AI, firms and wages: Evidence from India

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How is AI affecting services hiring in India?

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- Also critical for countries pursuing a services-led development model (Susskind & Susskind 2015, Baldwin 2019, Baldwin & Forslid 2020, Korinek & Stiglitz 2021)

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- India is a key case: archetype of services-led growth; large + young popn.

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[redacted] 3.6 ★ (98 Reviews)

3 - 8 years

₹ 7,00,000 - 10,00,000 P.A.

Mumbai, Bangalore/Bengaluru, Delhi / NCR

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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
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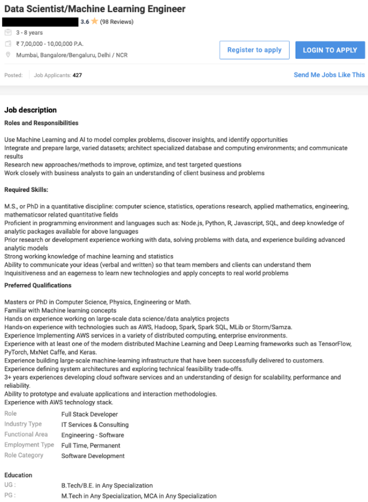

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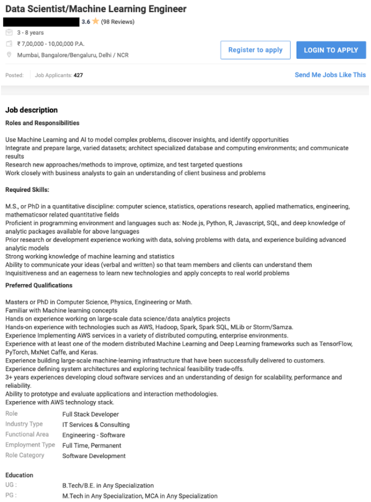

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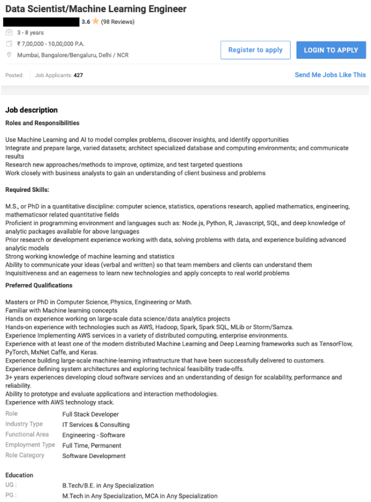

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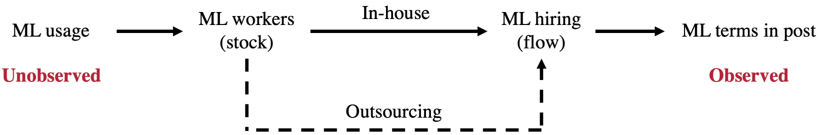

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- Use demand for AI skills in vacancies to proxy for AI usage (Rock 2019, Benzell et al. 2019, Acemoglu et al. 2021, Stapleton 2021)
- Exploit that primary method for sourcing AI capabilities is external hiring (McKinsey Global Institute 2019)

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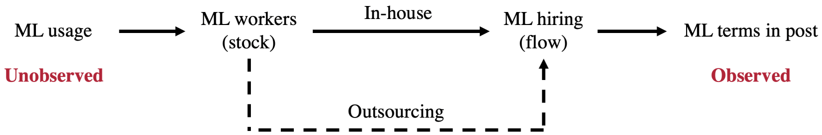

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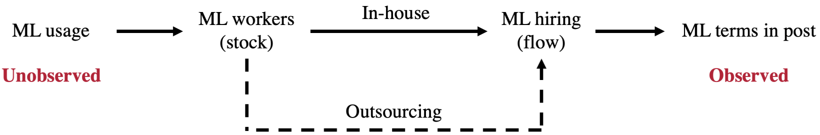
Measuring demand for machine learning skills



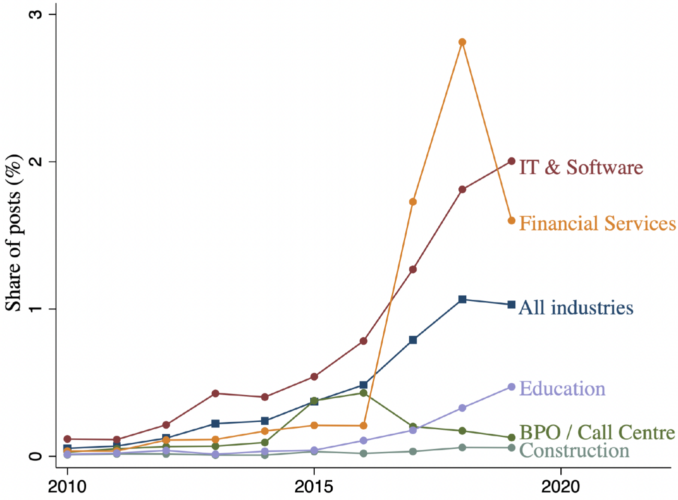
- Classify a post as an AI vacancy if it includes words from list of specific AI terms (Acemoglu et al. 2021)

- Use demand for AI skills in vacancies to proxy for AI usage
(Rock 2019, Benzell et al. 2019, Acemoglu et al. 2021, Stapleton 2021)

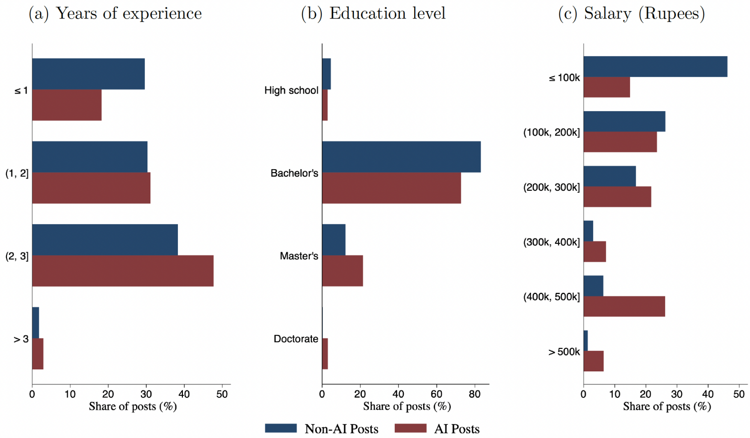
- Exploit that primary method for sourcing AI capabilities is external hiring
(McKinsey Global Institute 2019)

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

AI share of total posts, by industry



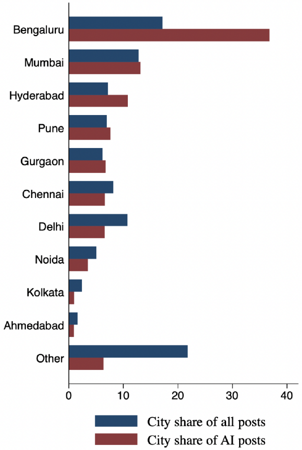
2. AI roles require more education, but offer substantially higher wages than other white-collar services jobs



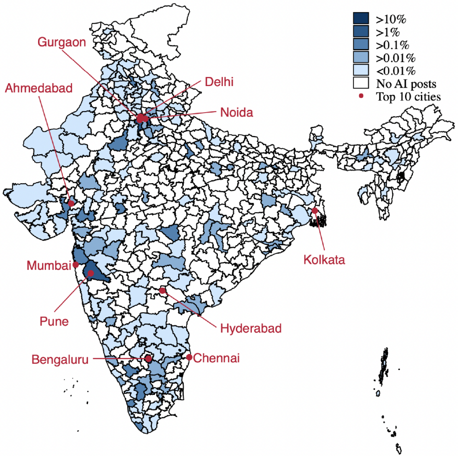
⇒ AI posts pay a 13% salary premium, even after controlling for education, experience, and detailed fixed effects (industry-region, industry-year, region-year, firm, occupation).

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

(a) Shares of posts across cities

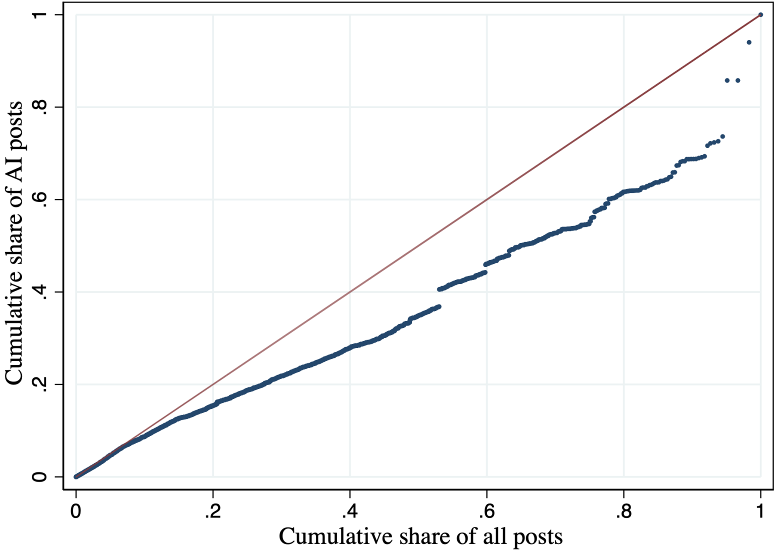


(b) Share of all AI posts, by city, 2010-2019

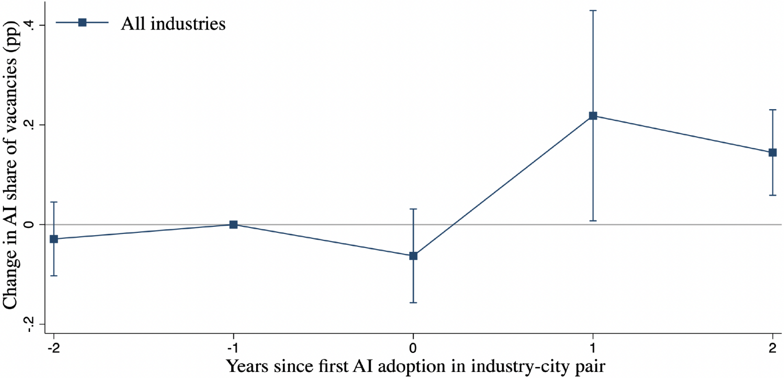


4. AI roles are highly concentrated in the largest firms

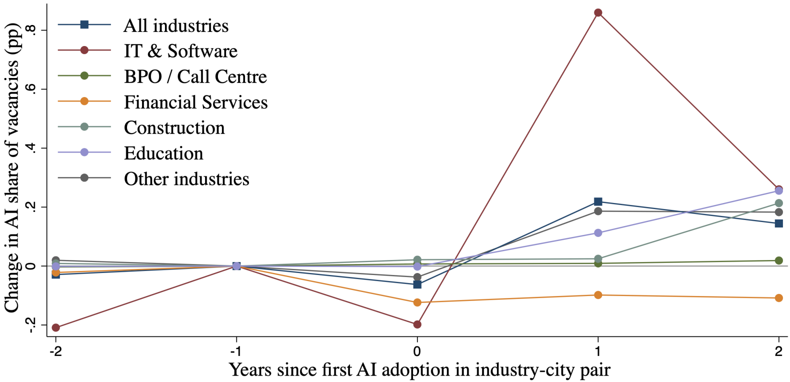
Distribution of AI posts across all firms, 2010-2019



5. AI adoption can spur local AI diffusion, over and above industry and region trends



5. AI adoption can spur local AI diffusion, over and above industry and region trends, particularly in the IT sector



2SLS: *AI exposure ⇒ AI adoption ⇒ #Posts + Wage offers*

First stage:

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

- 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

2SLS: *AI exposure* ⇒ *AI adoption* ⇒ *#Posts* + *Wage offers*

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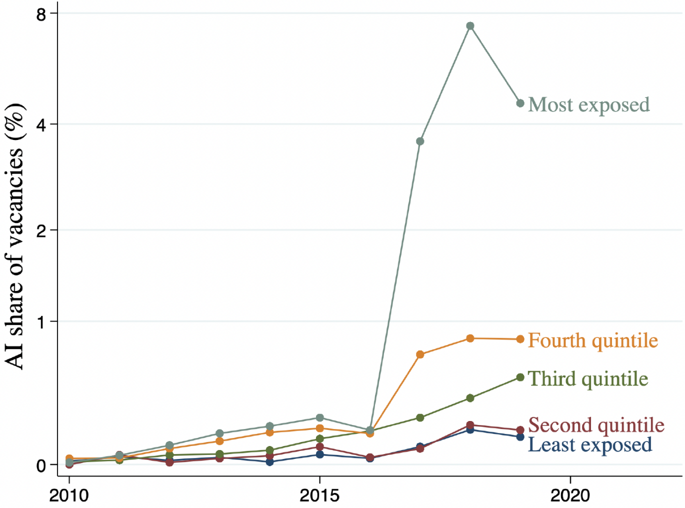
First stage: AI exposure predicts AI demand



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***	-3.605***	-3.534***	-5.909***	-3.566***
	(1.168)	(1.624)	(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

	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 far outweighs the rise in AI vacancies.

Decline in demand hits higher-skilled occupations

Examine the impact on posts for particular categories of occupations:

	Growth in Non-AI Vacancies				
	Personal, sales & security	Clerks	Associate Professionals	Professionals	Managers
Growth in AI Vacancies	2.094***	1.092***	5.121***	$\boxed{-6.222^{***}}$	$\boxed{-12.19^{***}}$
	(0.487)	(0.354)	(1.252)	$\boxed{(1.581)}$	$\boxed{(2.632)}$
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

Disaggregate the negative results for 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

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

Likewise, 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 ($p < 0.01$).

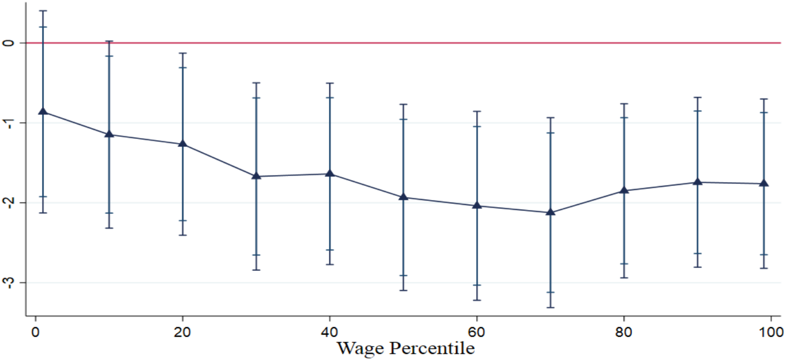
Unpicking wage impacts

- Impacts on establishment-level median wages could be driven by:
    1. **Between occupation effects:** AI changing the occupational composition & where the median lies
    2. **Within occupation effects:** AI affecting wage offers for the same occupations
- Already showed that AI lowers growth in demand for the highest paid occupations & raises demand for the lowest paid

    $\Rightarrow$ Between occupation effects
- Next explore impacts of AI on establishment wage offers for specific wage percentiles, then control for changing occupation shares.

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

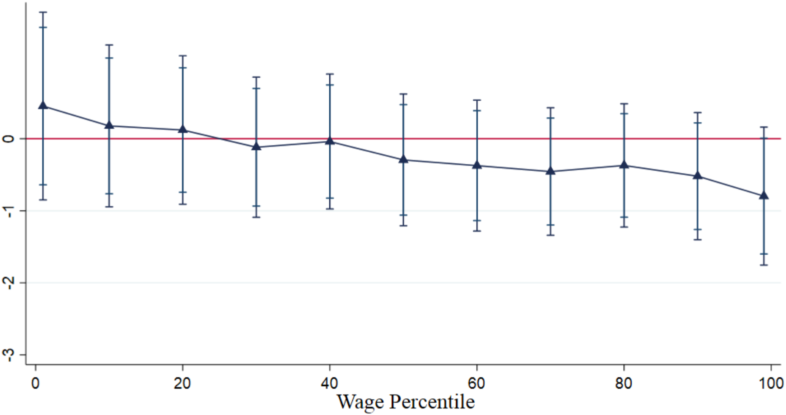
Impact of 1% higher establishment AI demand on non-AI wage growth:



Except for the lowest 10 percent of jobs, AI lowers the distribution of wage offers.

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

Impact of 1% higher establishment AI demand on non-AI wage growth:



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.

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
    6. Emotion, Religion, and Morality: the human heart and soul

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Most over-represented verbs in AI job ads

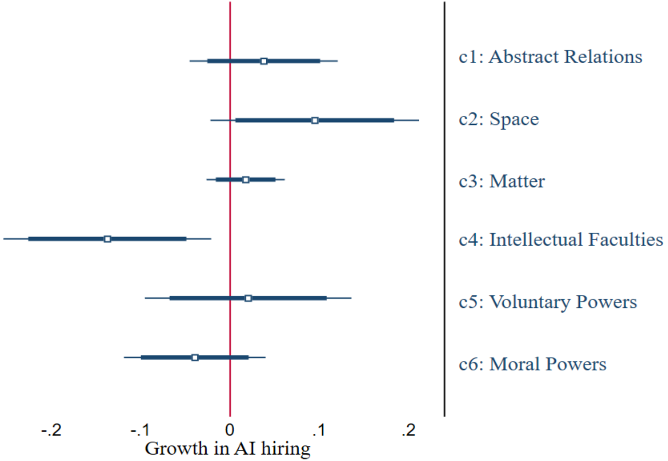
Extract the verbs in AI and non-AI job ads, then calculate the share of each verb relative to all verbs, and rank by difference in shares between AI and non-AI job ads:

	Less likely to include	**More likely to include**
1	Call	Experience
2	Manage	Develop
3	Job	Build
4	Shift	Program
5	Plan	Design
6	Account	Work
7	Tar	Predict
8	Look	Deliver
9	Graduate	Use
10	Recruit	Advance

The task view: AI reduces demand for intellectual tasks

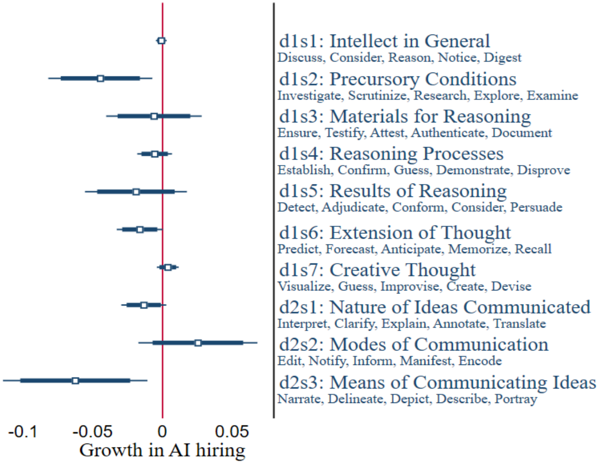
Evaluate the impact of AI on change in verb usage by verb class, using classification from Michaels, Rauch and Redding (2018) described above

Impact of 1% higher establishment AI demand on verb usage by class:



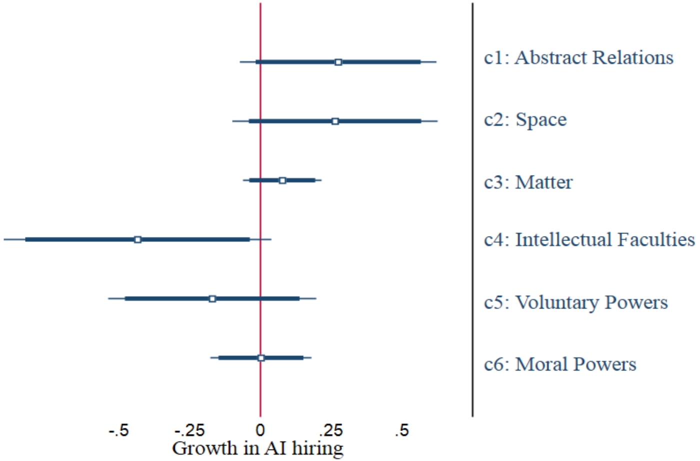
The task view: AI reduces demand for intellectual tasks

Impact of 1% higher establishment AI demand on verb usage by section within c4 Intellectual Faculties:



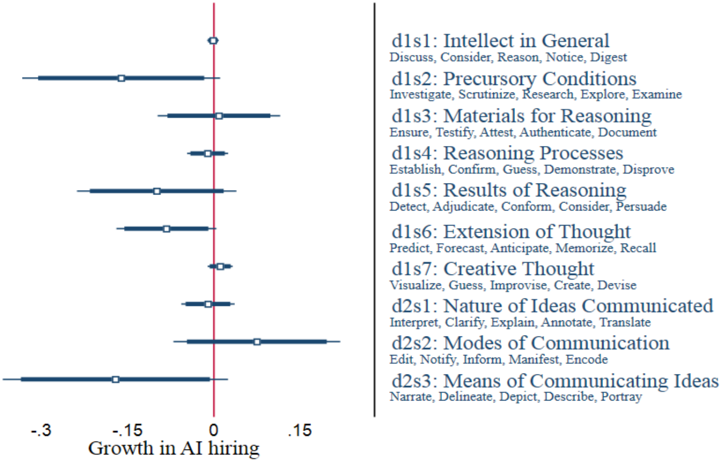
Similar results found *within* top 1 % highest paid roles

Impact of 1% higher establishment AI demand on verb usage by class, keeping only top 1% highest paid roles within establishments:



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

Impact of 1% higher establishment AI demand on verb usage by section within c4 Intellectual Faculties, keeping only top 1% highest paid roles within establishments:



‘Extension of thought’ tasks have high wage premia, even within occupations

Evaluate the wage ‘premium’ for these verb categories in postings.

	log Annual Salary			
	(1)	(2)	(3)	(4)
Precusory Conditions and Operations	-0.170	-0.143*	-0.326***	-0.350***
	(0.128)	(0.0824)	(0.0832)	(0.0760)
Extension of Thought	3.320***	2.406***	1.494***	0.855***
	(0.211)	(0.159)	(0.149)	(0.124)
Means of Communicating Ideas	-0.214*	-0.180**	-0.132	0.0158
	(0.122)	(0.0821)	(0.0810)	(0.0752)
Fixed Effects:				
– Industry-Region	✓	✓	✓	✓
– Industry-Year	✓	✓	✓	✓
– Region-Year	✓	✓	✓	✓
– Firm		✓	✓	✓
– Occupation Code			✓	
– Role Label				✓
Observations	1,438,305	1,438,072	1,365,369	1,438,062

Regressions on share of verbs from a given section. Controls for experience and education not shown. Results on the three sections from separate regressions.

Taking stock of the role of AI (v. early)

- Occupation/wage distribution:
  - ⇒ Changing labor demand *between occupations*: lower growth for higher skilled occupations & higher growth for lower skilled occupations, which alters the wage distribution
  - ⇒ Declining wage offer growth *within* the top 1% highest paid job ads
- Verbs/tasks:
  - ⇒ Lower demand for intellectual tasks, for the full sample
  - ⇒ Lower demand within the 1% highest paid job ads

⇒ Suggestive evidence that declining wage offers for highest paid roles could be due to declining demand for tasks related to ‘extension of thought’, which commands a high wage premium even within occupations.

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) ✓

Conclusion

Our paper:

⇒ Rich new data on AI demand and wage offers in a developing country

⇒ AI jobs pay a substantial wage premium, but they are highly concentrated in certain industries, cities and firms.

⇒ AI adoption results in lower growth in postings and wages for non-AI roles + total postings.

⇒ Early evidence that these displacement effects are driven by high-skilled occupations and tasks relating to the use of 'intellect', such as analysis, projections and measurement.

Key open questions:

⇒ To what extent does AI adoption generate new tasks &/or firms?

⇒ How do 'creative' vs 'destructive' effects compare?

⇒ GE: is overall 'creation' > 'destruction'?

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AI, firms and wages: Evidence from India

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

June 23, 2022

[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)

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 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 various technological innovations occurring only shortly beforehand – hence occupation shares in baseline plausibly exogenous with respect to the future shock.
- 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

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 as pre-period and ask whether exposure based on 2010 shares predicts growth differences between endline and baseline excluding 2010.
- Violation of assumption of no pre-trends invalidates our approach. We regress employment and wage growth on the instrument based on 2010 shares.
- For instrument, find pre-trend for employment. No pre-trend for wages. Same if include industry, city, and baseline f.e. Pre-trends
- For top 5 industries: generally no 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

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VARIABLES	(1) Employment growth	(2) Wage growth
Instrument based on 2010 shares	-1.286**	-0.162
	(0.569)	(0.149)
Constant	0.276	0.329***
	(0.180)	(0.0540)
Observations	8,892	8,847
R-squared	0.005	0.001

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

- Employment and wage growth defined from 2017-2019 (endline) to shortened baseline (2011-2012), leaving out 2010 as here the instrument is constructed purely on 2010 shares.
- No pre-trends for wages, but pre-trends for employment.

Test 3: Alternative estimators and over-identification tests

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	Interpretation	Result
Alternative estimators		
HFUL vs LIML	similarity reassuring	only similar for wages without controls
MBTSLS vs overid. TSLS	similarity reassuring	always quite similar
Bartik vs LIML	similarity reassuring	points towards misspecification
HFUL vs. MBTSLS	similarity reassuring	points towards misspecification
Over-identification tests		
H0 of validity of	not rejecting	in most cases, reject null, in particular:
over-ident. restr.	H0 reassuring	-always reject H0 for wages with or without controls
		-almost always for employment with or without controls
Misspecification tests		
Bartik sensitive	prefer not to be	estimates differ sign. across models for employment
to controls		do not differ sign. for wages

- Generally strong support for wage results, less for employment results.