AI and services-led growth:

Evidence from Indian job adverts

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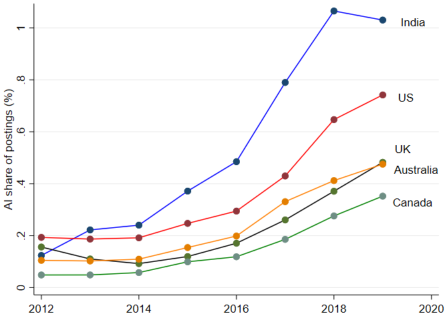
Roadmap

Motivation: Rapid progress in AI, limited evidence on developing countries

- Rapid growth in AI skills demand in various countries since 2015
- Limited detailed evidence on impacts & research heavily focused on US
- Potentially important consequences for development
  - ⇒ India a critical case as pioneer of services-led development model

Figure 1: Share of online job adverts including AI skills



Motivation: Contrasting views on implications

Krugman vs Korinek & Stiglitz vs Baldwin

"There is this concept called artificial intelligence that you should be wary of. In the future, while diagnosis may be outsourced to a doctor in India, it could also go to a firm based on artificial intelligence"

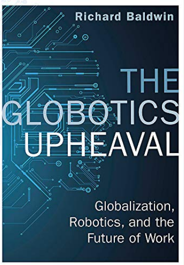
Artificial Intelligence, Globalization, and Strategies for Economic Development

Anton Korinek & Joseph E. Stiglitz

WORKING PAPER 28453 DOI 10.3386/w28453 ISSUE DATE February 2021

Progress in artificial intelligence and related forms of automation technologies threatens to reverse the gains that developing countries and emerging markets have experienced from integrating into the world economy over the past half century, aggravating poverty and inequality. The new technologies have the tendency to be labor-saving, resource-saving, and to give rise to winner-takes-all dynamics that advantage developed countries. We analyze the economic forces behind these developments and describe economic policies that would mitigate the adverse effects on developing and emerging economies while leveraging the potential gains from technological advances. We also describe reforms to our global system of economic governance that would share the benefits of AI more widely with developing countries.

"Progress in artificial intelligence... threatens to reverse the gains that developing countries and emerging markets have experienced"



"Our conclusion is that the service-led development path may become the norm rather than the exception"

This paper

Question: How is AI affecting labor demand in India's service sector?

1. Measures the **demand for AI skills** in India's predominantly white-collar service sector using online job adverts data from India's largest jobs website

2. Documents the **characteristics of AI-related jobs and diffusion** of AI skills demand across establishments, regions and industries

3. Studies the **impact of establishment-level AI demand** on non-AI adverts, wage offers and tasks in two ways:

   ⇒ **In the medium term**: instrumenting for AI demand with *ex ante* establishment task compatibility with future AI inventions

   ⇒ **In the short-term**: using a propensity score matching event study design

Preview of findings

$\Rightarrow$ Demand for AI skills has **grown by 34%** on average over the past decade, concentrated in the largest firms, tech clusters and IT & Finance industries

$\Rightarrow$ AI hiring within establishments has a **negative effect on demand for high-skilled** managerial and professional occupations, non-routine work & analytical tasks

$\Rightarrow$ By contrast **lower-skilled occupations and routine work are positively affected**

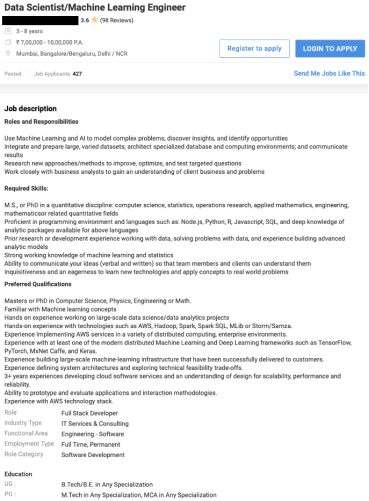
$\Rightarrow$ Net effects negative: $\uparrow$1% in the AI vacancy growth rate $\Rightarrow$ $\downarrow$3.6pp in establishment non-AI vacancy growth + $\downarrow$2.6pp in non-AI median wage offers

- **Clarifications:** (i) ML, (ii) job-level exposure & adoption, not broader systems; (iii) 'posts/wage offers' not 'hiring/wages'; (iv) direct establishment-level effects

Roadmap

Vacancy data from India's largest online job postings platform

- Platform hosts 60% of online job posts in India, we received anonymised 80% sample of posts across 2010-19
- Predominantly urban, full-time, formal white-collar services jobs
- 150k+ firms posted >1 one vacancy; average of 80 posts per firm
- Fields: job title, industry, role category, location, skills required, salary and experience ranges and educational requirements



Data Scientist/Machine Learning Engineer

[redacted] 3.6 ★ (98 Reviews)

3 - 8 years

₹ 7,00,000 - 10,00,000 P.A.

Mumbai, Bangalore/Bengaluru, Delhi / NCR

Register to apply | LOGIN TO APPLY

Posted: | Job Applicants: 427

Send Me Jobs Like This

Job description

Roles and Responsibilities

Use Machine Learning and AI to model complex problems, discover insights, and identify opportunities
Integrate and prepare large, varied datasets; architect specialized database and computing environments; and communicate results
Research new approaches/methods to improve, optimize, and test targeted questions
Work closely with business analysts to gain an understanding of client business and problems

Required Skills:

M.S., or PhD in a quantitative discipline: computer science, statistics, operations research, applied mathematics, engineering, mathematicsor related quantitative fields
Proficient in programming environment and languages such as: Node.js, Python, R, Javascript, SQL, and deep knowledge of analytic packages available for above languages
Prior research or development experience working with data, solving problems with data, and experience building advanced analytic models
Strong working knowledge of machine learning and statistics
Ability to communicate your ideas (verbal and written) so that team members and clients can understand them
Inquisitiveness and an eagerness to learn new technologies and apply concepts to real world problems

Preferred Qualifications

Masters or PhD in Computer Science, Physics, Engineering or Math.
Familiar with Machine learning concepts
Hands on experience working on large-scale data science/data analytics projects
Hands-on experience with technologies such as AWS, Hadoop, Spark, Spark SQL, MLib or Storm/Samza.
Experience Implementing AWS services in a variety of distributed computing, enterprise environments.
Experience with at least one of the modern distributed Machine Learning and Deep Learning frameworks such as TensorFlow, PyTorch, MxNet Caffe, and Keras.
Experience building large-scale machine-learning infrastructure that have been successfully delivered to customers.
Experience defining system architectures and exploring technical feasibility trade-offs.
3+ years experiences developing cloud software services and an understanding of design for scalability, performance and reliability.
Ability to prototype and evaluate applications and interaction methodologies.
Experience with AWS technology stack.

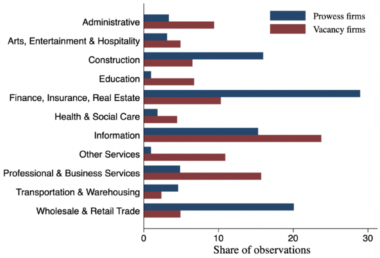
Role	Full Stack Developer
Industry Type	IT Services & Consulting
Functional Area	Engineering - Software
Employment Type	Full Time, Permanent
Role Category	Software Development

Education

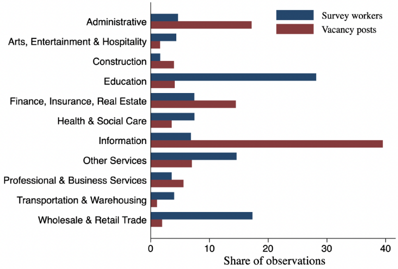
UG :	B.Tech/B.E. in Any Specialization
PG :	M.Tech in Any Specialization, MCA in Any Specialization

Representativeness of the vacancy data

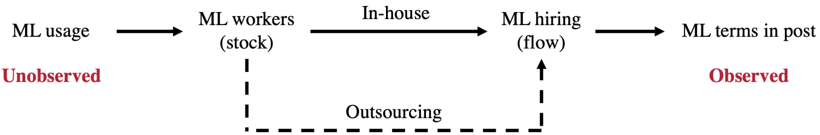
(a) Firm distribution



(b) Worker/vacancy distributions



Measuring demand for machine learning skills



- Classify a post as an AI vacancy if it includes words from list of specific AI terms (Acemoglu et al. 2021)
- Use demand for AI skills in vacancies to proxy for AI usage (Rock 2019, Benzell et al. 2019, Acemoglu et al. 2021, Stapleton 2021)
- Exploit that primary method for sourcing AI capabilities is external hiring (McKinsey Global Institute 2019)

Example of an AI-related job adverts

- **Title:** Algorithm Engineer
- **Role overview:** Role of on ML-algorithms engineer would involve analyze terabytes of data and billions of rows to discover correlations and patterns that empowers Optimization Technology. We are looking for candidates who have deep data mining algorithms knowledge and are interested in applying this to huge datasets to build large scale data processing and analytics systems. It will be a very exciting and a hands-on role and you would get to enjoy working with a team of very smart engineers.Job Functions: Lead and own complete development and designing of the algorithms and frameworks involved in the same; Natural Language Processing: the interactions between computers and humans; Machine learning: Research and implement data mining and machine learning algorithms; Conceptual modeling: To be able to share and articulate modeling; Statistical analysis: To understand and work around possible limitations in models; ¡br¿¡br¿- Predictive modeling: Use R, Mahout, Vowel Wabbit towards being able to predict future outcomes; Hypothesis testing: Being able to develop hypothesis and test them with careful experiments; ¡br¿¡br¿- Develop extensible, scalable, reliable software for high volume, real-time data processing
- **Location:** Pune
- **Education/experience:** BTech /MTech/ PHD in computer science/ statistics/ mathematics with in-depth knowledge in data mining / machine learning / artificial intelligence / operational research with 5+ years of hands-on experience in this fields. Able to program, preferably in different programming languages such as Python, R, Java, Ruby, Pig or SQL. Need to have an understanding of Hadoop, Hive and/or MapReduce Being able to advice senior management in clear language about the implications of their work for the organisation Being able to create examples, prototypes, demonstrations to help management better understand the work Being able to work autonomously Good communication skills and enthusiasm to learn new technologies
- **Keywords:** Hadoop,Natural Language Processing,Hive,R,Mapreduce,SQL,Python,Machine Learning,Java,Analytics
- **Salary:** 2500000-3500000 rupees

Assessing the types of tasks in AI job adverts

- Follow Michaels, Rauch and Redding (2018) in using a list of 1,665 English verbs and the meaning of verbs from Roget's Thesaurus, which classifies words according to their underlying concepts and meanings

- Roget's Thesaurus is organized into 6 classes, 10 divisions, 38 sections, and around 1,000 categories. Classes are:

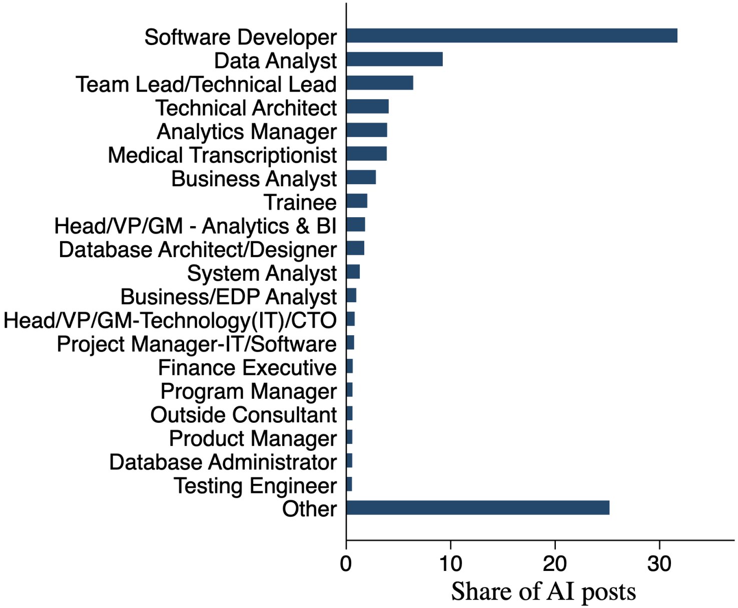
  1. Abstract Relations: ideas such as number, order and time
  2. Space: movement, shapes and sizes
  3. Matter: the physical world and humankind's perception of it by means of the five senses
  4. Intellect: the human mind
  5. Volition: the human will and the human heart and soul
  6. Emotion, Religion, and Morality: the human heart and soul

Most over-represented verbs in AI job ads

Extract the verbs in AI and non-AI job ads, then calculate the share of each verb relative to all verbs, and rank by difference in shares between AI and non-AI job ads:

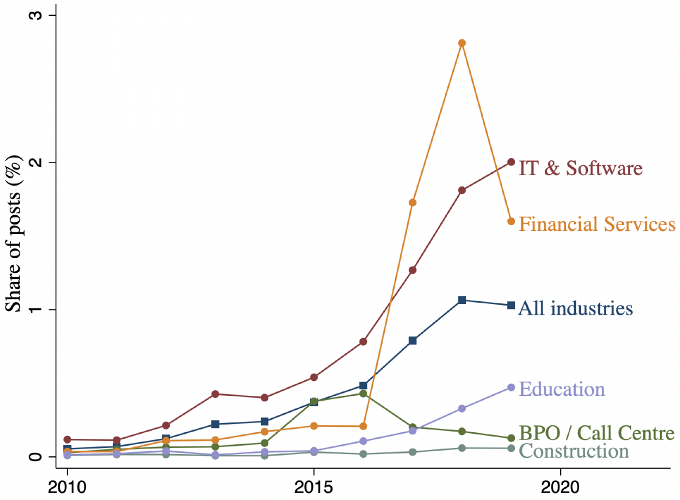
	Less common	**More common**
1	Call	Experience
2	Manage	Develop
3	Shift	Build
4	Plan	Program
5	Account	Design
6	Tar	Work
7	Look	Predict
8	Recruit	Deliver
9	Apply	Use
10	Report	Advance

Occupations demanding AI skills

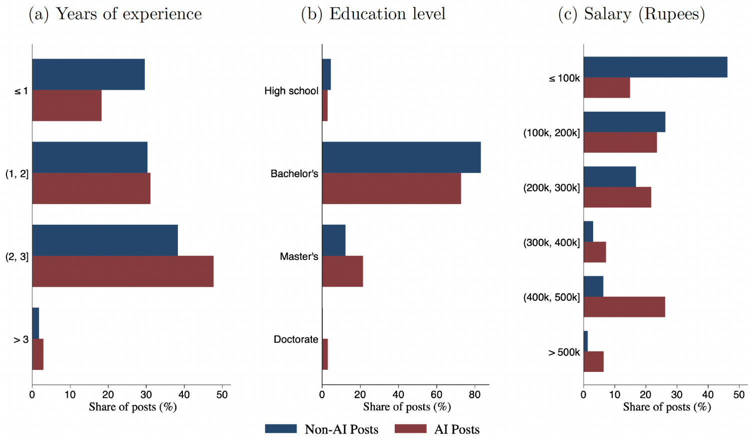


Roadmap

1. AI demand increased rapidly from 2015, particularly in IT and financial services



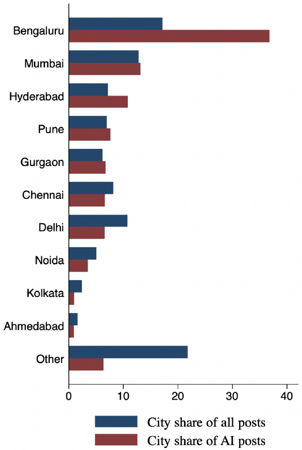
2. AI roles require more education, but offer substantially higher wages than other white-collar services jobs



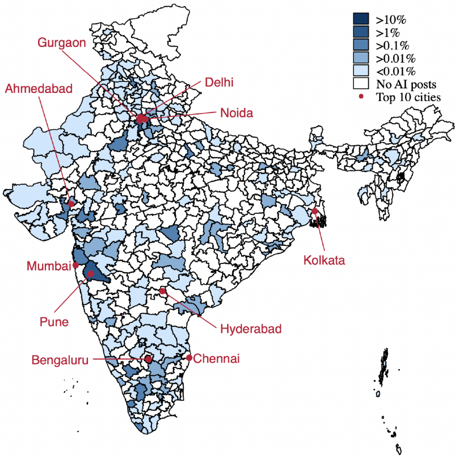
⇒ AI posts pay a 13% salary premium, even after controlling for education, experience, and detailed fixed effects (industry-region, industry-year, region-year, firm, occupation).

3. AI roles are highly concentrated in a few key technology clusters, particularly Bangalore

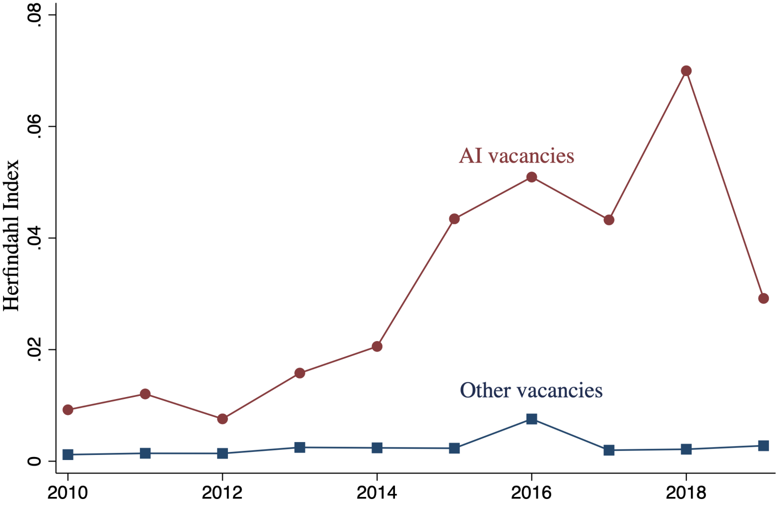
(a) Shares of posts across cities



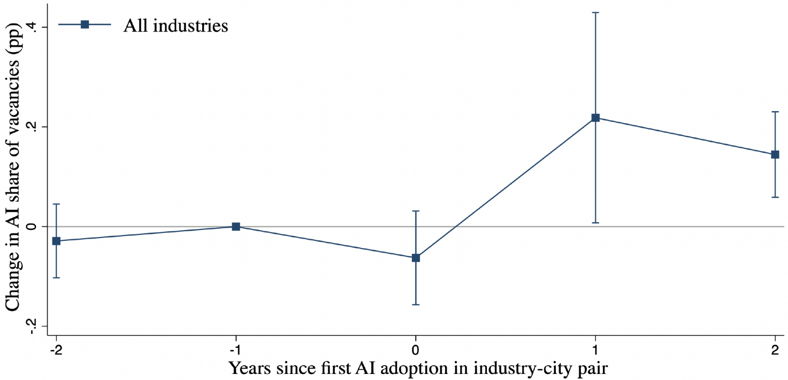
(b) Share of all AI posts, by city, 2010-2019



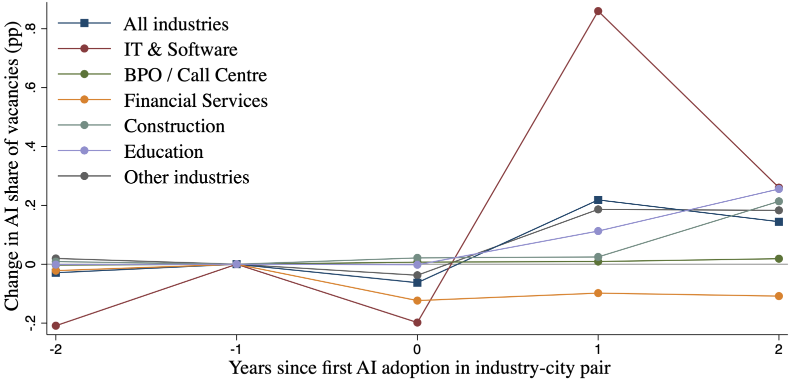
4. AI roles are disproportionately concentrated in the largest firms



5. Once one firm adopts AI, other firms in the same city and industry are more likely to adopt, over and above industry and region trends



5. Once one firm adopts AI, other firms in the same city and industry are more likely to adopt, particularly in the IT sector



Roadmap

How would we expect AI to affect labor demand?

- Advances in AI conceptualized as reducing cost, or improving quality, of task of 'prediction', prevalent across occupations (Agrawal et al. 2018)

- This could theoretically displace tasks but could also expand labor demand through improved productivity or the creation of new tasks (Acemoglu & Restrepo 2018; Webb 2020; Autor et al. 2022

- In addition, AI could complement human labour or incentivise changes in organisational structure; there is growing evidence that AI is a general-purpose technology (GPT), an 'invention of a method of invention' (Brynjolfsson et al. 2017, Cockburn et al. 2018, Klinger et al. 2018, Goldfarb et al. 2020, Agrawal et al. 2021)

Long-difference empirical strategy

First stage:

$$\Delta Adoption_{fr,t-t_0} = \gamma \cdot Exposure_{fr,t_0} + \alpha_r + \alpha_i + \alpha_{f10} + \epsilon_{fr,t-t_0} \quad (1)$$

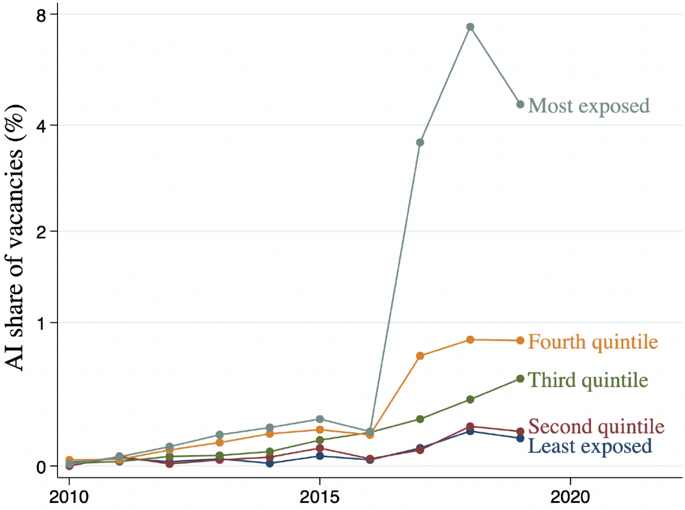
- We instrument demand for AI skills (our proxy for adoption) with Webb (2020) AI exposure measure

Second stage:

$$\Delta y_{fr,t-t_0} = \beta \cdot \Delta Adoption_{fr,t-t_0} + \alpha_r + \alpha_i + \alpha_{f10} + \epsilon_{fr,t-t_0} \quad (2)$$

- Final sample: 2M vacancies from 25k establishments across 2010/12−2017/19
- Our primary unit of analysis are **firm-city pairs ('establishments')**; we cluster standard errors at the firm level and take IHS of *Adoption* and y
- Increasing the growth rate of AI demand by 1% between 2010-12 and 2017-19 (long difference) leads to a β **percentage point rise in the growth rate** of the outcome variable across the same time period

First stage: AI exposure predicts AI demand



A one s.d. rise in establishment AI exposure is associated with a 1.93% increase ($p < 0.01$) in growth rate of AI vacancies between 2010-12 and 2017-19.

Second stage: AI lowers growth in non-AI postings...

	Growth in Non-AI Vacancies			Growth in Total Vacancies		
	(1)	(2)	(3)	(4)	(5)	(6)
Growth in AI Vacancies	-3.574***	-5.942***	$\boxed{-3.605^{***}}$	-3.534***	-5.909***	-3.566***
	(1.168)	(1.624)	$\boxed{(1.139)}$	(1.166)	(1.624)	(1.137)
Fixed Effects:						
– Region	✓	✓	✓	✓	✓	✓
– Industry	✓		✓	✓		✓
– Firm Decile		✓	✓		✓	✓
First Stage F-Stat	26.06	26.31	27.17	26.06	26.31	27.17
Observations	22,251	22,251	22,251	22,251	22,251	22,251

A 1% increase in the establishment growth rate of AI vacancies results in a 3.6pp decrease ($p < 0.01$) in the growth rate of non-AI vacancies between 2010-12 and 2017-19, controlling for region, industry and firm size fixed effects.

… and total postings (including AI postings)

	Growth in Non-AI Vacancies			Growth in Total Vacancies		
	(1)	(2)	(3)	(4)	(5)	(6)
Growth in AI Vacancies	-3.574***	-5.942***	-3.605***	-3.534***	-5.909***	-3.566***
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Fixed Effects:						
– Region	✓	✓	✓	✓	✓	✓
– Industry	✓		✓	✓		✓
– Firm Decile		✓	✓		✓	✓
First Stage F-Stat	26.06	26.31	27.17	26.06	26.31	27.17
Observations	22,251	22,251	22,251	22,251	22,251	22,251

There is a similarly-sized decrease of 3.57pp in the growth rate of total vacancies ⇒ the negative effect on non-AI vacancies outweighs the rise in AI vacancies.

Decline in demand hits higher-skilled occupations

	Growth in Non-AI Vacancies				
	Personal, sales & security	Clerks	Associate Professionals	Professionals	Managers
Growth in AI Vacancies	2.094***	1.092***	5.121***	-6.222***	-12.19***
	(0.487)	(0.354)	(1.252)	(1.581)	(2.632)
Fixed Effects:					
– Region	✓	✓	✓	✓	✓
– Industry	✓	✓	✓	✓	✓
– Firm Decile	✓	✓	✓	✓	✓
First Stage F-Stat	27.17	27.17	27.17	27.17	27.17
Observations	22,251	22,251	22,251	22,251	22,251

Negative impact largest for corporate managers & engineering professionals

Impacts within the categories of managers and professionals:

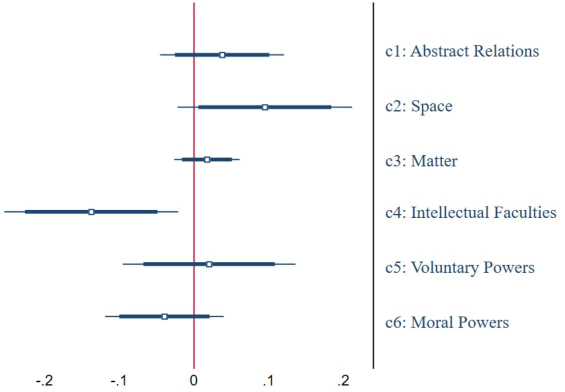
	Growth in Non-AI Vacancies					
	Professionals				Managers	
	Engineering Professionals	Health Professionals	Teaching Professionals	Other Professionals	Corporate Managers	General Managers
Growth in AI Vacancies	-4.951***	0.548*	0.284***	-2.687***	-12.18***	-2.403***
	(1.198)	(0.332)	(0.107)	(0.926)	(2.592)	(0.827)
Fixed Effects:						
– Region	✓	✓	✓	✓	✓	✓
– Industry	✓	✓	✓	✓	✓	✓
– Firm Decile	✓	✓	✓	✓	✓	✓
First Stage F-Stat	27.17	27.17	27.17	27.17	27.17	27.17
Observations	22,251	22,251	22,251	22,251	22,251	22,251

AI lowers demand for non-routine task intensive occupations...

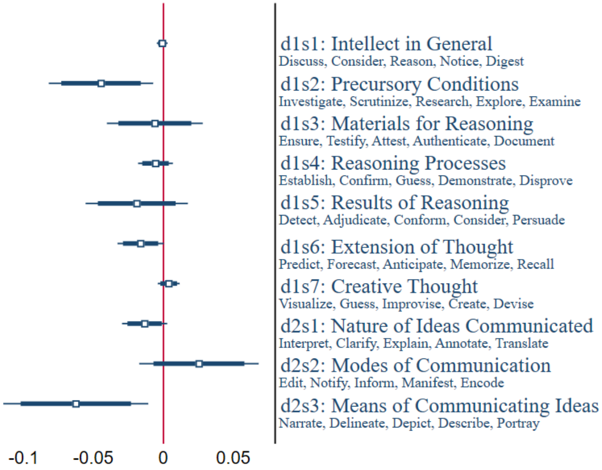
	Growth in Non-Routine Tasks			Growth in Routine Tasks		
	(1)	(2)	(3)	(4)	(5)	(6)
Growth in AI Vacancies	-5.871***	-7.200***	-5.701***	0.298	0.599**	0.349
	(1.179)	(1.432)	(1.126)	(0.216)	(0.283)	(0.219)
Fixed Effects:						
– Region	✓	✓	✓	✓	✓	✓
– Industry	✓		✓	✓		✓
– Firm Decile		✓	✓		✓	✓
First Stage F-Stat	26.06	26.31	27.17	26.06	26.31	27.17
Observations	22,251	22,251	22,251	22,251	22,251	22,251

AI reduces demand for verbs relating to 'intellectual faculties'

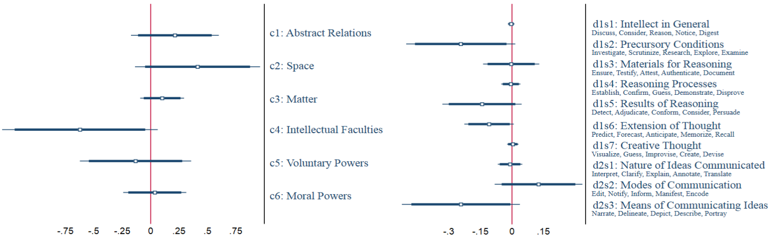
Evaluate the impact of AI on change in verb usage by verb class, using classification from Michaels, Rauch and Redding (2018).



Particularly synonyms of 'forecast', 'research' and 'describe'



Similar patterns found *within* top 1 % highest paid roles

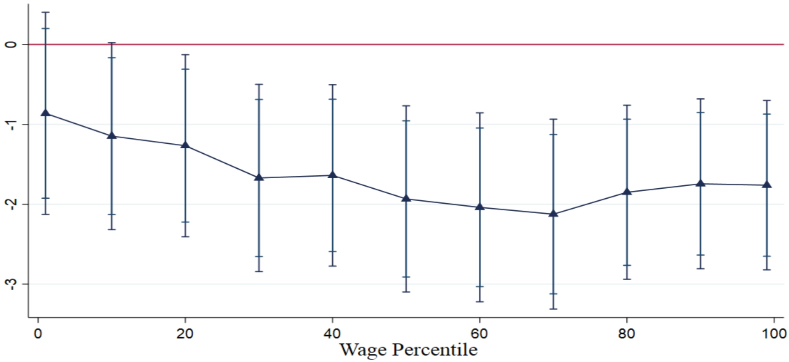


Second stage: AI lowers median wage growth

	Growth in Non-AI Median Wage			Growth in Overall Median Wage		
	(1)	(2)	(3)	(4)	(5)	(6)
Growth in AI Vacancies	-2.703***	-3.101***	-2.599***	-2.632***	-3.017***	-2.527***
	(0.799)	(0.895)	(0.758)	(0.770)	(0.862)	(0.730)
Fixed Effects:						
– Region	✓	✓	✓	✓	✓	✓
– Industry	✓		✓	✓		✓
– Firm Decile		✓	✓		✓	✓
First Stage F-Stat	25.32	25.64	26.39	26.61	26.84	27.71
Observations	22,064	22,064	22,064	22,071	22,071	22,071

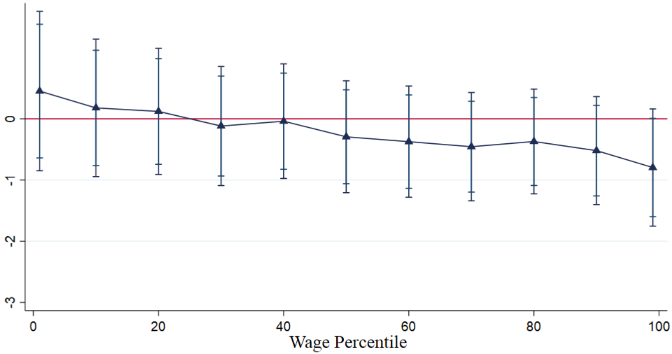
A 1% higher growth rate in AI vacancies between 2010-12 and 2017-19 reduces the growth rate of non-AI wage offers by 2.6 percentage points ($p < 0.01$).

AI results in a downwards shift of the wage distribution...



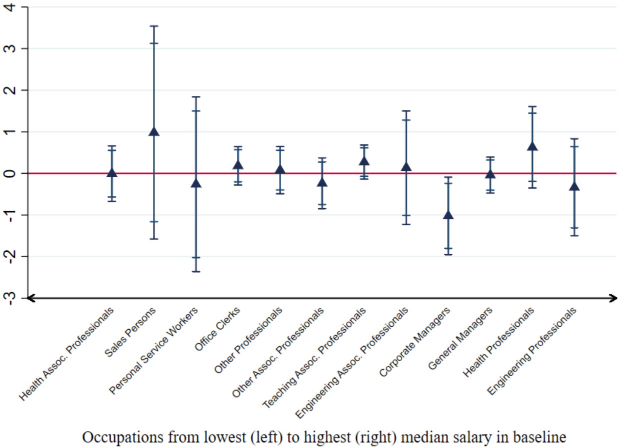
Except for the lowest 10 percent of jobs, AI lowers the distribution of wage offers. Includes industry, firm decile, and region fixed effects, and controls for experience and education

…but holding occupational composition fixed, only top 1% see declining wage offers



Controlling for changing occupation shares, we find a statistically significant effect on wage offers at the 10 percent level for the top 1 % highest paid roles. Includes industry, firm decile, and region fixed effects, and controls for experience and education

Corporate Managers suffer wage growth losses



Includes industry, firm decile, and region fixed effects, and controls for experience and education

Taking stock

$\Rightarrow$ AI results in changing labor demand *between occupations*: lower growth for higher skilled occupations & higher growth for lower skilled occupations alters the wage distribution

$\Rightarrow$ AI also results in declining wage offer growth *within* the top 1% highest paid job ads

$\Rightarrow$ AI lowers demand for tasks relating to forecasting, research and description for the full sample, and also within the 1% highest paid job ads

Roadmap

Event study with propensity score matching

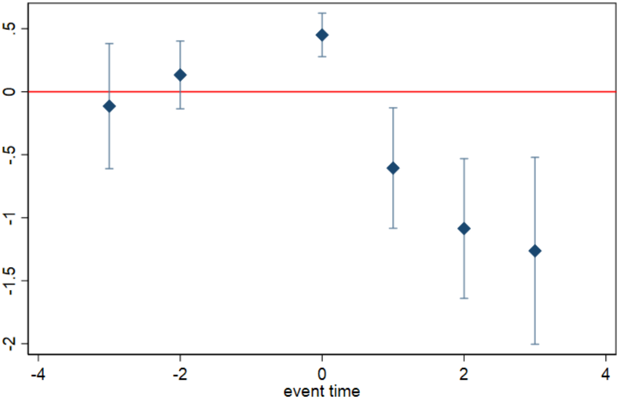
- Also use an event study with AI adopters matched to non-adopters based on propensity scores (similar to Koch et al. (2021))
- Run a Probit regression and construct propensity scores. Conditional on these propensity scores, treatment is orthogonal to establishment characteristics
- Find AI adopters differ from non-AI adopters in that they are larger and pay higher wages
- Results similar to long-difference specification: AI demand leads to lower non-AI hiring

Event study specification

$$Y_{it} = \alpha_i + \beta_t + \sum_{k=-3\backslash -1}^{2} \gamma_k 1(K_{it} = k) + \gamma_{3+} 1(K_{it} \geq 3) + \epsilon_{it},$$

- Y_{it} is the outcome, α_i and β_t are establishment and time fixed effects, K_{it} is the time difference between the current year and adoption of AI, ϵ_{it} is the error term, and the parameters γ_k are the outcomes of interest. We include 3 lags and leads, leaving out the first lead
- For the construction of propensity scores, we use the following variables:
  - lags of firmsize decile, hiring, median salary, 90th percentiles of salary and experience, firm age, salary dispersion, squared firmsize decile, standard deviation of experience, and interaction of standard deviation of salaries and firm age
- For employment, we need to account for non-hiring following adoption, and thus balance the panel. For wages, this imputation is not possible.

AI lowers non-AI hiring one year after adoption



Two way fixed effects on a balanced panel. Similar results on region-year and industry-year levels. Results robust to using imputation estimator by Borusyak et al. (2021)

Baseline results are robust to:

1. Alternative exposure measure (Felten et al. 2018) ✓
2. Alternative baseline period (2013-15) ✓
3. Weighting by baseline establishment size ✓
4. AI adoption dummy instead of ihs-transformed AI hiring ✓
5. Shift-share robustness checks (Goldsmith-Pinkham et al., 2020) ✓
6. Alternative data sources (NSS/PLFS, Prowess) ✓

Roadmap

Conclusion

⇒ **Surprisingly negative implications** of within-establishment AI hiring on high-skilled, routine and analytical work in India

- Stark contrast to literature studying computerization & robots

⇒ Potentially **positive implications of AI** for lower-skilled workers & for the few extremely highly educated workers that obtain AI jobs

⇒ **Caveats**: we only study **within-establishment** effects in 'AI consuming' industries, could be other positive effects in 'AI producing' industries e.g. tech firms, new startups

Conclusion

⇒ **Surprisingly negative implications** of within-establishment AI hiring on high-skilled, routine and analytical work in India

- Stark contrast to literature studying computerization & robots

⇒ Potentially **positive implications of AI** for lower-skilled workers & for the few extremely highly educated workers that obtain AI jobs

⇒ **Caveats**: we only study **within-establishment** effects in 'AI consuming' industries, could be other positive effects in 'AI producing' industries e.g. tech firms, new startups

Key open questions:

⇒ Do these negative impacts for high-skilled workers matter for development?

⇒ To what extent does AI adoption create new tasks & firms, and how do overall 'creative' vs. 'destructive' effects compare?

AI and services-led growth:

Evidence from Indian job adverts

Alexander Copestake[1], Max Marczinek[2], Ashley Pople[2], Katherine Stapleton[3]

[1]International Monetary Fund
[2]University of Oxford
[3]World Bank

May 17, 2023

Classifying AI posts

Back

Posts are categorised as AI-related if any of the following terms appear in either the 'job description' or 'skills required' fields:

Machine Learning, Computer Vision, Machine Vision, Deep Learning, Virtual Agents, Image Recognition, Natural Language Processing, Speech Recognition, Pattern Recognition, Object Recognition, Neural Networks, AI ChatBot, Supervised Learning, Text Mining, Support Vector Machines, Unsupervised Learning, Image Processing, Mahout, Recommender Systems, Support Vector Machines (SVM), Random Forests, Latent Semantic Analysis, Sentiment Analysis / Opinion Mining, Latent Dirichlet Allocation, Predictive Models, Kernel Methods, Keras, Gradient boosting, OpenCV, Xgboost, Libsvm, Word2Vec, Chatbot, Machine Translation and Sentiment Classification

(Acemoglu et al. 2021)

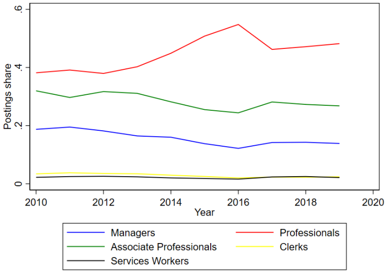
What are the characteristics of adopters of AI? Back

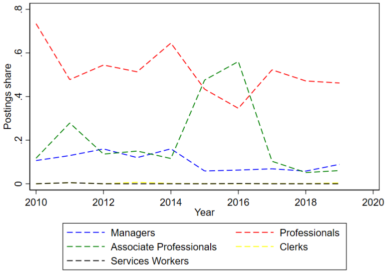
	AI adoption
Lag of Total Vacancies	0.286***
	(0.00830)
Lag of Vacancy Growth	-0.0975***
	(0.0112)
Lag of Median Salary	0.523***
	(0.0216)
Lag of Median Salary Growth	-0.220***
	(0.0212)
Lag of Median Experience	-0.542***
	(0.0366)
Lag of Median Experience Growth	0.222***
	(0.0398)
Lag of Postgrad Share	-0.0463
	(0.0628)
Lag of Postgrad Share Growth	0.0679
	(0.0581)
Constant	-8.965***
	(0.251)
Observations	129242
R^2	

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Does the composition of jobs change over time? Back

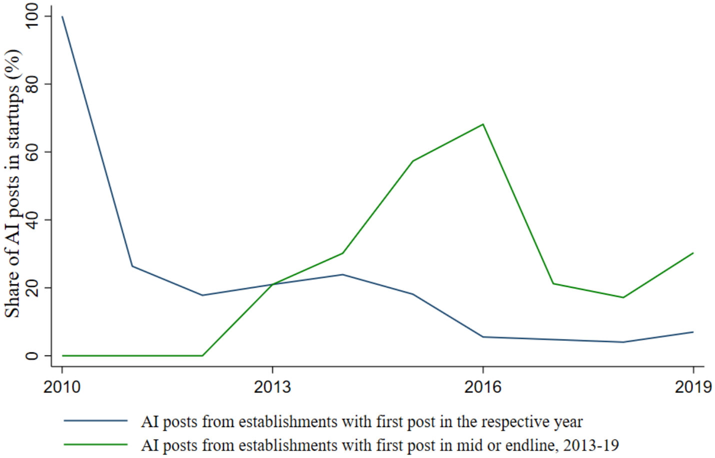




AI vacancies in firms that never hired before

Back

- Share of AI posts in establishments that never hired before (blue line) and in establishments that did not hire in the baseline, 2010-2012 (green line).



Probit regression for propensity scores

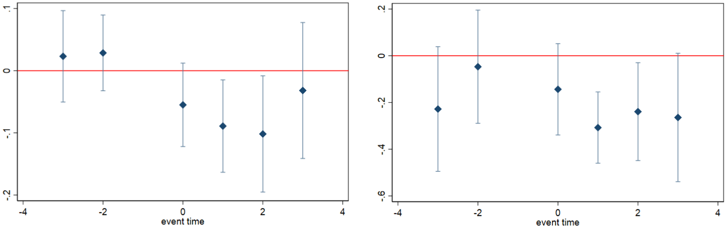
Back

	AI adoption
Lag of Firmsize Decile	-0.0125
	(0.0478)
Lag of Hiring	0.292***
	(0.0139)
Lag of Median Salary	0.111***
	(0.0210)
Lag of 90th Percentile of Salary	0.384***
	(0.0260)
Lag of 90th Percentile of Experience	-0.527***
	(0.0343)
Lag of Firm Age	0.0353***
	(0.00432)
Lag of Salary Dispersion	-0.000000584***
	(0.000000120)
Lag of squared Firmsize Decile	-0.00267
	(0.00347)
Lag of Salary Dispersion x Lag of Firm Age	7.96e-08***
	(1.71e-08)
Lag of Experience Dispersion	0.323***
	(0.0274)
Constant	-8.743***
	(0.310)
N	207,379

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

AI adoption leads to reduced non-AI hiring also on the level of regions and industries ◂ Back



Employment on region-year level (left) and on industry-year level (right) with two way fixed effects.

Instrument validity

Back

- Construct instrument from baseline occupation shares at the establishment level and their respective exposure to AI according to Webb (2020):

$$Exposure_{fr,t_0} = \sum_o PostShare_{fro}^{t_0} \cdot ExposureMeasure_o \quad (3)$$

- This is a shift=share approach with establishment level baseline occupation shares 'shares' and common occupational AI 'shocks'
  - ⇒ Identification requires that either the shares are plausibly randomly assigned or shocks are plausibly randomly assigned - here we see case for causal identification as stemming from the exogeneity of the shares as patenting shocks less likely to be random
- We can test for this following Goldsmith-Pinkham et al. (2020), who propose several validity checks by analogy with GMM and DiD:
  - ⇒ investigating correlates of shares
  - ⇒ examing pre-trends
  - ⇒ comparing different estimators and running over-identification tests

Goldsmith- Pinkham et al. tests

Back

- Correlates of shares: investigate extent to which baseline shares correlate with baseline establishment controls which could themselves affect hiring/wage offer trends. We regress the instrument on baseline controls (education, experience, and salary.) Find that shares are not correlated with these controls. Correlates
- **Examining pre-trends:** Ask whether baseline (2010-12) exposure predicts year-on-year growth in future outcome variables from 2013-19. Find baseline exposure does not predict growth in these variables Pre-trends
- **Alternative estimators and over-identification tests** Next compare a range of estimators (OLS, a range of IV estimators, an ML estimator and a Fuller-like estimator) and run over-identification tests. Similarity of different estimators and over-identification tests are reassuring for the validity of our approach.

Alternative estimators

Test 1: Correlates

Back

VARIABLES	(1) Instrument	(2) Instrument
Share of Highschool Education	-0.166	-0.166
	(0.204)	(0.204)
Share of Undergraduate Education	-0.232	-0.232
	(0.204)	(0.204)
Share of Postgraduate Education	-0.221	-0.221
	(0.204)	(0.204)
Mean Salary	4.86e-09	4.86e-09
	(4.34e-09)	(4.34e-09)
Mean Experience	-0.00217	-0.00217
	(0.00355)	(0.00355)
Constant	0.635***	0.635***
	(0.204)	(0.204)
Observations	22,201	22,201

Robust standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

- Baseline controls (education, experience, salary) do not correlate significantly with the overall instrument.

Test 2: Pre-trends

Back

	(1) Growth in Non-AI Vacancies	(2) Growth in Total Vacancies	(3) Growth in Non-AI Median Wage	(4) Growth in Overall Median Wage
Instrument	-0.00885	-0.00833	0.0184	0.0185
	(0.0130)	(0.0130)	(0.0298)	(0.0298)
Constant	-0.124***	-0.123***	-0.411***	-0.410***
	(0.0164)	(0.0164)	(0.0344)	(0.0344)
Observations	296730	296730	296730	296730

Standard errors in parentheses

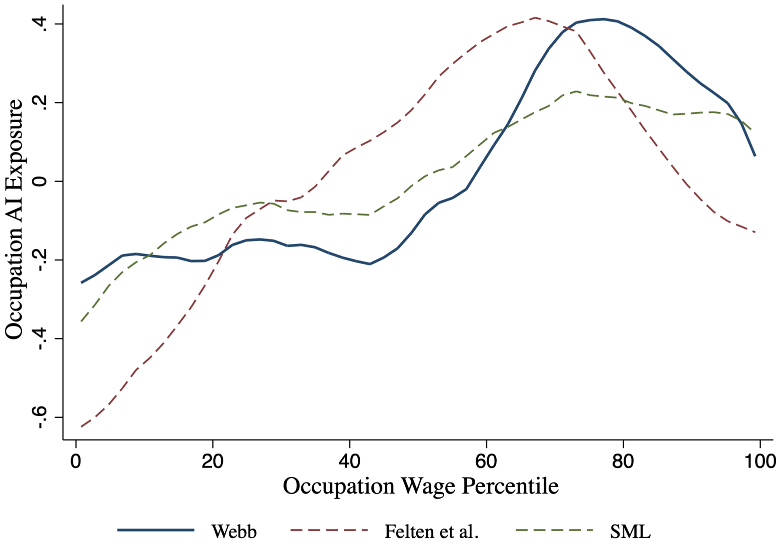
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Test 3: Alternative estimators and over-identification tests

Back

	Interpretation
Alternative estimators	
HFUL vs LIML	similarity reassuring
MBTSLS vs overid. TSLS	similarity reassuring
Bartik vs LIML	similarity reassuring
HFUL vs. MBTSLS	similarity reassuring
Over-identification tests	
H0 of validity over-ident. restr.	not rejecting H0 reassuring
Misspecification tests	
Bartik sensitive to controls	no

AI exposure by occupation wage offers



Alternative exposure measures

TABLE 1. FIRST STAGE: IMPACT OF AI EXPOSURE ON ESTABLISHMENT AI ADOPTION – ALTERNATIVE EXPOSURE MEASURES

	Growth in AI Vacancies			
	(1)	(2)	(3)	(4)
AI Exposure	0.0202***	0.0142***	-0.0151***	-0.0102***
	(0.00342)	(0.00308)	(0.00265)	(0.00276)
Exposure Measure	Felten et al.	Felten et al.	SML	SML
Fixed Effects:				
– Region	✓	✓	✓	✓
– Firm Decile	✓	✓	✓	✓
– Industry		✓		✓
R^2	.0349	.0481	.0338	.0476
Observations	22,251	22,251	22,251	22,251

NOTES: STANDARD ERRORS IN PARENTHESES. * P <0.10, ** P <0.05, *** P <0.01. STANDARD ERRORS CLUSTERED AT THE FIRM LEVEL. THE DEPENDENT VARIABLE IS THE GROWTH IN ESTABLISHMENT AI VACANCIES BETWEEN 2010-12 AND 2017-19, APPROXIMATED BY THE CHANGE IN THE INVERSE HYPERBOLIC SINE. THE INDEPENDENT VARIABLE IS ESTABLISHMENT AI EXPOSURE, CALCULATED AS THE STANDARDIZED AVERAGE OF OCCUPATION AI EXPOSURE (FROM EITHER **?**, OR **?** BUILDING ON **?**), OVER THE OCCUPATIONS FOR WHICH THE ESTABLISHMENT POSTS VACANCIES IN 2010-12, WEIGHTED BY THE NUMBER OF VACANCIES POSTED PER OCCUPATION, AS IN **?**. EACH COEFFICIENT THEREFORE REPRESENTS THE PROPORTIONAL IMPACT ON AI HIRING OF A ONE-STANDARD DEVIATION RISE IN AI EXPOSURE.

Alternative exposure measures

TABLE 2. SECOND STAGE: IMPACT OF AI ADOPTION ON ESTABLISHMENT NON-AI VACANCIES, 2013-15 TO 2017-19

	Growth in Non-AI Vacancies		Growth in Total Vacancies	
	(1)	(2)	(3)	(4)
Growth in AI Vacancies	-5.708***	-3.741**	-5.696***	-3.722**
	(2.065)	(1.627)	(2.072)	(1.632)
Fixed Effects:				
– Region	✓	✓	✓	✓
– Firm Decile	✓	✓	✓	✓
– Industry		✓		✓
First Stage F-Stat				
Observations	24.882	23.11134	24.882	23.11134
N	38,490	38,490	38,490	38,490

NOTES: STANDARD ERRORS IN PARENTHESES. * P $<$0.10, ** P $<$0.05, *** P $<$0.01. STANDARD ERRORS CLUSTERED AT THE FIRM LEVEL. THE INDEPENDENT VARIABLE IS THE GROWTH IN ESTABLISHMENT AI VACANCIES BETWEEN 2013-15 AND 2017-19, APPROXIMATED BY THE CHANGE IN THE INVERSE HYPERBOLIC SINE. LIKEWISE THE DEPENDENT VARIABLES ARE THE CHANGE IN THE INVERSE HYPERBOLIC SINE OF THE RESPECTIVE ESTABLISHMENT-LEVEL OUTCOMES. EACH COEFFICIENT THEREFORE REPRESENTS THE PERCENTAGE POINT IMPACT UPON THE OUTCOME VARIABLE OF A ONE PERCENT INCREASE IN ESTABLISHMENT AI HIRING. THE LATTER IS INSTRUMENTED BY ESTABLISHMENT AI EXPOSURE. THIS IS CALCULATED AS THE STANDARDIZED AVERAGE OF OCCUPATION AI EXPOSURE (FROM **?**), OVER THE OCCUPATIONS FOR WHICH THE ESTABLISHMENT POSTS VACANCIES IN 2013-15, WEIGHTED BY THE NUMBER OF VACANCIES POSTED PER OCCUPATION, AS IN **?**.