-estimates Column 6 of Table 3 in the main text for alternative largest size classes. Column 1 is our baseline sample of firms with at least 50 employees. Column 2 (subsample of firms with 100+ employees) is the same as Column 2 in Table 4. Robust standard errors clustered by state are in parentheses.

TABLE B17 Heterogeneous effects of NCA on adoption by industry-location size: Alternative threshold (50 employees) for large vs. small establishments

VARIABLES	(1)	(2)	(3)	(4)
NCA(-1,0,1)	-0.004	-0.003	-0.004	-0.003
	(0.002)	(0.002)	(0.002)	(0.002)
NCA x Log number of small establishments by MSA-SIC4 industry	-0.000		0.001	0.001
	(0.001)		(0.001)	(0.001)
Log number of small establishments by MSA-SIC4 industry	0.001		0.002	0.001
	(0.001)		(0.001)	(0.002)
NCA x Log number of larg*e* establishment*s* by MSA-SIC4 industry		**-0.001**	**-0.002**	**-0.002**
		(0.001)	**(0.001)**	**(0.001)**
Log number of large establishments by MSA-SIC4 industry		0.001	-0.001	-0.002
		(0.001)	(0.002)	(0.002)
NCA x Sizable MSA (with over 1m population)				-0.003
				(0.004)
Sizable MSA				0.008
				(0.002)
Establishments	153,090	153,090	153,090	153,090
R^2	0.238	0.238	0.238	0.238

All regressions include controls listed for column (6) of Table 3. Robust standard errors clustered by state are in parentheses.

TABLE B18 Manufacturing and non-manufacturing

VARIABLES	(1) Manufacturing	(2) Non-manufacturing
NCA(-1,0,1)	-0.005	-0.006
	(0.001)	(0.003)
Log number of site employees in 2010	0.022	0.022
	(0.003)	(0.002)
Log number of sites in the enterprise in 2010	0.047	0.050
	(0.001)	(0.001)
Top quartile county high-tech employment fraction	0.005	0.019
	(0.003)	(0.001)
Establishments	37,059	116,031
R^2	0.187	0.249
Mean adoption rate in 2018	0.0772	0.1039

All regressions include controls listed for column (6) of Table 3. Robust standard errors clustered by state are in parentheses.

TABLE B19 Standalone establishments

VARIABLES	Standalone establishments – ML
NCA(-1,0,1)	-0.006
	(0.002)
Log number of site employees in 2010	0.024
	(0.001)
Top quartile county high-tech employment fraction	0.013
	(0.001)
Establishments	74,081
R^2	0.084
Mean adoption rate in 2018	0.0308

All regressions include controls listed for column (6) of Table 3. Control for number of sites dropped because it is identical (=1) for all observations in this sample. Robust standard errors clustered by state are in parentheses.

TABLE B20: Tests of hypotheses 2–4 as interactions

VARIABLES	(1) ML adoption
NCA(-1,0,1)	-0.003
	(0.002)
MSA with pop over 1m in 2010	0.008
	(0.002)
MSA with pop over 1m in 2010 X NCA	-0.004
	(0.004)
Log number of site employees in 2010	0.021
	(0.002)
Log number of sites in the enterprise in 2010	0.049
	(0.001)
top quantile county hightech employment fraction in 2010	0.012
	(0.002)
Observations	153,090
R-squared	0.237
SIC4 Industry FE	YES
Effect of NCA for MSA with pop over 1m in 2010	-0.007
	(0.004)

Table above replicates the analysis in Table 6 but using interactions rather than split samples to identify the parameters of interest. All regressions include controls listed for column (6) of Table 3. Robust standard errors clustered by state are in parentheses.

VARIABLES	(2) ML adoption
NCA(-1,0,1) x Post	-0.002
	(0.003)
Industry PA adoption rate ≥ 0.75	0.022
	(0.004)
Industry PA adoption rate ≥ 0.75 x NCA	-0.004
	(0.005)
Log number of site employees in 2010	0.018
	(0.003)
Log number of sites in the enterprise in 2010	0.045
	(0.001)
top quantile county hightech employment fraction in 2010	0.006
	(0.003)
Constant	-0.120
	(0.026)
Observations	35,592
R-squared	0.198
SIC4 Industry FE	YES
Effect of NCA for PA adoption rate ≥ 0.75	-0.006
	(0.004)

Table above replicates the analysis in Table 5 but using interactions rather than split samples to identify the parameters of interest. All regressions include controls listed for column (6) of Table 3. Robust standard errors clustered by state are in parentheses.

Appendix C: NCA Enforceability Changes Considered Only in Robustness Checks

Alabama (2016): Effective 1/1/2016, Ala. Code 8-1-193 was amended to permit judicial reformation of covenants overbroad as written (Malsberger, Carr, Pedowitz, & Tate, 2017, pp. 45, 1299). However, this was part of Ala. Code 8-1-190 to 8-1-197, which replaced the old Ala. Code 8-1-1. These codes seem to have some worker-favorable features such as consideration (Malsberger, Carr, Pedowitz, & Tate, 2017, p. 1318) and presumptions of reasonableness (Malsberger, Carr, Pedowitz, & Tate, 2017, p. 1321). Moreover, it appears that judicial reformation was the norm prior to the repeal (Malsberger, Carr, Pedowitz, & Tate, 2017, p. 1333). Given that the changes had features favorable and unfavorable to workers, we set the baseline to ***0*** and performed a robustness check with values –1 and +1.
Idaho (2016) *as favoring employers:* In 2016, the Idaho legislature passed law HB 487, which adjusted Idaho's noncompete laws to say that if a "key employee…is in breach of an agreement, a rebuttable presumption of irreparable harm has been established." This effectively put the onus on the employee to prove they did not cause irreparable harm to the employer. However, shortly thereafter, and following some controversy, SB 1287 was introduced in 2018 to eliminate the language that was added through HB 487.[4] Furthermore, there was a decision in 2008 that favored employers (Ewens & Marx 2018), the effects of which could have lingered in the early years of the sample. Hence, we set the baseline to ***0*** and considered a robustness check as the change favoring employers.
Illinois (2011) *as favoring employers*: In *Reliable Fire Equipment Co v. Arredondo,* the state supreme court ruled that the enforceability of the employees' covenant not to compete should be judged by the three-prong test of reasonableness, of which the employer's legitimate business interest continues to be a part, and which looks to the totality of all of the circumstances, rather than focusing on named specific factors (*Reliable Fire Equipment Co. v. Arredondo, 2011 IL 111871*). Thus, it possibly expanded the scope of legitimate business interest. In contrast to this, subsequently, in *Fifield v. Premier Dealer Services, Inc., 2013 IL App (1st) 120327*, the appellate court set a "bright line rule" that said a minimum of two years of continued employment is necessary to establish adequate consideration. However, this bright line rule does not appear to have been universally adopted. For instance, in *R.J. O'Brien & Associates, LLC v. Williamson*, the United States District Court for the Northern District of Illinois Eastern Division observed, "Indeed, some Illinois courts have adopted a two year bright line rule" but that "[o]ther courts, however, have rejected the two year bright line rule in favor of considering other factors in determining whether sufficient consideration was given to enforce a restrictive covenant." Hence, we set the baseline to ***0*** and considered robustness checks as the change favoring employers and favoring workers.
Nevada (2016) *as favoring workers:* In *Golden Rd v. Islam,* the state supreme court affirmed that if even one provision were invalid, the whole contract would be invalid. This would favor workers since employers would be hesitant to write overly broad contracts. However, this was superseded by Assembly Bill 276 (signed into law on 6/3/2017), which amended the law to allow courts to modify any unreasonable or overbroad restrictions.[5] Hence, we set the baseline to ***0*** and considered a robustness check as the change favoring workers.

[4] https://idahofreedom.org/sb-1287-non-compete-contracts/, retrieved Oct. 28, 2019.
[5] https://www.jacksonlewis.com/publication/new-law-brings-changes-nevada-s-non-compete-law, retrieved Oct. 28, 2019.

New York (6/11/2015): In *Brown & Brown v. Johnson*, the court of appeals held that Florida law on restrictive covenants would violate New York public policy.[6] It also dismissed an overbroad restriction that prohibited the worker from working with any of the employer's customers, regardless of whether she had met them. Malsberger, Carr, Pedowitz, and Tate (2017, p. 4063) note, "Following *BDO Seidman* [1999], and consistent with…*Brown & Brown*, NY courts have declined to partially enforce an overly broad noncompete provision." Our research and inputs from lawyers suggest that the impact of *Brown & Brown* was mainly clarificatory and marginal. Hence, we also test for robustness to treating this state as a "no change."

[6] https://law.justia.com/cases/new-york/court-of-appeals/2015/92.html, retrieved Oct. 28, 2019.

Appendix D: Generalizations of model

In this appendix, we discuss the (a) possibility of some non-adopters at the end of the technology lifecycle (b) a more general speed of mobility cost reduction.

A. Generalizing to include non-adopters by the end

For ease of reference, we rewrite the first two equations from the text below:

$$bq - \frac{m}{\theta}(1-t) \geq F \tag{1}$$

$$t \geq t^* = 1 + \frac{\theta}{m}(F - bq) \tag{2}$$

If there remain some firms that do not adopt by *t*=1 (the end of the technology's lifecycle), then, it must mean that for those firms, $(F - bq > 0)$. That is, for those firms, the benefits from ML are negative even if there were no mobility costs.

Based on this, and since *b*>0, we can define a size cut-off $q^* = \frac{F}{b}$ such that for all $q < q^*$, there is no adoption. Intuitively, this means there are some small firms that never adopt.

Then, taking the derivative of $t*$ with respect to *m*, we get, $\frac{\partial t^*}{\partial m} = -\frac{\theta(F-bq)}{m^2} > 0$ for $q > q^*$. This is the same inference as before. Hence, the adoption time for larger firms (i.e., those with $q > q^*$ increases with m).

For $q < q^*$, $\frac{\partial t^*}{\partial m} = -\frac{\theta(F-bq)}{m^2} < 0$ but these firms always remain non-adopters, and hence are economically irrelevant to the adoption process.

Thus, in the presence of perennial non-adopters, our prediction can be thought of as being applicable to those at risk of adoption during the technology's lifecycle.

B. Generalized speed of mobility cost reduction

Keeping $t \in [0,1]$, consider a more general form of Equation (1),

$$bq - \frac{m}{\theta}(1 - \omega t) \geq F\ , \omega > 0 \tag{A1'}$$

Note that if $\omega = 1$, we get the scenario considered in the main text. Also, the higher is the ω, the faster is the decline in mobility costs. As before, solving for the earliest optimal time of adoption,

$$t \geq t^* = \frac{1}{\omega} + \frac{\theta}{m\omega}(F - bq) \tag{A2'}$$

Taking the derivative of t^* with respect to *m*, we get:

$$\frac{\partial t^*}{\partial m} = -\frac{\theta(F-bq)}{\omega m^2} \tag{A3'}$$

Consider the (small) firms for which $(F - bq > 0)$. Let $q^* = \frac{F}{b}$ be the size for which $(F - bq = 0)$. In the baseline case of $\omega = 1$, as discussed in the subsection above, small firms with $q < q^*$ will not adopt by t=1, and remain perennial non-adopters.

However, this changes as ω increases beyond 1. Specifically, from (A2'), we can see that for large enough ω, t^* can be less than 1 (specifically if $\omega \geq 1 + \frac{\theta}{m}(F - bq)$). Then, we will have adoption by the small firms before the end of the technology lifecycle.

Then, from (A3') it is clear that for these small firms, $\frac{\partial t^*}{\partial m} < 0$. That is, mobility will accelerate adoption among such firms.

To summarize, the sign of $\frac{\partial t^*}{\partial m}$ will be influenced by two conditions: (1) whether or not fixed costs are sufficiently high relative to the benefits of adoption (i.e., whether $(F - bq > 0)$) and (2) the size of ω (the rate of decline of mobility costs over time). We characterize the sign of the derivative over the parameter space in the table below:

		Size of ω (rate of decline of mobility costs)	
		$\omega < 1 + \frac{\theta}{m}(F - bq))$	$\omega \geq 1 + \frac{\theta}{m}(F - bq))$
Size of fixed costs relative to benefits of adoption	$F - bq \leq 0$	$\frac{\partial t^*}{\partial m} \geq 0$	$\frac{\partial t^*}{\partial m} \geq 0$
	$F - bq > 0$	$\frac{\partial t^*}{\partial m} = 0$ (these firms never adopt)	$\frac{\partial t^*}{\partial m} < 0$

If there are firms for whom fixed costs are sufficiently high relative to benefits $(F - bq > 0)$, and the rate of decline in mobility costs is sufficiently large, mobility will accelerate adoption among such firms.

Appendix E: Details of Survey Data

We conducted an online survey of IT professionals using the survey development environment and survey panels provided by Qualtrics. To be included in the survey, respondents needed to indicate that:

1. The respondent had been employed as a project manager, technical lead, business lead, or similar role at a for-profit company. (Roles as an external consultant excluded.)
2. The respondent had been involved in two or more IT projects as a key team member. IT projects were defined as ones that involved the deployment of new software that will be used by many people in the organization, and that typically require a large investment.
3. The respondent was currently in an organization with 50 or more employees.
4. The respondent was located in the US.

Several quality checks, some internally within Qualtrics and others jointly by Qualtrics and the researchers, were performed after the initial data collection and respondents who did not meet these checks were replaced with ones that did. These checks are described below.

Internal Quality Checks by Qualtrics

1. Checks for potential duplicates through technical means such as deploying cookies and checking the metadata on the respondent's machine.
2. Uses geocoding to ensure the respondent is within the target country.
3. Flags respondents who take the survey too quickly. For this survey, we went beyond the baseline Qualtrics norm (1/3rd of median completion time) and set a minimum completion time of 5 minutes.
4. Employs Captcha for bot detection (captcha scores < 0.5).

Joint Quality Checks by Qualtrics and Researchers

1. Deploy attention check and commitment check questions. (Attention checks are questions that are used to identify respondents who aren't paying attention. Commitment check questions ask respondents whether they commit to providing high-quality answers.)
2. Check of open-ended responses. One of our questions asked respondents whether they had familiarity with new technologies like AI/ML, IoT, or Blockchain. We manually checked responses and asked Qualtrics to remove those that included text that was gibberish or did not match the question that was asked (e.g., a response of "I enjoyed the customer service ads" when asked for new technologies that the respondent had previously worked on).
3. Identify respondents who had been involved in "straightlining," or the practice of providing the same answer on a grid of questions with the goal of quickly finishing the questions.

The final data set included 197 observations, and the median completion time was 575 seconds (roughly 9.5 minutes). We provide some details on our data below.

Appendix F: Survey Results

This appendix provides the verbatim questions (including any bold, italics or underlined highlights) along with the summary results for the key questions in this survey. For brevity, we have excluded from our discussion here most questions not directly related to the theoretical arguments, such as screening, attention, commitment and demographic questions. We have also not presented the skip logic, display logic and randomizations used in the survey. A copy of the complete questionnaire is available from the authors on request.

DEFINITIONS AND KEY INSTRUCTIONS PROVIDED TO RESPONDENTS

This research project aims to better understand employee turnover in large IT systems implementation projects ("IT projects") **at large for-profit businesses**.

IT projects: A project that involves the deployment of new software that will be used by many people in the organization, and typically <u>requires a large investment by the organization</u>. This could include, but not limited to, software such as packaged enterprise software systems, custom developed software, etc.

New technologies: Technologies that companies in your industry have only <u>recently</u> (in the last 5 years) begun using, and that <u>require a large investment by the organization</u> (e.g., machine learning/AI, Internet of Things, AR and VR, Big Data, and Blockchain in many industries).

Existing technologies: Technologies that are <u>well-established</u> in your industry for more than 5 years and that <u>require a large investment by the organization</u> (e.g., ERP software). IT projects with existing technologies can involve both completely new systems, and/or major upgrades and modifications of existing systems.

Throughout, please *only* consider IT projects in **for-profit businesses**.

SUMMARY OF RESULTS

In the following analyses, **N=197** unless stated otherwise. In such cases, lower sample sizes were typically because some respondents were not familiar with new technologies or less frequently, due to non-response. In some tables, proportions may not add to 100% due to rounding.

Q How many employees work at your current employer? Please provide your best guess.

Size Class	**Proportion of Responses**
50-99	12%
100-499	32%
500-4999	40%
5000 or more	17%

Q How many projects have you been involved as a key team member (i.e., project manager, technical lead, business lead or a similar role)?

Number of projects	**Proportion of Responses**
2-5	43%
>5	57%

Q How many months did your projects typically take to complete? If it is a range, pick the middle of the range. Choose 36 months if more than 3 years.

Mean number of months (from slider): 13.99 months

Q How would you describe your familiarity with IT projects involving **new technologies** (e.g., ML/AI, IoT, AR/VR, Big Data, Blockchain etc.)?

Familiarity	**Proportion of Responses**
Not familiar[$]	12% (N=23)
Familiar but no experience	8% (N=16)
Have experience with these technologies	80% (N=158)

$ Note: These respondents did not generally receive further questions related to new technologies. In a few cases where they received such questions, their responses were excluded from the analyses to make numbers comparable.

The total number of respondents who were familiar or had experience with new technologies was **174**.

Q How many months did your projects involving these new technologies typically take to complete? If it is a range, pick the middle of the range. Choose 36 months if more than 3 years.

Mean number of months (from slider): 15.27 months (N=158 of 158)

Q What industry is your current employer? If the company is more than one industry, choose the main industry that it is in. [drop-down menu of NAICS-2 codes]

Top 3 industries
Information: 21%; Manufacturing: 16%; Professional, Scientific, and Technical: 16%

Q In the last 3 years, has your current company implemented any **new technologies** (e.g., ML/AI, IoT, AR/VR, Big Data, Blockchain etc.)?

Yes: 92%; No: 8%; N=192 of 197

Q If you were hiring a key team member for an IT project, how would you rate the importance of the following in your hiring decision? Rate 1 if not important and 5 if extremely important

	Mean rating
Having completed a college degree or non-degree program related to IT	4.15
Experience working on an IT project at another company (in any industry)	4.35
Experience working on an IT project at a competitor or a company in the same industry as your company	4.03
Experience working on projects with a similar technology as your project	4.44

Q If you were hiring a key team member for an IT project, where would the following criteria be **more important** in your hiring decision?

N=174

	Share of Respondents		
	More Important in Existing Technology Projects	More Important in New Technology Projects	About the same importance for both types of projects
Having completed a college degree or non-degree program related to IT	28%	28%	44%
Experience working on an IT project at another company (in any industry)	30%	39%	31%
Experience working on an IT project at a competitor or a company in the same industry as your company	29%	39%	32%
Experience working on projects with a similar technology as your project	31%	34%	35%

Q For which type of projects is on-the-job learning (i.e., learning about aspects that can only be learnt by being on the project after hiring) for key team members **more important**?

N=174

	Proportion of Responses
More important for projects involving existing technologies	25%
More important for projects involving new technologies	41%
About the same for both types of projects	34%

Q After being hired, how important is on-the-job learning (learning about aspects that can only be learnt by being on the project) for key team members to be fully effective?

N=174

	Share of respondents rating "extremely important"	Share of respondents rating "very important"	Share of respondents rating "not important" or "moderately important"
Projects involving existing technologies	37%	44%	19%
Projects involving new technologies	55%	40%	6%

Q Thinking about IT projects in your industry, how often do key team members (i.e., project managers, leads or similar roles) **voluntarily** leave employment during the project for a different job? Please provide your best guess.

Frequency of voluntary departure	**Proportion of Responses**
Not very often (less than 10% of projects)	36%
Somewhat often (11-25% of projects)	25%
Often (26-50% of projects)	28%
Very often (>50% of projects)	11%

Q For which type of projects is the likelihood of key team members voluntarily leaving employment during the project **higher**?

N=174

Type of project	**Proportion of Responses**
Projects involving existing technologies	17%
Projects involving new technologies	51%
About the same for both types of projects	32%

Q Considering only **projects where you were a key team member**, has a key team member including yourself ever voluntarily left employment during the project?

Yes: 53%; No: 47%

Q Based on your experience, how would you rate the percentage chance of a key team member voluntarily quitting during a project?

(N=170 of 174)

	Mean (from slider)
For projects with existing technologies	33%
For projects with new technologies	40%

Q Based on your experience, what factors may increase the likelihood of the **voluntary** departure of key team members during a project? Choose all that apply.

	Proportion of Responses
Larger size and complexity of the project	49%
Larger size of the employer	26%
Technology involved in the project is new	49%
Being in a location with many companies nearby	32%
Being in a location close to many competitors in the same industry	32%
Problems with project progress	47%
Not being bound by contractual agreements such as noncompete agreements	38%

Note: Proportions add up to more than 100% because respondents could choose multiple answers.

Q Based on your experience, where do voluntarily departing key team members usually go to?

Destination	**Proportion of Responses**
Competitor in the same industry	55%
Company in a different industry	27%
Become a consultant	12%
Become an entrepreneur	6%
Other	1%

Q For projects using **existing technologies**, which of the following are likely to be a major problem if key team members quit during the project.
N=174

	Proportion of responses
Difficulties finding replacement	47%
Difficulties training and onboarding replacement	43%
Delays in meeting project milestones	52%
Higher project costs	40%
Issues with quality of deliverables	33%
Loss of competitive advantage/valuable knowledge to competitors	34%

Note: Proportions add up to more than 100% because respondents could choose multiple answers.

Q For projects using **new technologies** (e.g., ML/AI, IoT, AR/VR, Big Data, Blockchain etc.), which of the following are likely to be a major problem if key team members quit during the project.
N=174

	Proportion of responses
Difficulties finding replacement	48%
Difficulties training and onboarding replacement	47%
Delays in meeting project milestones	46%
Higher project costs	36%
Issues with quality of deliverables	35%
Loss of competitive advantage/valuable knowledge to competitors	36%

Note: Proportions add up to more than 100% because respondents could choose multiple answers.

Q Where is the **replacement** for the quitting key team member usually from?

Source	Proportion of Responses
From within the company	53%
From a competitor or another company in the same industry	26%
From a company in a different industry	9%
From a consulting company	11%
Other	1%

Q For which type of projects does it take **longer** to find, train and onboard a replacement so that the new team member is fully effective in their new position?

N=174

Type of project	Proportion of Responses
Projects involving existing technologies	20%
Projects involving new technologies	54%
About the same for both types of projects	26%

Q How many months does it usually take to find, train and onboard a replacement **so that the new team member is fully effective** in their new position? If it is likely to be a range, pick the middle of the range as your response. Choose 12 months if more than a year.

N=174

Type of project	Mean number of months (from slider)
Projects involving existing technologies	4.64 (N=171 of 174)
Projects involving new technologies	5.80 (N=168 of 174)

Q For which type of projects is the **cost impact** of a key team member's departure **higher**?

N=174

Type of project	Proportion of Responses
Projects involving existing technologies	17%
Projects involving new technologies	52%
About the same for both types of projects	30%

Q How much does the departure of a key team member typically add to the total project cost? If it is likely to be a range, pick the middle of the range as your response. Choose 100 if more than 100%.

N=174

Type of project	Mean % increase (from slider)
Projects involving existing technologies	38.20% (N=167 of 174)
Projects involving new technologies	45.54% (N=166 of 174)

Q To the best of your knowledge, how common are non-compete agreements (NCAs) in your local market among your competitors? *Note: NCAs are agreements that prohibit employees from joining their employers' competitors or starting a competing business.*

N=194 of 197

	Proportion of Responses
Very uncommon (0-10% of people have them)	6%
Somewhat uncommon (11-25% of people have them)	24%
Somewhat common (26-50% of people have them)	43%
Very common	26%

Q Does your company generally require NCAs for key team members (i.e., project managers, leads or similar roles)?

	Proportion of Responses
Yes	66%
No	29%
Not sure/don't know	5%

Q Did you sign an NCA in your current job?

N=196 of 197

	Proportion of Responses
Yes	57%
Probably yes	10%
Probably no	2%
No	31%

Q Has an NCA ever made it difficult for you to move to a new job in the past?

Yes: 6%; No: 94%

Q Have NCAs ever hindered you from hiring a key team member in any of your projects?

Yes: 34%; No: 66%