Intangible Capital Meets Skilled Labor: The Implications for Productivity Dynamics

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Introduction

- Hot discussion on how technological change shapes **productivity**
- In the U.S., we observe:
  - **Rising productivity dispersion** between small and large firms Andrews et al. (2016), Van Ark (2016), Gutiérrez & Philippon (2017), Autor et al. (2020), Akcigit & Ates (2023), and many more
  - **Rising intangible capital** economy-wide Corrado et al. (2009), O'Mahony & Vecchi (2009), Van Ark et al. (2009), Niebel et al. (2017), Peters & Taylor (2017), Haskel & Westlake (2018), Brynjolfsson et al. (2019), De Ridder (2019), Ewens et al. (2019), Chiavari & Goraya (2020), McGrattan (2020), and many more
  - **Higher skill-biased** technological change Greenwood & Yorukoglu (1997), Acemoglu (1998), Krusell et al. (2000), Aghion et al. (2002), Autor et al. (2008), Violante (2008), and many more

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- complementarity between intangible capital and skilled labor
- its impacts on productivity dispersion between small and large firms

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Motivation

- Distinct feature of intangible capital: scalability
  - More pronounced in large firms (with multiple business lines)
- Skilled labor is required to utilize their intangible capital

Anecdotal Example

Firm	Intangible Ratio	Skill Intensity	Intangible Capital	Skilled Labor
Amazon	0.73	0.46	Consumer data	Ph.D. researchers
Apple	0.77	0.47	Design	Product designers
Google	0.68	0.54	Branding	Data analytics
IBM	0.85	0.47	R&D	Inventors
Microsoft	0.85	0.72	Software	IT engineers
Economy average	0.53	0.3		

- We proxy skilled labor by firm-level share of AI workers

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What We Do

Stylized Facts:

- Intangible capital, skilled labor, and productivity across firm-size distribution

Empirical Analysis:

- Exploit a shock to AI worker effectiveness and implement a DiD analysis
- Quantify intangible capital - skilled labor complementarity
- Estimate the association between the complementarity and firm-level productivity

Robustness Checks:

- Firm-level TFP (OP, LP, WRDG, ACF)
- Industry-level measures
- Placebo test
- Propensity score matching
- Alternative measures and controlling other factors

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- increasing productivity dispersion between small and large firms
- increasing share of intangible capital by large firms
- increasing share of skilled labor in large firms

Empirical Analysis:

- Complementarity between intangible capital and skill labor
  - higher for large firms
- Intangible capital - skilled labor complementarity brings higher productivity
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Literature

- **U.S. business dynamism**

  Andrews et al. (2016), Gutierrez & Philippon (2017), Decker et al. (2018), Akcigit & Ates (2019), Crouzet & Eberly (2019), Autor et al. (2020), De Loecker et al. (2021), and many more

  This paper: the role of intangibles in business dynamism

- **Secular rise in intangible capital**

  Corrado et al. (2009), O'Mahony & Vecchi (2009), Van Ark et al. (2009), Niebel et al. (2017), Peters & Taylor (2017), Brynjolfsson et al. (2019), De Ridder (2019), Ewens et al. (2019), Chiavari & Goraya (2020), Falato et al. (2020), McGrattan (2020), and many more

  This paper: the role of skill requirement of intangibles

- **Technical change and labor market dynamics**

  Griliches (1969), Katz & Murphy (1992), Greenwood & Yorukoglu (1997), Acemoglu (1998), Krusell et al. (2000), Aghion et al. (2002), Autor et al. (2008), Violante (2008), and many more

  This paper: the role of intangibles as a new form of technical change

Outline

Measurement

Stylized Facts

Descriptive Analysis

DiD Analysis

Robustness Checks

Conclusion

Measurement

Measurement 1/2

Intangible Capital ▸ Details ▸ Histogram ▸ Industry Variation

- Computstat data. Perpetual inventory method (Peters and Taylor (2017))

Externally acquired + Knowledge capital + Organizational capital

Skill Intensity ▸ Details

- Quarterly Workforce Indicators (QWI) from U.S. Census Bureau

Skill intensity = share of "Bachelor's degree or advanced degree"

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Measurement 2/2

Share of AI workers

Details · Histogram · Industry Variation

- Measure provided by Babina et al. (2024), Journal of Financial Economics (JFE).
- Firm-level share of AI workers as a measure of firms' AI-intensity

Productivity

- Compustat data. Sales per worker (usual in empirical macro)
  (Comin & Philippon (2005), Gutierrez & Philippon (2016), Autor et al. (2020))
- Firm-level TFP as robustness.
  (Olley and Pakes (1996), Levinsohn and Petrin (2003), Wooldridge (2009), Ackerberg, Caves and Frazer (2015))

Sample Construction · Sample Composition · Summary Statistics · Pairwise Correlation

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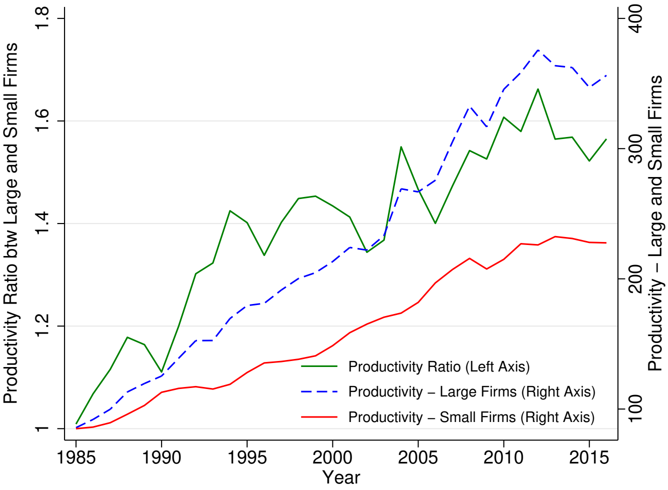
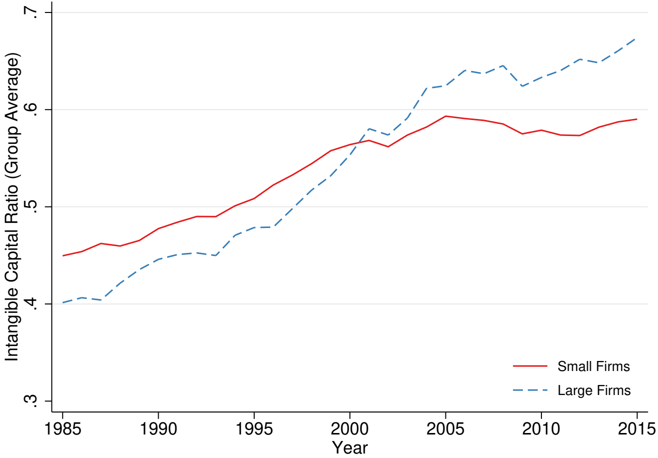
Stylized Facts

1. Increasing productivity gap, driven by large firms

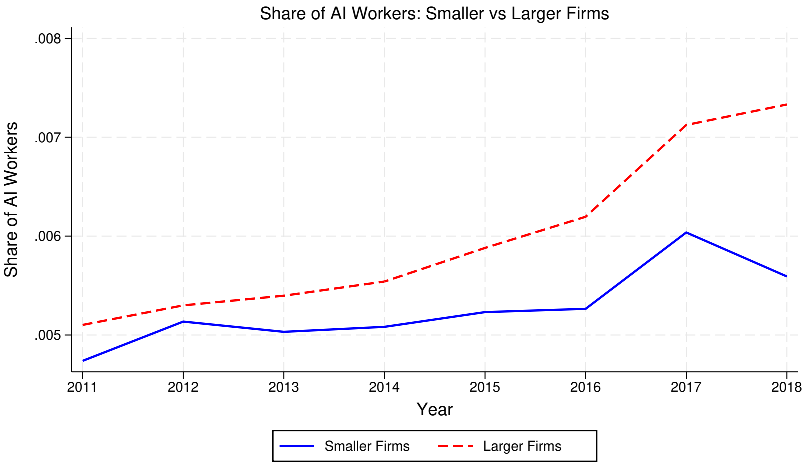


2. Increasing intangible capital by large firms

▸ All Sample

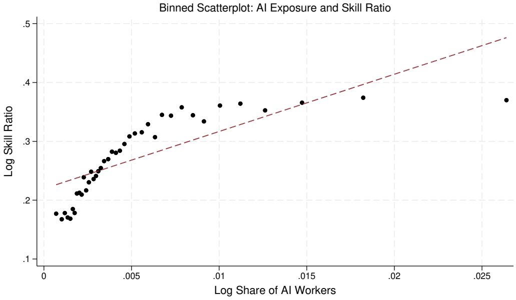


3. Increasing share of AI workers by large firms



Descriptive Analysis

Skill Ratio, Intangible Capital, and AI Workers



(a) Skill Ratio vs. AI Workers

(b) Intangible Capital vs. AI Workers

Association between AI Workers, Skill Labor and Intangible Capital

	(1)	(2)	(3)	(4)	(5)	(6)
	Dependent Variable: Skill Ratio					
Share of AI Workers	9.114***	9.254***	1.488***	5.798***	5.955***	0.893***
	(0.690)	(0.695)	(0.245)	(0.588)	(0.593)	(0.222)
Control Variables	No	No	No	Yes	Yes	Yes
Year FE	No	Yes	Yes	No	Yes	Yes
Industry FE	No	No	Yes	No	No	Yes
Adjusted R^2	0.170	0.175	0.756	0.294	0.300	0.775
Observation	15180	15180	15167	14745	14745	14732
	Dependent Variable: Log Intangible Capital					
Share of AI Workers	9.272**	7.005	20.35***	10.45***	10.23***	5.103***
	(4.403)	(4.418)	(4.647)	(1.976)	(1.977)	(1.717)
Control Variables	No	No	No	Yes	Yes	Yes
Year FE	No	Yes	Yes	No	Yes	Yes
Industry FE	No	No	Yes	No	No	Yes
Adjusted R^2	0.001	0.009	0.249	0.714	0.714	0.842
Observation	17599	17599	17587	16266	16266	16253

Standard errors (in parentheses) are clustered at the firm level. $^{*}\ p < .10$, $^{**}\ p < .05$, $^{***}\ p < .01$.

DiD Analysis

Identification Strategy

- 2015 release of Google TensorFlow as an exogenous shock (Rock (2019))

  Identification Assumptions

  - widely adopted open-source machine learning platform
  - provides cost-effective way of deploying AI technologies
- Economic value of AI-related innovations rises after TensorFlow (Chen et al. (2024))
- Firm job posting references to TensorFlow jump from zero before 2015 to 26,000+ between 2016–2021 (Chen et al. (2025))
- Difference-in-differences (DiD) design
  - estimate how the effectiveness of AI labor affects intangibles and productivity
- Dynamic DiD design to investigate the dynamic role of firm-size

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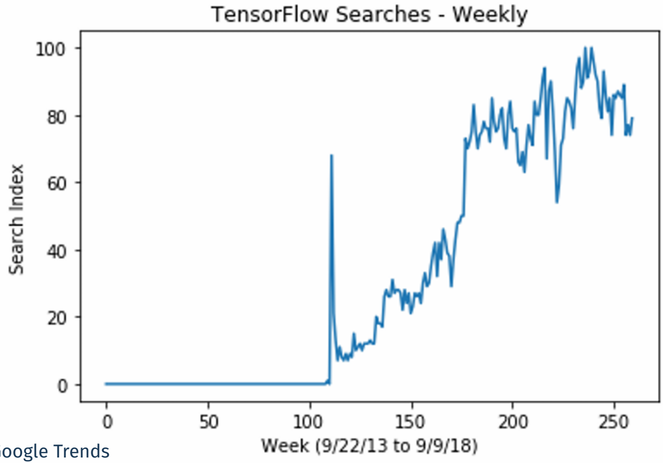
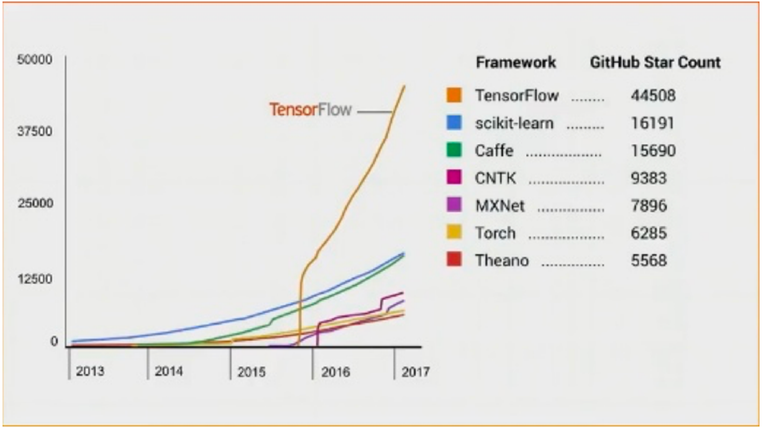
TensorFlow as Surprise



Source: Rock (2019), Google Trends

TensorFlow as Deep Learning Library



Source: Rock (2019), Jeff Dean (Talk at MIT 2018)

Empirical Strategy

$$\boxed{\text{Y}_{it} = \beta_1 \text{Post}_t \times \text{Share of AI Workers}_{i,2014} + X'_{it-1}\gamma + \lambda_t + \theta_s + \delta_j + \mu_i + \varepsilon_{it}}$$

- Y_{it}: firm-level log of intangible capital or log of labor productivity
- Post$_t$: 1 for years following the release of TensorFlow (i.e., $t \geq 2015$), and 0 otherwise
- Share of AI Workers$_{i,2014}$: firm's share of AI-related workers in 2014
- X_{it-1}: 1-year lagged log of {total assets, R&D expenditures, capital expenditures}, the cash-to-asset ratio, markup, and dividend-to-asset ratio
- $\{\lambda_t, \theta_s, \delta_j, \mu_i\}$: {year, state, industry, and firm fixed effects}
- Standard errors are clustered at the firm level

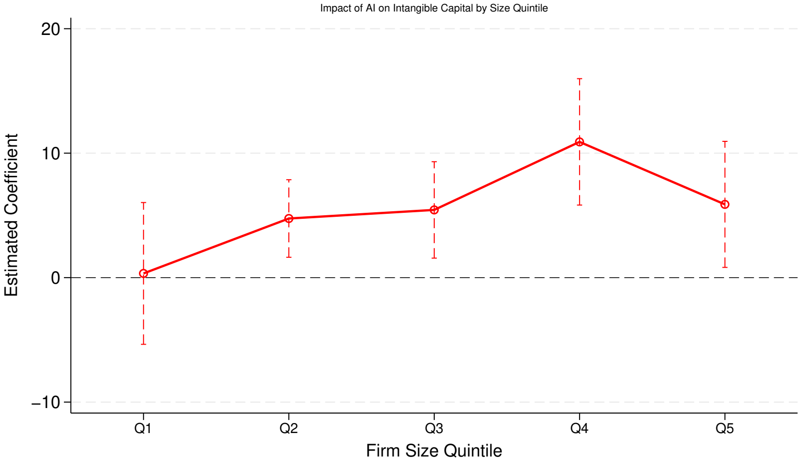
DiD Estimates: Intangible Capital and AI Worker

	(1) Log Intangible	(2) Log Intangible	(3) Log Intangible	(4) Log Intangible
Post × Share of AI Workers$_{2014}$	8.222***	7.792***	7.792***	8.067***
	(1.480)	(1.464)	(1.475)	(1.558)
Control Variables	Yes	Yes	Yes	Yes
Year FE	No	Yes	Yes	Yes
Industry FE	No	No	Yes	Yes
State FE	No	No	No	Yes
Firm FE	Yes	Yes	Yes	Yes
Adjusted R^2	0.945	0.946	0.945	0.949
Observation	32920	32920	32920	27712

$^{*}\ p < .10$, $^{**}\ p < .05$, $^{***}\ p < .01$.

- 2.4% increase in intangible capital for the average firm
    - corresponds to an increase of $\sim$ \$3 million

DiD Estimates by Firm Size Quintiles: Intangible Capital and AI Worker



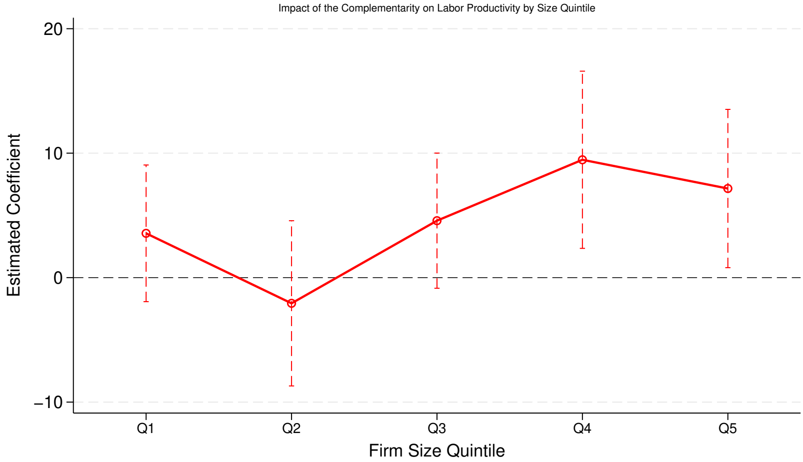
DiD Estimates: Labor Productivity, AI Worker, and Intangible Capital

	Dependent Variable: Log Productivity				
	(1)	(2)	(3)	(4)	(5)
Post $\times$ Share of AI W.$_{2014}$	3.639^{***}	3.633^{***}	3.633^{***}	5.269^{***}	4.440^{***}
	(1.249)	(1.257)	(1.267)	(1.319)	(1.362)
Post $\times$ Share of AI W.$_{2014}$ $\times$ L.Intangible					6.097^{***}
					(1.822)
Control Variables	Yes	Yes	Yes	Yes	Yes
Year FE	No	Yes	Yes	Yes	Yes
Industry FE	No	No	Yes	Yes	Yes
State FE	No	No	No	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.951	0.951	0.950	0.954	0.954
Observation	32919	32919	32919	27711	27711

$^{*}\ p < .10,\ ^{**}\ p < .05,\ ^{***}\ p < .01.$

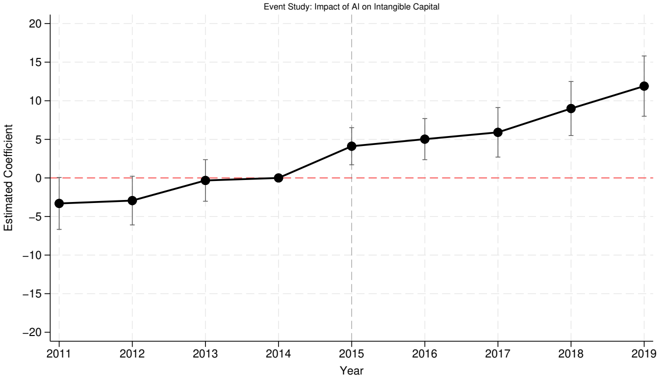
- an increase of $\sim \$3,400$ in productivity for 25th pct. and $\sim \$6,400$ for 75th pct.

DiD Estimates by Firm Size Quintiles: Productivity



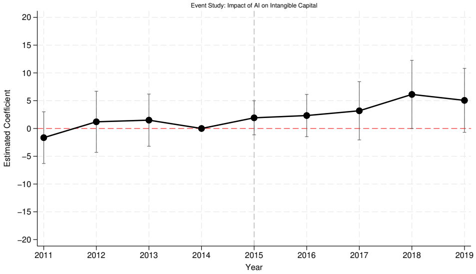
Dynamic DiD Estimates: Intangible Capital and AI Worker

$$Y_{it} = \sum_{\tau \neq -1} \beta_\tau \left(\mathbb{1}\{t = \tau\} \times \text{Share of AI Workers}_{i,2014} \right) + X'_{it-1}\gamma + \lambda_t + \theta_s + \delta_j + \mu_i + \varepsilon_{it}$$

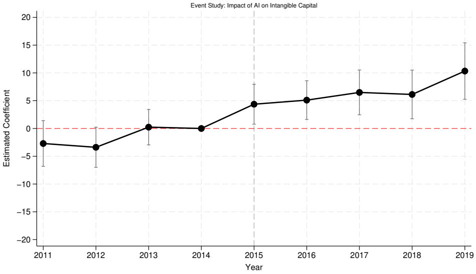


Confidence intervals are shown at the 95% level.

Dynamic DiD Estimates by Firm Size: Intangible Capital and AI Worker



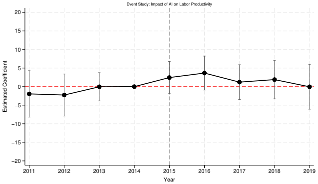
(a) Smaller Firms



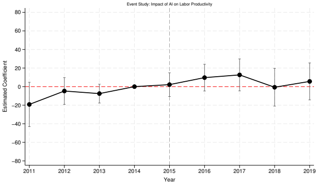
(b) Larger Firms

Confidence intervals are shown at the 95% level.

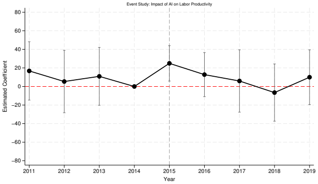
Dynamic DiD Estimates: Labor Productivity, AI Worker, and Intangible Capital



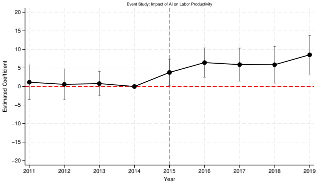
(a) Smaller Firms & Lower Intangible



(b) Smaller Firms & Higher Intangible



(c) Larger Firms & Lower Intangible



(d) Larger Firms & Higher Intangible

Robustness Checks

TFP, AI Worker, and Intangible Capital

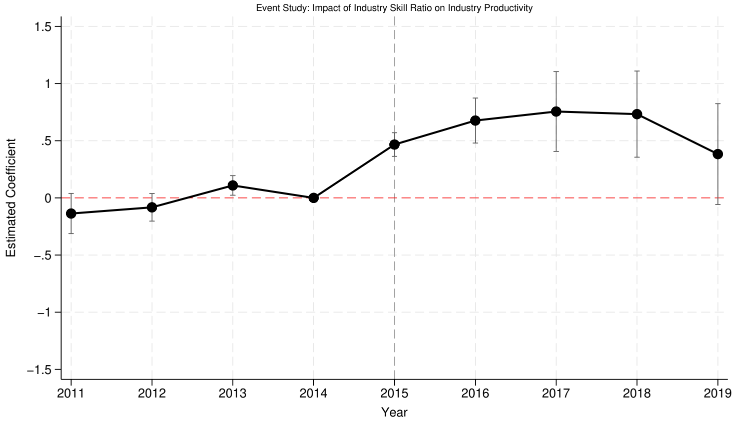
- Dep. var: Firm-level TFP based on Olley and Pakes (OP, 1996), Levinsohn and Petrin (LP, 2003), Wooldridge (WRDG, 2009), and Ackerberg, Caves and Frazer (ACF, 2015)

Dependent Variable: Log TFP	OP	LP	WRDG	ACF
Post $\times$ Share of AI W.$_{2014}$	1.767	2.071*	1.963*	2.252*
	(1.344)	(1.133)	(1.129)	(1.183)
Post $\times$ Share of AI W.$_{2014}$ $\times$ L.Intangible	10.50***	4.877**	5.085**	4.247*
	(2.604)	(2.184)	(2.225)	(2.178)
Control Variables	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Adjusted R^2	0.887	0.800	0.807	0.788
Observation	32919	32918	32918	32918

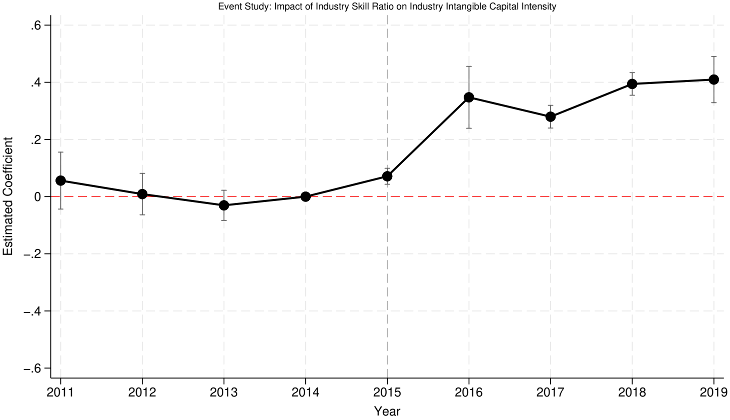
$^{*}\ p < .10$, $^{**}\ p < .05$, $^{***}\ p < .01$.

Industry-level Measures - Industry Skill Ratio and Productivity

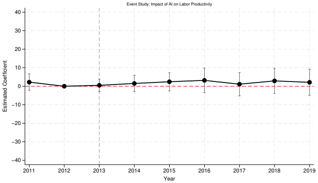
- Integrated Industry-Level Production Account (KLEMS) data



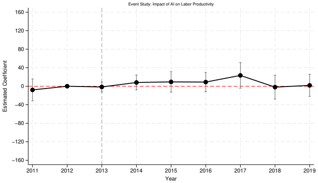
Industry-level Measures - Skill Ratio and Intangible Capital Intensity



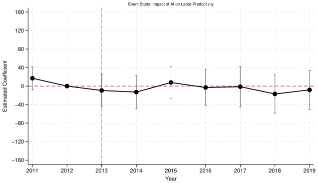
Placebo Test



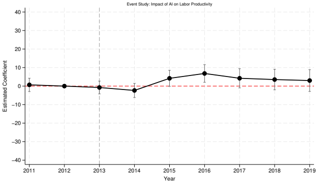
(a) Smaller Firms & Lower Intangible



(b) Smaller Firms & Higher Intangible

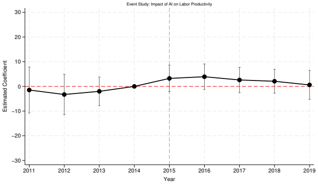


(c) Larger Firms & Lower Intangible

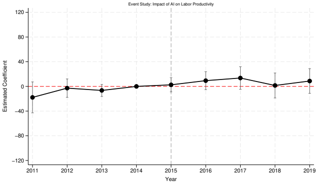


(d) Larger Firms & Higher Intangible

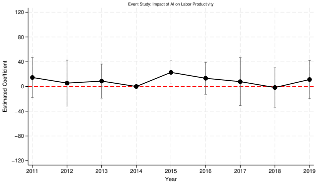
Propensity Score Matching



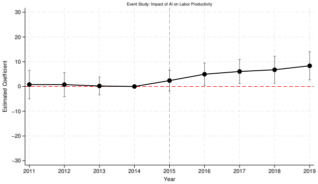
(a) Smaller Firms & Lower Intangible



(b) Smaller Firms & Higher Intangible



(c) Larger Firms & Lower Intangible



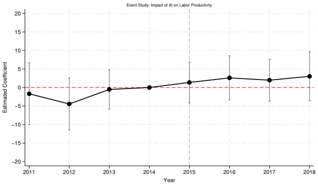
(d) Larger Firms & Higher Intangible

Controlling for Time Trends

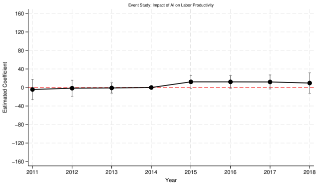
	(1) Log Productivity	(2) Log Productivity	(3) Log Productivity
Post × Share of AI W.$_{2014}$	4.302***	4.815***	5.051***
	(1.407)	(1.514)	(1.545)
Post × Share of AI W.$_{2014}$ × L.Intangible	6.008***	6.500***	6.485***
	(1.838)	(1.838)	(1.850)
Control Variables	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes
State FE	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
State Time Trend	Yes	No	Yes
Industry Time Trend	No	Yes	Yes
Adjusted R^2	0.954	0.955	0.955
Observation	27711	27711	27711

$^{*}\ p < .10$, $^{**}\ p < .05$, $^{***}\ p < .01$.

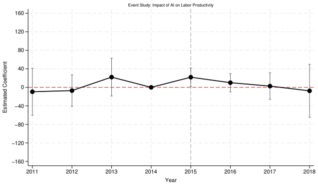
Controlling for Other Firm-level Technologies (Babina et al. (2024))



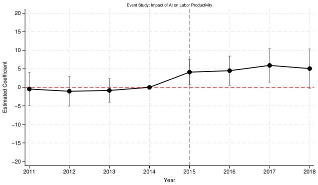
(a) Smaller Firms & Lower Intangible



(b) Smaller Firms & Higher Intangible

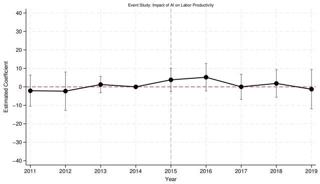


(c) Larger Firms & Lower Intangible

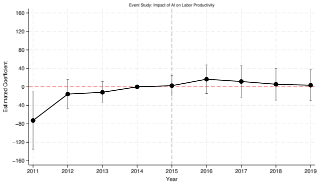


(d) Larger Firms & Higher Intangible

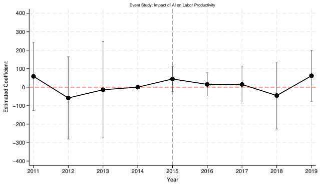
Alternative AI Measure - Narrow AI Skills (Babina et al. (2024))



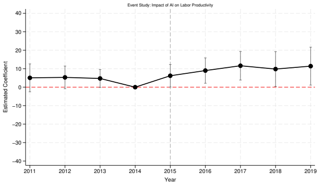
(a) Smaller Firms & Lower Intangible



(b) Smaller Firms & Higher Intangible



(c) Larger Firms & Lower Intangible



(d) Larger Firms & Higher Intangible

Intangible Capital Components

	(1) Knowledge C.	(2) Organizational C.	(3) Off-Balance-Sheet Int.	(4) R&D
Post $\times$ Share of AI W.$_{2014}$	13.11***	9.809***	8.480***	10.61***
	(1.794)	(1.895)	(1.530)	(1.670)
Control Variables	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Adjusted R^2	0.990	0.963	0.970	0.985
Observation	27712	27712	27712	27712

* $p < .10$, ** $p < .05$, *** $p < .01$.

Conclusion

Conclusion

- Complementarity between intangible capital and skilled labor

Empirical Takeaway:

- The complementarity increases firm-level productivity at large firms
  - would be a key factor of observed $\Uparrow$ in productivity dispersion

Potential Extensions:

- Underlying forces (e.g. market concentration, monopsony power)
- Labor market dynamics (e.g. labor mobility, job reallocation)

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Thank you!

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Appendix

Measurement

Intangible Capital ▸ Back

- Intangible capital stock (INT_{it}) is defined as (Peters and Taylor (2017))

$$INT_{it} = \underbrace{G_{it}}_{\text{Externally acquired}} + \underbrace{A_{it} + B_{it}}_{\text{Internally acquired}}$$

  - G_{it}: Externally acquired intangible capital
  - A_{it}: Knowledge capital stock

$$A_{it} = (1 - \delta_{R\&D})A_{it-1} + R\&D_{it}$$

    $\delta_{R\&D}$: industry-specific R&D depreciation rates (Ewens et al. (2020))

  - B_{it}: Organizational capital stock

$$B_{it} = (1 - \delta_{SG\&A})B_{it-1} + \gamma \times SG\&A_{it}$$

    $\delta_{SG\&A} = 0.2$ and γ: industry-specific percent of SG&A (Ewens et al. (2020))

Skill Intensity

Back

- Quarterly Workforce Indicators (QWI) from U.S. Census Bureau
- Skill intensity = share of "Bachelor's degree or advanced degree"
- Merge the measurement of skill intensity with Compustat
  - using a crosswalk by state, year, 4-digit NAICS and firm size

Example - Variation across Industry, State, Firm Size and Year

Firm	4-digit NAICS	State	Firm Size	Year	Skill Intensity
MORNINGSTAR INC	Other Information Services	IL	Large	2008	0.57
SABA SOFTWARE INC	Other Information Services	CA	Large	2008	0.7
ROCK ENERGY RESOURCES INC	Metal Ore Mining	TX	Small	1996	0.15
MIND TECHNOLOGY INC	Electronic Instrument Manufacturing	TX	Small	1996	0.24

Sample Construction and Summary Statistics

Sample Construction: Firm-Year Panel

Back

Step	Dropped Firms	Dropped Obs.	Remaining Firms	Remaining Obs.
Initial sample (2011–2019)			14,571	84,522
Exclude Financials, Utilities, and Other Industries	6,354	37,286	8,217	47,236
After dropping singletons and missing values in regressions	4,257	19,525	3,960	27,711
Final sample			**3,960**	**27,711**

Sample Composition

Back

Panel A: Sample Composition by Year		
Year	Number of Observations	Percentage of Observations
2011	2,810	10.1
2012	2,960	10.7
2013	3,199	11.5
2014	3,461	12.5
2015	3,401	12.3
2016	3,296	11.9
2017	3,071	11.1
2018	2,863	10.3
2019	2,650	9.6
Total	27,711	100.0

Panel B: Sample Composition by Industry		
Industry	Number of Observations	Percentage of Observations
Consumer Non-Durables	1,484	5.4
Consumer Durables	880	3.2
Manufacturing	3,100	11.2
Oil, Gas, and Coal	1,894	6.8
Chemicals	997	3.6
High Tech	6,164	22.2
Telephone and Television	804	2.9
Wholesale and Retail	3,185	11.5
Healthcare	4,786	17.3
Other	4,417	15.9
Total	27,711	100.0

Summary Statistics

Back

	Mean	SD	P25	P50	P75	Min	Max	Count
Log Assets	5.4431	2.4689	3.6973	5.6356	7.2095	0	12.5495	27711
Log R&D	-3.7840	2.8017	-5.9557	-3.6378	-1.7157	-12.4934	5.0502	27711
Log Capital Expenditures	2.4772	2.0666	0.4906	2.2548	3.9287	-0.0066	9.9667	27711
Cash-to-Assets	0.1645	0.1905	0.0342	0.0980	0.2164	-0.8256	1	27659
Log Firm Age	3.1772	0.8137	2.7081	3.2581	3.7842	0.6931	5.1874	27711
Markup	2.0992	9.7264	1.0628	1.3217	1.9042	-22.6266	1115.2	27425
Dividends-to-Assets	0.0155	0.0926	0	0	0.0118	-0.0001	9.7985	27711
Log Labor Productivity	3.8965	1.7053	2.9871	4.2938	5.0159	-0.2807	10.1950	27711
Log Intangible Capital	4.7996	2.2689	3.1371	4.8632	6.3939	0	12.1650	27711
Share of AI Workers	0.0029	0.0054	0	0.0009	0.0036	0	0.1577	27711

Pairwise Correlation Matrix

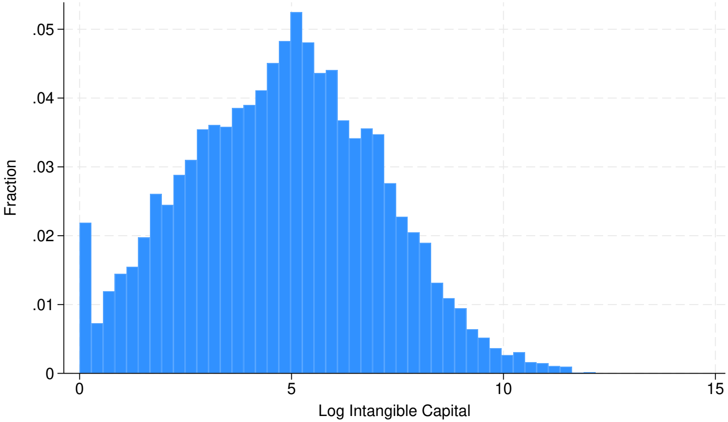
Back

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
(1) Log Assets	1.00									
(2) Log R&D	-0.66*	1.00								
(3) Log Capital Expenditures	0.89*	-0.65*	1.00							
(4) Cash-to-Assets	-0.37*	0.49*	-0.38*	1.00						
(5) Firm Age	0.38*	-0.35*	0.33*	-0.21*	1.00					
(6) Markup	-0.02*	0.06*	-0.03*	0.06*	-0.03*	1.00				
(7) Dividends-to-Assets	0.05*	-0.06*	0.04*	0.00	0.01	-0.00	1.00			
(8) Log Labor Productivity	0.83*	-0.71*	0.71*	-0.41*	0.36*	-0.02*	0.06*	1.00		
(9) Log Intangible Capital	0.83*	-0.42*	0.68*	-0.21*	0.41*	0.00	0.02*	0.64*	1.00	
(10) Share of AI Workers	0.16*	0.11*	0.09*	0.09*	0.02*	0.03*	-0.01*	0.16*	0.24*	1.00

Intangible Capital

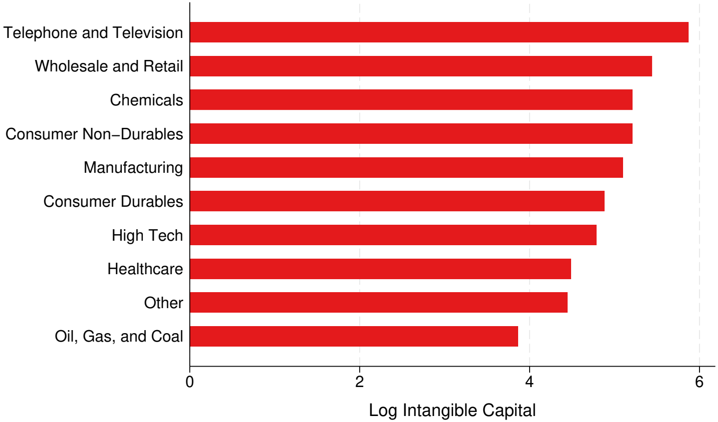
Histogram - Intangible Capital

Back



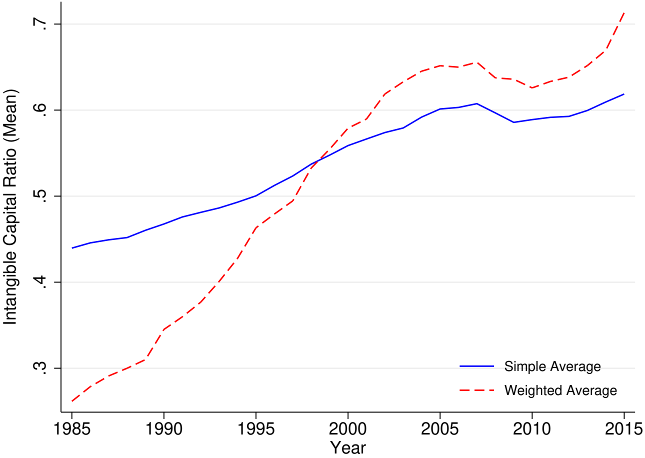
Intangible Capital by Industry

Back



Intangible Capital Ratio over Time

▸ Back



Share of AI Workers

Skills with Highest AI-Relatedness Measures ▸ Back

Note: This table is adapted from Babina et al. (2024).

#	Skills	AI-relatedness Score
1	Artificial Intelligence	1.000
2	Computer Vision	1.000
3	Machine Learning	1.000
4	Natural Language Processing	1.000
5	ND4J (software)	0.980
6	Kernel Methods	0.979
7	Microsoft Cognitive Toolkit	0.975
8	Xgboost	0.972
9	Sentiment Classification	0.971
10	Long Short-Term Memory (LSTM)	0.971
11	Libsvm	0.968
12	Semi-Supervised Learning	0.968
13	Recurrent Neural Network (RNN)	0.965
14	Word2Vec	0.956
15	MXNet	0.953
16	Caffe Deep Learning Framework	0.950
17	Autoencoders	0.949
18	MLPACK (C++ library)	0.942
19	Keras	0.941
20	Theano	0.938
21	Torch (Machine Learning)	0.932
22	Wabbit	0.929
23	Boosting (Machine Learning)	0.905
24	TensorFlow	0.904
25	Vowpal	0.903
26	Convolutional Neural Network (CNN)	0.897
27	Jung Framework	0.894
28	OpenNLP	0.894
29	Natural Language Toolkit (NLTK)	0.892
30	Unsupervised Learning	0.891
31	Dlib	0.891
32	Scikit-learn	0.889
33	Latent Semantic Analysis	0.889
34	Latent Dirichlet Allocation	0.889
35	Stochastic Gradient Descent (SGD)	0.881
36	Gradient boosting	0.872
37	Dimensionality Reduction	0.861
38	Deep Learning	0.859
39	DBSCAN (Density-Based Spatial Clustering of Applications with Noise)	0.855
40	AI ChatBot	0.844
41	Recommender Systems	0.842
42	Random Forests	0.840
43	Deeplearning4j	0.839
44	Support Vector Machines (SVM)	0.817
45	Unstructured Information Management Architecture	0.806
46	Apache UIMA	0.805
47	Maximum Entropy Classifier	0.799
48	Hidden Markov Model (HMM)	0.796
49	Pybrain	0.786
50	Computational Linguistics	0.780
51	Naive Bayes	0.768
52	H2O (software)	0.763
53	Expectation-Maximization (EM) Algorithm	0.763
54	WEKA	0.761
55	Clustering Algorithms	0.740
56	Matrix Factorization	0.739
57	Object Recognition	0.727
58	Classification Algorithms	0.721
59	Information Extraction	0.709
60	Image Recognition	0.706
61	Bayesian Networks	0.705
62	Supervised Learning (Machine Learning)	0.695
63	OpenCV	0.688
64	K-Means	0.683
65	Sentiment Analysis / Opinion Mining	0.679
66	Machine Translation (MT)	0.655
67	Neural Networks	0.640

Examples of AI and Non-AI Job Postings

Back

Note: This table is adapted from Babina et al. (2024).

	Job Title	Employer	Skills	Score
	AI jobs			
1	Research Engineer - Natural Language Processing	InterActiveCorp	Machine Learning (1), Natural Language Processing (1), Natural Language Toolkit (0.895), Computational Linguistics (0.777), WEKA (0.760), Information Extraction (0.709), Mahout (0.593), Information Retrieval (0.360), Apache Hadoop (0.204), Lucene (0.188), SOLR (0.142), C++ (0.067), Software Engineering (0.043), Python (0.116), Lexical Semantics (0.625), Ontologies (0.326), Java (0.040), PERL Scripting Language (0.034), Relational Databases (0.024), SQL (0.023), Search Analytics (0.022), Shell Scripting (0.020), Web Analytics (0.012), Research (0.011), Online Research (0.010), Extensible Markup Language (0.010)	0.31
2	Computer Vision & Image Processing Researcher	Rambus Incorporated	Computer Vision (1), Object Recognition (0.725), OpenCV (0.689), Pattern Recognition (0.442), CUDA (0.362), Image Processing (0.179), Troubleshooting Technical Issues (0.006), C++ (0.067), Communication Skills (0.003), MATLAB (0.113), Self-Motivation (0.002), Optical System Design and Analysis (0.019), Research (0.011), Writing (0.004), OpenGL (0.117), Prototyping (0.042), Very Large Scale Integration (0.037), Creativity (0.007)	0.21
3	Algorithm Developer	IBM	Natural Language Processing (1), Machine Learning (1), IBM Watson (0.125), Java (0.040), Software Development (0.027), Candidate Generation (0.013), Creativity (0.007), Troubleshooting (0.003), English (0.002)	0.25
4	Senior Autonomous Vehicle Localization Software Engineer	Nvidia Corporation	Computer Vision (1), Deep Learning (0.859), Linear Algebra (0.187), OpenGL (0.117), C++ (0.067), Software Engineering (0.043), Geometry (0.009), Motor Vehicle Operation (0.006), Teamwork / Collaboration (0.005), Calibration (0.004)	0.230
5	Speech Recognition Scientist	Vocera Communications	Computational Linguistics (0.780), Automatic Speech Recognition (0.457), Speech Recognition (0.215), Experiments (0.045), Performance tuning (0.011), Research (0.011), Written Communication (0.003)	0.217
6	Data Scientist	Zappos	Machine Learning (1), Natural Language Processing (1), Boosting (Machine Learning) (0.902), Support Vector Machines (0.816), Naive Bayes (0.759), Matrix Factorization (0.738), Classification Algorithms (0.718), Data Science (0.379), Data Mining (0.159), NoSQL (0.119), Clustering (0.103), Data Structures (0.069), Relational DataBase Management System (0.028), SQL (0.023), Attribution Modeling (0.072), Detail-Oriented (0.002), Revenue Projections (0.003), Traffic Maintenance (0.002)	0.384
7	Data Mining Engineer	Apple Inc.	Artificial Intelligence (1), Natural Language Processing (1), Machine Learning (1), Unsupervised Learning (0.891), Supervised Learning (0.696), Mahout (0.593), Pattern Recognition (0.442), Apache Hadoop (0.204), Image Processing (0.179), Data Mining (0.159), NoSQL (0.119), Data Collection (0.008), Communication Skills (0.003), Java (0.040), Detail-Oriented (0.002), MATLAB (0.113), SQL (0.023), Network Engineering (0.007), Research (0.011), Python (0.116), Meeting Deadlines (0.002), R (0.248), Predictive Models (0.243)	0..309
8	Big Data Engineer	Socialwire	Machine Learning (1), Recommender Systems (0.843), MapReduce (0.285), Apache Hadoop (0.204), Big Data (0.196), Facebook (0.006), R (0.248), Pinterest (0.003), Writing (0.004), MATLAB (0.113)	0.290
9	Big Data Senior Data Scientist	AT&T	Machine Learning (1), WEKA (0.760), Clustering Algorithms (0.738), Mahout (0.593), Data Science (0.379), Big Data (0.196), Data Mining (0.159), Clustering (0.103), Simulation (0.028), Experimental Testing (0.039), R (0.248), SPSS (0.067), Creativity (0.007), SAS (0.053), Information Systems (0.007), Experiments (0.045), Presentation Skills (0.006), Research (0.011), Data Quality (0.025)	0.235
10	Data Scientist	Warby Parker	Natural Language Processing (1), Natural Language Toolkit (0.895), Random Forests (0.839), Pandas (0.498), Data Science (0.379), PIG (0.290), Apache Hadoop (0.204), Data Mining (0.159), Data Visualization (0.136), Tableau (0.074), Pentaho (0.058), NumPy (0.552), SQL (0.023), Python (0.116), Java (0.040), DevOps (0.039), Agile Development (0.030), Creativity (0.007), Django (0.039), Apache Webserver (0.034), Predictive Models (0.243), Relational Databases (0.024), Data Modeling (0.037)	0.249
	Non-AI jobs			
11	Director Of Business Intelligence	Odesus Incorporated	Data Science (0.379), Data Transformation (0.060), SQL (0.023), Communication Skills (0.003), SQL Server Reporting Services (0.009), SQL Server (0.009), SQL Server Analysis Services (0.034), Budgeting (0.001), Microsoft Sharepoint (0.002), Data Warehousing (0.025), MySQL (0.028), Key Performance Indicators (0.006), Problem Solving (0.005), Web Analytics (0.012), Market Research (0.006), Data Modeling (0.037), Business Intelligence (0.026), Creativity (0.007)	0.037
12	Director, Data & Analytics	Decision Resources	Big Data (0.196), Business Intelligence (0.026), Business Intelligence Industry Knowledge (0.020), Teamwork / Collaboration (0.005), Biopharmaceutical Industry Knowledge (0.004), Communication Skills (0.003)	0.042
13	Senior Healthcare Economics Data Analyst	UnitedHealth Group	Tableau (0.076), Advanced Statistics (0.149), SAS (0.053), Data Analysis (0.026), SQL (0.023), Economics (0.016), Database Design (0.014), Clinical Data Analysis (0.012), Clinical Data Review (0.010), Business Process (0.006)	0.039
14	Data Analyst	United Technologies Corporation	Data Analysis (0.026), Data Quality (0.025), Data Management (0.018), Database Design (0.014), Proposal Writing (0.007), Product Improvement (0.007), Business Planning (0.002)	0.014
15	Sas Database Administrator	Pitney Bowes	SAS (0.053), SQL (0.023), Business Strategy (0.009), Teradata DBA (0.005), Self-Starter (0.004), Database Administration (0.004), Pivot Tables (0.004), Market Analysis (0.004), Technical Support (0.002), Microsoft Excel (0.002)	0.011
16	Delivery Driver And Technician	Rotech Healthcare	Physical Abilities (0.000), Lifting Ability (0.000), Caregiving (0.000), Patient Contact (0.000), Patient Transportation and Transfer (0.000), HAZMAT (0.000), Hazardous Materials Endorsement (0.000)	0
17	Vice President Underwriting	Morgan Stanley	Workflow Management (0.005), Written Communication (0.003), Detail-Oriented (0.002), Financial Analysis (0.001), Mortgage Underwriting (0.001), Staff Management (0.001)	0.002
18	Quality Assurance Engineer	Amazon	Computer Engineering (0.034), Software Development (0.027), User Interface (UI) Design (0.016), Software Quality Assurance (0.010), Black-box testing (0.009), Quality Assurance and Control (0.003), Consumer Electronics (0.002)	0.014
19	Sales Associate	GNC	Sales (0.001), Retail Industry Knowledge (0.000), Retail Sales (0.000), Basic Mathematics (0.000)	0
20	Dog And Cat Department Manager	Petco	Creativity (0.007), Leadership (0.003), Budgeting (0.001), Sales Goals (0.001), Retail Industry Knowledge (0.000), Physical Abilities (0.000), Inventory Management (0.000)	0.002

Histogram of Share of AI Workers

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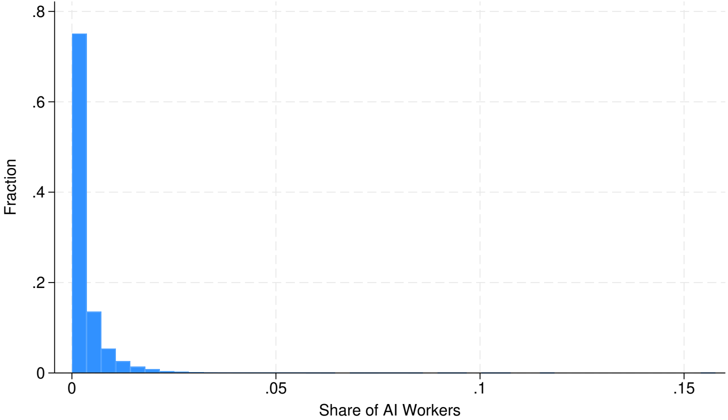

Share of AI Workers by Industry

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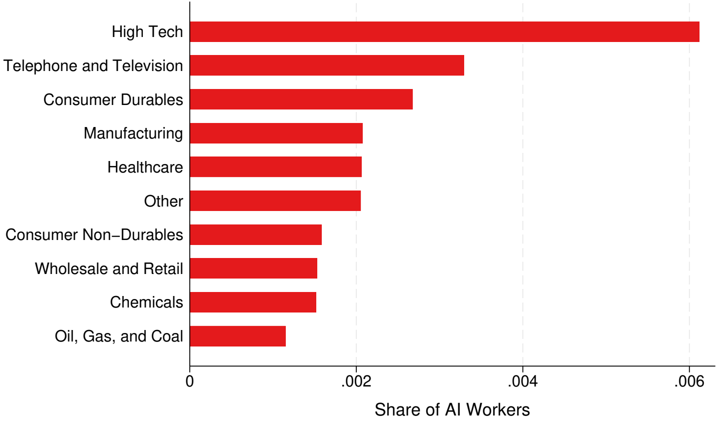

DiD Analysis

Identification Assumptions

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1. **Parallel Trends:** In absence of TensorFlow, firms with different pre-2015 AI shares would have followed similar trends in productivity and intangibles.
2. **Exogenous Shock:** The 2015 TensorFlow release was an unanticipated, industry-wide AI improvement not targeted to specific sectors or firm types.
3. **Fixed Effects Control:** Firm, industry, year, and state FEs absorb unobserved heterogeneity and time-varying confounders.