AI and Services-Led Growth: Evidence from Indian Job Adverts

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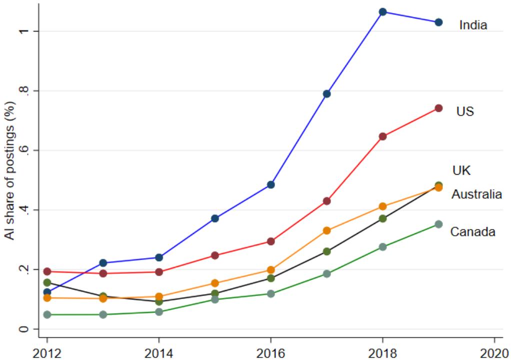
Motivation

- Rapid growth in demand for AI skills across countries since 2015

Online job posts listing AI skills (%)



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- Impact on jobs ambiguous (displacement vs. productivity/new tasks)
  (Brynjolfsson et al. 2017, Acemoglu & Restrepo 2018, Agrawal et al. 2018, Cockburn et al. 2018, Klinger et al. 2018, Goldfarb et al. 2020, Agrawal et al. 2021)
- Limited empirical evidence, focused on high-income countries (adoption)
  (E.g. Acemoglu et al. 2021 in USA, Stapleton 2021 in UK)
- Important potential consequences for development (call centre vs. chatbot)
  (Susskind & Susskind 2015, Baldwin 2019, Baldwin & Forslid 2020, Korinek & Stiglitz 2021)
- India a key case: archetype of services-led growth; large + young population
  - ⇒ E.g. IT/BPO employs 4M, 8% of GDP (SESEI 2019)
  - ⇒ 200M ageing into labor market by 2030 (UN 2019)

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How did AI affect labor demand in India's white-collar service sector?

What we do:

⇒ Document the demand for AI skills in India's white-collar service sector using online job adverts from India's largest jobs website

⇒ Study the impact of establishment-level AI demand on non-AI adverts, wage offers and tasks in short-term using a PSM event study and in medium term using ex-ante exposure to future AI inventions

What we find:

⇒ Demand for AI skills highly concentrated across firms, industries, cities

⇒ AI hiring within establishments reduces demand for high-skilled managerial and professional occupations, non-routine work & analytical tasks

⇒ Overall net effects negative: ↑1% in the AI vacancy growth rate ⇒ ↓3.6pp in establishment total vacancy growth + ↓2.5pp in median wage offers

Clarifications: (i) ML, pre-GAI, (ii) 'posts/wage offers' not 'hiring/wages'; (iii) direct establishment-level effects

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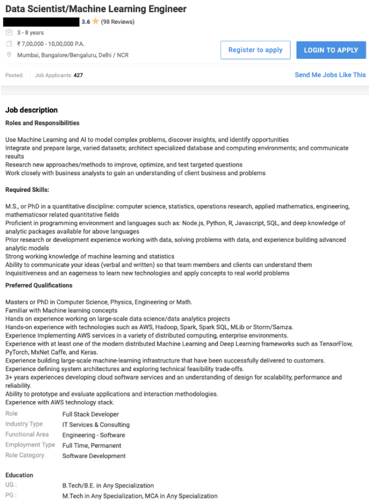
Vacancy data from India's largest online job postings platform

- 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

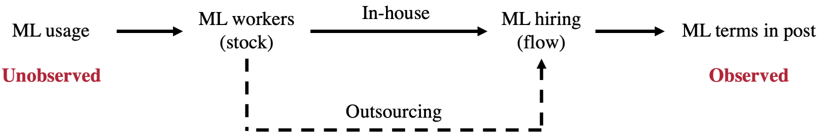
Masters or PhD in Computer Science, Physics, Engineering or Math.
Familiar with Machine learning concepts
Hands on experience working on large-scale data science/data analytics projects
Hands-on experience with technologies such as AWS, Hadoop, Spark, Spark SQL, MLib or Storm/Samza.
Experience Implementing 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

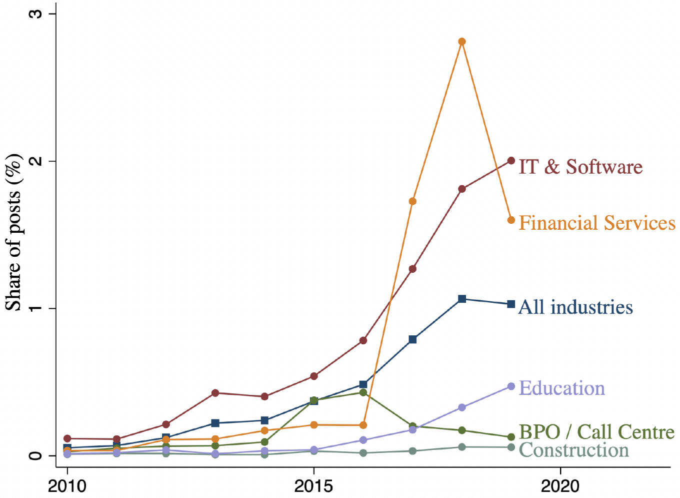
UG :	B.Tech/B.E. in Any Specialization
PG :	M.Tech in Any Specialization, MCA in Any Specialization

Measuring demand for machine learning skills

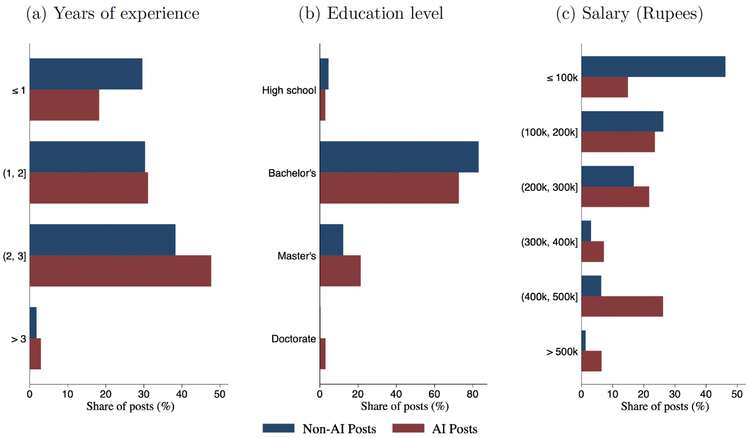


- Classify a post as an AI vacancy if it includes words from list of specific AI terms (Acemoglu et al. 2021)
- Use demand for AI skills in vacancies to proxy for AI usage (Rock 2019, Benzell et al. 2019, Acemoglu et al. 2021, Stapleton 2021)
- Exploit that primary method for sourcing AI capabilities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

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



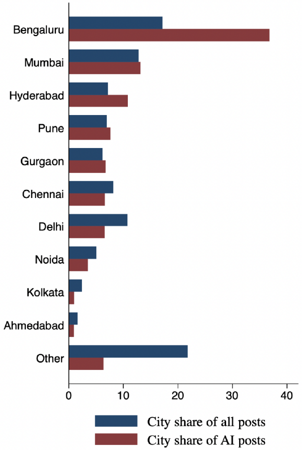
2. AI roles require more education, but offer substantially higher wages than other white-collar services jobs



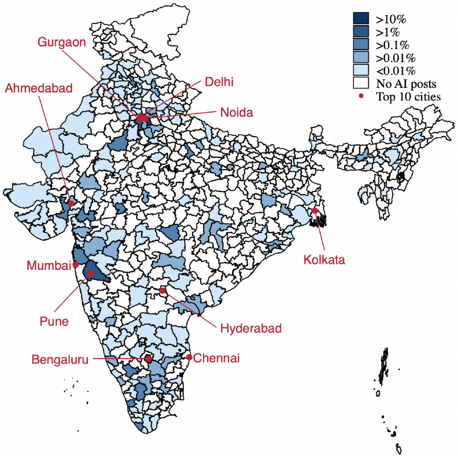
⇒ AI posts pay a 13% salary premium, even after controlling for education, experience, and detailed fixed effects (industry-region, industry-year, region-year, firm, occupation).

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



PSM event study: initial impact of AI adoption

- Match AI adopters to similar non-adopters based on propensity scores following Koch et al. (2021)
  - ⇒ Focus on AI 'users' not 'producers' (drop educ., IT as in Acemoglu et al. 2021)
  - ⇒ AI adopters are larger and pay higher wages
  - ⇒ Run probit regression on lagged establishment characteristics to construct propensity scores
  - ⇒ Conditional on these, treatment is orthogonal to characteristics
- PS-weighted regression of the IHS-transformed number of non-AI job posts Y_{frt} by (firm-city) establishment fr on AI adoption events:

$$Y_{frt} = \alpha_{fr} + \alpha_t + \sum_{k=-3\backslash-1}^{2} \gamma_k \mathbb{1}(K_{frt} = k) + \gamma_{3+} \mathbb{1}(K_{frt} \geq 3) + \epsilon_{frt}$$

- Coefficients γ_k are semi-elasticities: the proportionate difference in posting by AI adopters vs. non-adopters in event-year k

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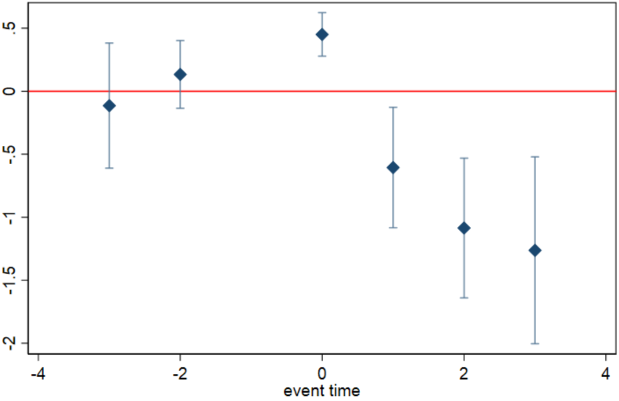
AI adoption leads to lower non-AI hiring

Non-AI hiring is 0.7% lower for adopters in the second year after adoption, and 1.3% lower three years after adoption.



Similar results at region-year and industry-year levels. Robust to using the imputation estimator of Borusyak et al. (2021).

Long difference: *AI exposure ⇒ AI adoption ⇒ #posts + wage offers*

First stage:

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

- Instrument demand for AI skills (proxy for adoption) with Webb (2020) exposure measure based on overlap between patents and task descriptions

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
- IHS of *Adoption* and outcomes y; city, industry and firm size decile fixed effects; standard errors clustered at the firm level
- Interpretation: increasing the growth rate of AI demand between 2010-12 and 2017-19 by 1% leads to a β **percentage point rise in the growth rate** of the outcome variable across the same time period

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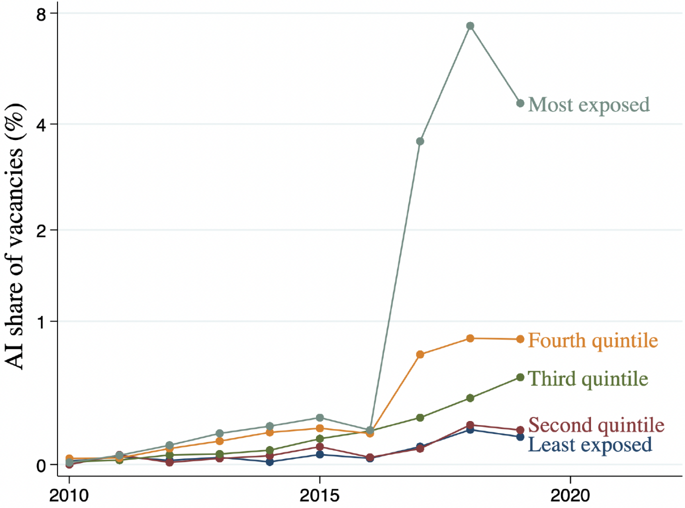
First stage: AI exposure predicts AI demand



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.

Second stage: AI lowers growth in non-AI postings and total postings

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

Lower demand hits higher-skilled occupations...

Examining the impact on establishments' posts for particular 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

...with negative impacts largest for corporate managers

Disaggregate by sub-categories of professionals and managers:

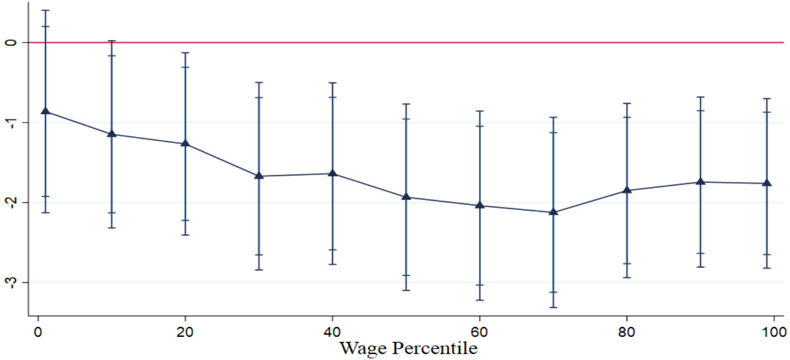
	Growth in Non-AI Vacancies					
	Professionals				Managers	
	Engineering Professionals	Health Professionals	Teaching Professionals	Other Professionals	Corporate Managers	General Managers
Growth in AI Vacancies	-4.951***	0.548*	0.284***	-2.687***	-12.18***	-2.403***
	(1.198)	(0.332)	(0.107)	(0.926)	(2.592)	(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

Wage offers also fall ⇒ demand effect not constrained supply

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

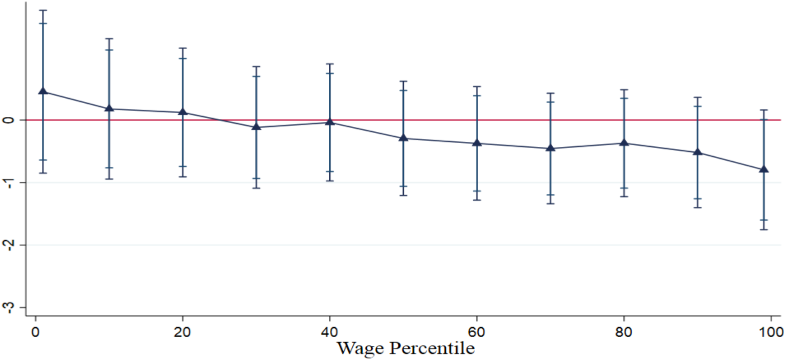
	Growth in Non-AI Median Wage			Growth in Overall Median Wage		
	(1)	(2)	(3)	(4)	(5)	(6)
Growth in AI Vacancies	-2.703***	-3.101***	-2.599***	-2.632***	-3.017***	-2.527***
	(0.799)	(0.895)	(0.758)	(0.770)	(0.862)	(0.730)
Fixed Effects:						
– Region	✓	✓	✓	✓	✓	✓
– Industry	✓		✓	✓		✓
– Firm Decile		✓	✓		✓	✓
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

AI lowers the distribution of wage offers...



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

...driven primarily by the change in occupational composition



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

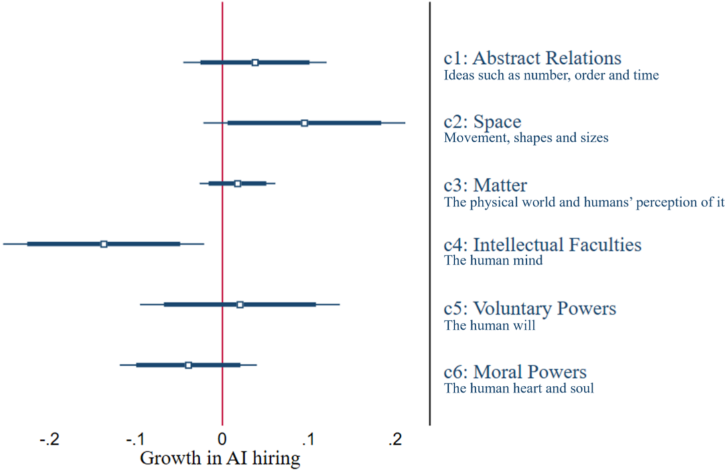
AI lowers demand for non-routine task-intensive occupations

Map the measures of Acemoglu & Autor (2011) onto India's occupational classification and standardize, then assess the impact of AI hiring on the change in IHS-transformed establishment-level routine and non-routine scores

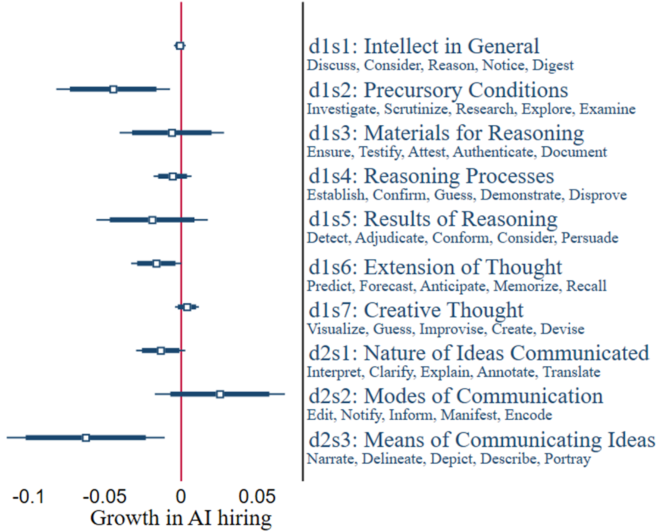
	Growth in Non-Routine Tasks			Growth in Routine Tasks		
	(1)	(2)	(3)	(4)	(5)	(6)
Growth in AI Vacancies	-5.871***	-7.200***	$\boxed{\text{-5.701***}}$	0.298	0.599**	0.349
	(1.179)	(1.432)	$\boxed{\text{(1.126)}}$	(0.216)	(0.283)	(0.219)
Fixed Effects:						
– Region	✓	✓	✓	✓	✓	✓
– Industry	✓		✓	✓		✓
– 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 intellectual tasks...

Extract the verbs in job descriptions and assign these to classes by meaning based on Roget's Thesaurus, following Michaels, Rauch and Redding (2018). Then assess the impact of AI on the change in verb usage by verb class

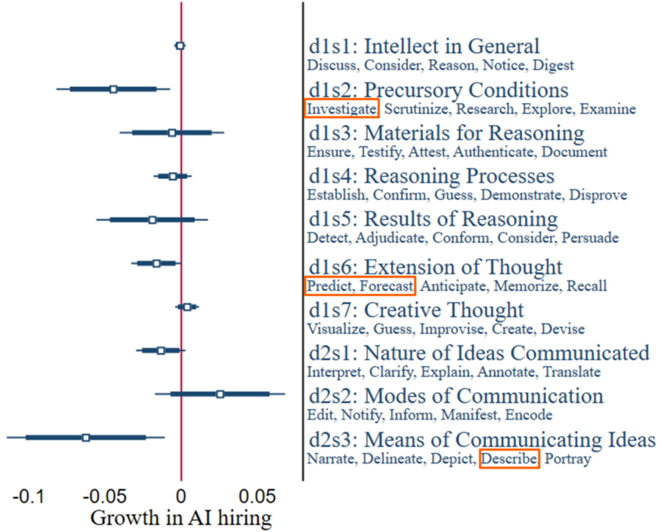


...especially analytical tasks involving description and prediction



Similar impact within top 1% highest-paid roles, in line with occupation results.

...especially analytical tasks involving description and prediction



Similar impact <u>within</u> top 1% highest-paid roles, in line with occupation results.

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. IHS robustness checks (Chen & Roth, 2022) ✓
6. Shift-share robustness checks (Goldsmith-Pinkham et al., 2020) ✓
7. Standard errors corrected for correlation following (Adão et al., 2019) ✓

Conclusion

- AI jobs pay a substantial wage premium, but are highly concentrated in certain industries, cities and firms
- AI adoption has a net negative impact on labor demand within incumbent Indian white-collar services firms in AI-consuming industries
- This displacement effect is driven by lower demand for high-skill, managerial, non-routine, analytical labor

  $\Rightarrow$ Stark contrast to literatures on computerization and industrial robotics

- Key open question: to what extent does AI adoption create new tasks and firms, and how do the 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]

October 12, 2023

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

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)

Probit regression for propensity scores

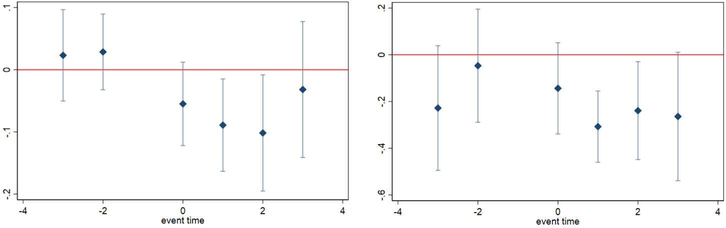
Back

	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

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

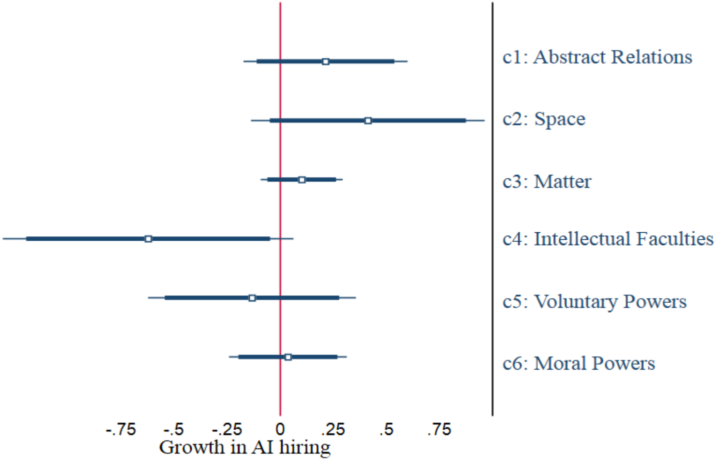
AI adoption leads to reduced non-AI hiring also at the level of regions and industries ◂ Back



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

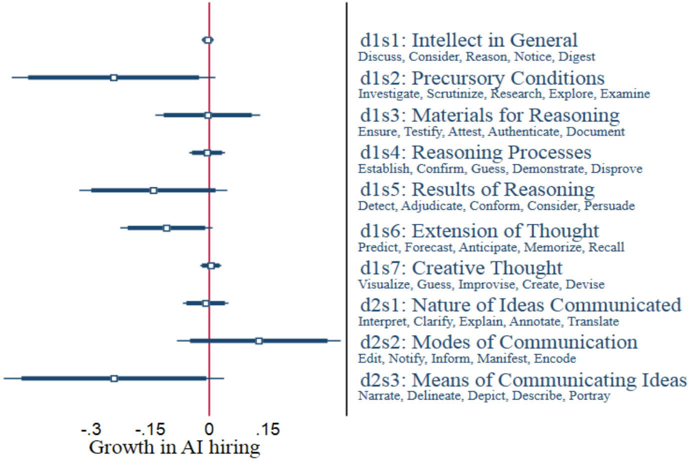
Similar results found *within* top 1% highest paid roles

Back



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

Back



Instrument validity

Back

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

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

- This is a Bartik approach: occupation shares measure exposure to a common shock. Identification – i.e. the validity of our instrument – is based on exogeneity of shares.
  - ⇒ AI shock occurred around 2015, with important technological innovations occurring only shortly beforehand – hence occupation shares in baseline plausibly exogenous with respect to the future shock.

- We can assess 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

Test 1: Investigating correlates of shares

Back

- If baseline shares are correlated with other controls, the instrument could seem to have an effect which is instead properly attributed to the impact of the controls.
- Investigate extent to which baseline shares correlate with baseline controls which could themselves affect hiring/wage offer trends. We regress the instrument on baseline controls (education, experience, and salary).
- Not an issue for overall instrument. Correlates Some individual occupation shares warrant inclusion of controls, in particular experience.

Test 2: Examining pre-trends

Back

- Pre-trends: pick 2010-2012 as pre-period and ask whether exposure based on these shares predicts year-on-year growth differences after 2014, so 2010-2012 not contained in growth rates.
- Violation of assumption of no pre-trends invalidates our approach. We regress employment and wage growth on the instrument based on 2010-2012 shares.
- For instrument, find no pre-trends. Pre-trends

Test 3: Alternative estimators and over-identification tests

Back

- 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 is reassuring for the validity of our approach, and over-identification tests allow to test the validity of over-identifying restrictions.
- Find some general evidence for misspecification. Alternative estimators
- Comparing alternative estimators suggests validity of instrument for wages; so do misspecification tests. Both less favourable for employment results.
- Over-identification tests usually reject null of validity of over-identifying restrictions.
- Overall summary: lack of pre-trends, alternative estimators, and misspecification tests support Bartik instrument for wages, but less for employment.

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

	Growth in Non-AI Vacancies				Growth in Non-AI Median Wage			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Instrument	0.000223	0.00617	0.00477	0.00622	0.0106	0.0272	0.0283	0.0275
	(0.0112)	(0.00599)	(0.0107)	(0.00602)	(0.0271)	(0.0175)	(0.0270)	(0.0177)
Fixed Effects:								
– Region		✓	✓	✓		✓	✓	✓
– Industry		✓		✓		✓		✓
– Firm Decile			✓	✓			✓	✓
Observations	296,730	296,730	296,730	296,730	296,730	296,730	296,730	296,730

Test 3: Alternative estimators and over-identification tests

Back

- Following Goldsmith-Pinkham et al., we compare Bartik to OLS, over-identified TSLS, using each share as a separate instrument, the Modified Bias-corrected TSLS (MBTSLS) estimator, the Limited Information Maximum Likelihood (LIML) estimator, and the HFUL estimator.
- Similarity in results between HFUL and LIML on the one hand, and MBTSLS and over-identified TSLS on the other hand supports the validity of our instrument.
- Bartik estimates are similar to LIML estimates when including establishment controls. Results from HFUL and MBTSLS are also similar, further supporting our instrument. The comparison of alternative estimators suggests validity of our instrument as we find estimates to be quite similar.
- We then run over-identification tests for the HFUL, LIML, and over-identified TSLS estimators, where the null hypothesis is the validity of the over-identifying restrictions. These tests do not reject the null hypothesis when including controls.
- For misspecification tests, we test whether Bartik is sensitive to the inclusion of controls. Similarity in estimates would support our instrument, and indeed we find support for our instrument's validity.

Shift-share robust standard errors

Back

	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**
	(1.666)	(3.436)	(1.479)	(1.663)	(3.437)	(1.475)
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

IHS Robustness Checks

◂ Back

- Our results are robust to other approaches and do not hinge on the IHS transformation. Following Chen & Roth, 2022, we show results from several robustness checks:
  - As the independent variable, we use an AI adoption dummy in order to circumvent the issue of estimates' scale sensitivity. Our first set of robustness results winsorizes outcomes in levels at the 5% and 10% levels.
  - We also turn the dependent variables into binary outcomes for exceeding a threshold, e.g. the median.
  - Finally, regress changes in log(1+x) of AI hiring, instrumented by AI exposure, on changes in log(1+x) of vacancies and wages.
- Our findings survive all these tests, the results of which are available on request.

Firm-level employment results

Back

We study the establishment level, as geographical variation matters and the firm level does not allow us to include region fixed effects.

	Growth in Non-AI Vacancies			Growth in Total Vacancies		
	(1)	(2)	(3)	(4)	(5)	(6)
Growth in AI Vacancies	-1.456**	-4.353	-1.193	-1.461**	-4.369	-1.200
	(0.688)	(2.678)	(0.749)	(0.691)	(2.690)	(0.752)
Fixed Effects:						
– Industry	✓		✓	✓		✓
– Firm Decile		✓	✓		✓	✓
First Stage F-Stat	16.51	4.16	12.01	16.51	4.16	12.01
Observations	6,785	6,785	6,785	6,785	6,785	6,785

Firm-level wage results

Back

We study the establishment level, as geographical variation matters and the firm level does not allow us to include region fixed effects.

	Growth in Non-AI Median Wage			Growth in Overall Median Wage		
	(1)	(2)	(3)	(4)	(5)	(6)
Growth in AI Vacancies	-0.276	-0.860	-0.340	-0.273	-0.856	-0.337
	(0.234)	(0.621)	(0.287)	(0.233)	(0.617)	(0.285)
Fixed Effects:						
– Industry	✓		✓	✓		✓
– Firm Decile		✓	✓		✓	✓
First Stage F-Stat	16.56	4.172	11.88	16.71	4.226	11.99
Observations	6,764	6,764	6,764	6,766	6,766	6,766

Baseline results driven by 'incumbents', not 'startups'

Employment results for startups Back

	Growth in Non-AI Vacancies			Growth in Total Vacancies		
	(1)	(2)	(3)	(4)	(5)	(6)
Growth in AI Vacancies	-8.088	-17.32	-8.887	-8.053	-17.32	-8.853
	(7.710)	(13.90)	(7.827)	(7.741)	(13.96)	(7.858)
Fixed Effects:						
– Region	✓	✓	✓	✓	✓	✓
– Industry	✓		✓	✓		✓
– Firm Decile		✓	✓		✓	✓
First Stage F-Stat	2.637	2.469	2.801	2.637	2.469	2.801
Observations	21,085	21,085	21,085	21,085	21,085	21,085

Baseline results driven by ‘incumbents’, not ‘startups’

Employment results for incumbents Back

	Growth in Non-AI Vacancies			Growth in Total Vacancies		
	(1)	(2)	(3)	(4)	(5)	(6)
Growth in AI Vacancies	-3.043***	-2.530**	-2.998*	-3.035***	-2.520**	-2.983*
	(1.146)	(1.027)	(1.808)	(1.150)	(1.030)	(1.811)
Fixed Effects:						
– Region	✓	✓	✓	✓	✓	✓
– Firm Decile	✓	✓		✓	✓	
– Industry		✓			✓	
– Firm			✓			✓
First Stage F-Stat	24.51	24.33	7.454	24.51	24.33	7.454
Observations	17,348	17,348	14,729	17,348	17,348	14,729

Baseline results driven by ‘incumbents’, not ‘startups’

Wage results for startups Back

	Growth in Non-AI Median Wage			Growth in Overall Median Wage		
	(1)	(2)	(3)	(4)	(5)	(6)
Growth in AI Vacancies	-9.946*	-11.88*	-9.754*	-12.26	-14.77	-11.93
	(5.697)	(6.913)	(5.478)	(8.323)	(10.31)	(7.880)
Fixed Effects:						
– Region	✓	✓	✓	✓	✓	✓
– Industry	✓		✓	✓		✓
– Firm Decile		✓	✓		✓	✓
First Stage F-Stat	4.131	4.12	4.326	2.668	2.558	2.837
Observations	20,934	20,934	20,934	20,959	20,959	20,959

Baseline results driven by ‘incumbents’, not ‘startups’

Wage results for incumbents Back

	Growth in Non-AI Median Wage			Growth in Overall Median Wage		
	(1)	(2)	(3)	(4)	(5)	(6)
Growth in AI Vacancies	-1.781***	-1.813***	-4.630**	-1.824***	-1.858***	-4.645**
	(0.622)	(0.619)	(1.926)	(0.640)	(0.638)	(1.931)
Fixed Effects:						
– Region	✓	✓	✓	✓	✓	✓
– Firm Decile	✓	✓		✓	✓	
– Industry		✓			✓	
– Firm			✓			✓
First Stage F-Stat	25.64	25.58	7.519	24.48	24.35	7.529
Observations	17,259	17,259	14,648	17,266	17,266	14,652