AI, firms and wages: Evidence from India

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

December 19, 2021

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

How is AI affecting services hiring in India?

- Recent advances in machine learning (ML) have reduced the cost of prediction (Agrawal et al. 2018)
  - ⇒ This could theoretically displace workers or expand employment through improved productivity or the creation of new tasks (Brynjolfsson et al. 2017, Acemoglu & Restrepo 2018, Cockburn et al. 2018, Klinger et al. 2018, Goldfarb et al. 2020, Agrawal et al. 2021)
  - ⇒ Detailed empirical evidence limited by scarce data on adoption, and focuses on high-income countries (E.g. Acemoglu et al. 2021 in USA, Stapleton 2021 in UK)
- For countries pursuing a services-led growth model, this implies important risks and opportunities (Susskind & Susskind 2015, Baldwin 2019, Baldwin & Forslid 2020, Korinek & Stiglitz 2021)
  - ⇒ E.g. call centre operator vs. chatbot
- India is a key case: archetype of services-led growth; large + young popn.
  - ⇒ E.g. IT + Business Process Outsourcing sector employs 4M people, contributes 8% of GDP (SESEI 2019)
  - ⇒ 200M young people ageing into labour market over next 10 years (UN 2019)

How is AI affecting services hiring in India?

- Recent advances in machine learning (ML) have reduced the cost of prediction (Agrawal et al. 2018)
  - ⇒ This could theoretically displace workers or expand employment through improved productivity or the creation of new tasks (Brynjolfsson et al. 2017, Acemoglu & Restrepo 2018, Cockburn et al. 2018, Klinger et al. 2018, Goldfarb et al. 2020, Agrawal et al. 2021)
  - ⇒ Detailed empirical evidence limited by scarce data on adoption, and focuses on high-income countries (E.g. Acemoglu et al. 2021 in USA, Stapleton 2021 in UK)
- For countries pursuing a services-led growth model, this implies important risks and opportunities (Susskind & Susskind 2015, Baldwin 2019, Baldwin & Forslid 2020, Korinek & Stiglitz 2021)
  - ⇒ E.g. call centre operator vs. chatbot
- India is a key case: archetype of services-led growth; large + young popn.
  - ⇒ E.g. IT + Business Process Outsourcing sector employs 4M people, contributes 8% of GDP (SESEI 2019)
  - ⇒ 200M young people ageing into labour market over next 10 years (UN 2019)

How is AI affecting services hiring in India?

- Recent advances in machine learning (ML) have reduced the cost of prediction (Agrawal et al. 2018)
  - ⇒ This could theoretically displace workers or expand employment through improved productivity or the creation of new tasks (Brynjolfsson et al. 2017, Acemoglu & Restrepo 2018, Cockburn et al. 2018, Klinger et al. 2018, Goldfarb et al. 2020, Agrawal et al. 2021)
  - ⇒ Detailed empirical evidence limited by scarce data on adoption, and focuses on high-income countries (E.g. Acemoglu et al. 2021 in USA, Stapleton 2021 in UK)
- For countries pursuing a services-led growth model, this implies important risks and opportunities (Susskind & Susskind 2015, Baldwin 2019, Baldwin & Forslid 2020, Korinek & Stiglitz 2021)
  - ⇒ E.g. call centre operator vs. chatbot
- India is a key case: archetype of services-led growth; large + young popn.
  - ⇒ E.g. IT + Business Process Outsourcing sector employs 4M people, contributes 8% of GDP (SESEI 2019)
  - ⇒ 200M young people ageing into labour market over next 10 years (UN 2019)

How is AI affecting services hiring in India?

- Recent advances in machine learning (ML) have reduced the cost of prediction (Agrawal et al. 2018)
  - ⇒ This could theoretically displace workers or expand employment through improved productivity or the creation of new tasks (Brynjolfsson et al. 2017, Acemoglu & Restrepo 2018, Cockburn et al. 2018, Klinger et al. 2018, Goldfarb et al. 2020, Agrawal et al. 2021)
  - ⇒ Detailed empirical evidence limited by scarce data on adoption, and focuses on high-income countries (E.g. Acemoglu et al. 2021 in USA, Stapleton 2021 in UK)
- For countries pursuing a services-led growth model, this implies important risks and opportunities (Susskind & Susskind 2015, Baldwin 2019, Baldwin & Forslid 2020, Korinek & Stiglitz 2021)
  - ⇒ E.g. call centre operator vs. chatbot
- India is a key case: archetype of services-led growth; large + young popn.
  - ⇒ E.g. IT + Business Process Outsourcing sector employs 4M people, contributes 8% of GDP (SESEI 2019)
  - ⇒ 200M young people ageing into labour market over next 10 years (UN 2019)

How is AI affecting services hiring in India?

- Recent advances in machine learning (ML) have reduced the cost of prediction (Agrawal et al. 2018)
  - ⇒ This could theoretically displace workers or expand employment through improved productivity or the creation of new tasks (Brynjolfsson et al. 2017, Acemoglu & Restrepo 2018, Cockburn et al. 2018, Klinger et al. 2018, Goldfarb et al. 2020, Agrawal et al. 2021)
  - ⇒ Detailed empirical evidence limited by scarce data on adoption, and focuses on high-income countries (E.g. Acemoglu et al. 2021 in USA, Stapleton 2021 in UK)
- For countries pursuing a services-led growth model, this implies important risks and opportunities (Susskind & Susskind 2015, Baldwin 2019, Baldwin & Forslid 2020, Korinek & Stiglitz 2021)
  - ⇒ E.g. call centre operator vs. chatbot
- India is a key case: archetype of services-led growth; large + young popn.
  - ⇒ E.g. IT + Business Process Outsourcing sector employs 4M people, contributes 8% of GDP (SESEI 2019)
  - ⇒ 200M young people ageing into labour market over next 10 years (UN 2019)

How is AI affecting services hiring in India?

- Recent advances in machine learning (ML) have reduced the cost of prediction (Agrawal et al. 2018)
  - ⇒ This could theoretically displace workers or expand employment through improved productivity or the creation of new tasks (Brynjolfsson et al. 2017, Acemoglu & Restrepo 2018, Cockburn et al. 2018, Klinger et al. 2018, Goldfarb et al. 2020, Agrawal et al. 2021)
  - ⇒ Detailed empirical evidence limited by scarce data on adoption, and focuses on high-income countries (E.g. Acemoglu et al. 2021 in USA, Stapleton 2021 in UK)
- For countries pursuing a services-led growth model, this implies important risks and opportunities (Susskind & Susskind 2015, Baldwin 2019, Baldwin & Forslid 2020, Korinek & Stiglitz 2021)
  - ⇒ E.g. call centre operator vs. chatbot
- India is a key case: archetype of services-led growth; large + young popn.
  - ⇒ E.g. IT + Business Process Outsourcing sector employs 4M people, contributes 8% of GDP (SESEI 2019)
  - ⇒ 200M young people ageing into labour market over next 10 years (UN 2019)

How is AI affecting services hiring in India?

- Recent advances in machine learning (ML) have reduced the cost of prediction (Agrawal et al. 2018)
  - ⇒ This could theoretically displace workers or expand employment through improved productivity or the creation of new tasks (Brynjolfsson et al. 2017, Acemoglu & Restrepo 2018, Cockburn et al. 2018, Klinger et al. 2018, Goldfarb et al. 2020, Agrawal et al. 2021)
  - ⇒ Detailed empirical evidence limited by scarce data on adoption, and focuses on high-income countries (E.g. Acemoglu et al. 2021 in USA, Stapleton 2021 in UK)
- For countries pursuing a services-led growth model, this implies important risks and opportunities (Susskind & Susskind 2015, Baldwin 2019, Baldwin & Forslid 2020, Korinek & Stiglitz 2021)
  - ⇒ E.g. call centre operator vs. chatbot
- India is a key case: archetype of services-led growth; large + young popn.
  - ⇒ E.g. IT + Business Process Outsourcing sector employs 4M people, contributes 8% of GDP (SESEI 2019)
  - ⇒ 200M young people ageing into labour market over next 10 years (UN 2019)

How is AI affecting services hiring in India?

- Recent advances in machine learning (ML) have reduced the cost of prediction (Agrawal et al. 2018)
  - ⇒ This could theoretically displace workers or expand employment through improved productivity or the creation of new tasks (Brynjolfsson et al. 2017, Acemoglu & Restrepo 2018, Cockburn et al. 2018, Klinger et al. 2018, Goldfarb et al. 2020, Agrawal et al. 2021)
  - ⇒ Detailed empirical evidence limited by scarce data on adoption, and focuses on high-income countries (E.g. Acemoglu et al. 2021 in USA, Stapleton 2021 in UK)
- For countries pursuing a services-led growth model, this implies important risks and opportunities (Susskind & Susskind 2015, Baldwin 2019, Baldwin & Forslid 2020, Korinek & Stiglitz 2021)
  - ⇒ E.g. call centre operator vs. chatbot
- India is a key case: archetype of services-led growth; large + young popn.
  - ⇒ E.g. IT + Business Process Outsourcing sector employs 4M people, contributes 8% of GDP (SESEI 2019)
  - ⇒ 200M young people ageing into labour market over next 10 years (UN 2019)

Overview of the paper

- **What we do:**
  - ⇒ Investigate the impact of AI on service sector jobs using vacancy posts from India's largest jobs website.
  - ⇒ Measure establishment-level demand for ML skills and document a rapid take-off in ML demand from 2015.
  - ⇒ Exploit plausibly exogenous variation in exposure to advances in key AI technologies to examine the impacts of ML adoption on non-ML jobs.
- **What we find:**
  - ⇒ $\uparrow$1% in the ML vacancy growth rate ⇒ $\downarrow$3.6pp in establishment non-ML vacancy growth + $\downarrow$2.6pp in non-ML median wage offers over time.
  - ⇒ These negative effects on wage growth appear across the wage distribution.
- **Clarifications:** (i) ML, (ii) job-level exposure & adoption, not broader systems; (iii) 'posts/wage offers' not 'hiring/wages'; (iv) direct establishment-level effects.

Overview of the paper

- **What we do:**

  ⇒ Investigate the impact of AI on service sector jobs using vacancy posts from India's largest jobs website.

  ⇒ Measure establishment-level demand for ML skills and document a rapid take-off in ML demand from 2015.

  ⇒ Exploit plausibly exogenous variation in exposure to advances in key AI technologies to examine the impacts of ML adoption on non-ML jobs.

- **What we find:**

  ⇒ ↑1% in the ML vacancy growth rate ⇒ ↓3.6pp in establishment non-ML vacancy growth + ↓2.6pp in non-ML median wage offers over time.

  ⇒ These negative effects on wage growth appear across the wage distribution.

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

Overview of the paper

- **What we do:**
  - ⇒ Investigate the impact of AI on service sector jobs using vacancy posts from India's largest jobs website.
  - ⇒ Measure establishment-level demand for ML skills and document a rapid take-off in ML demand from 2015.
  - ⇒ Exploit plausibly exogenous variation in exposure to advances in key AI technologies to examine the impacts of ML adoption on non-ML jobs.
- **What we find:**
  - ⇒ $\uparrow$1% in the ML vacancy growth rate ⇒ $\downarrow$3.6pp in establishment non-ML vacancy growth + $\downarrow$2.6pp in non-ML median wage offers over time.
  - ⇒ These negative effects on wage growth appear across the wage distribution.
- **Clarifications:** (i) ML, (ii) job-level exposure & adoption, not broader systems; (iii) 'posts/wage offers' not 'hiring/wages'; (iv) direct establishment-level effects.

Overview of the paper

- **What we do:**
  - ⇒ Investigate the impact of AI on service sector jobs using vacancy posts from India's largest jobs website.
  - ⇒ Measure establishment-level demand for ML skills and document a rapid take-off in ML demand from 2015.
  - ⇒ Exploit plausibly exogenous variation in exposure to advances in key AI technologies to examine the impacts of ML adoption on non-ML jobs.
- **What we find:**
  - ⇒ ↑1% in the ML vacancy growth rate ⇒ ↓3.6pp in establishment non-ML vacancy growth + ↓2.6pp in non-ML median wage offers over time.
  - ⇒ These negative effects on wage growth appear across the wage distribution.
- **Clarifications:** (i) ML, (ii) job-level exposure & adoption, not broader systems; (iii) 'posts/wage offers' not 'hiring/wages'; (iv) direct establishment-level effects.

Overview of the paper

- **What we do:**
  - ⇒ Investigate the impact of AI on service sector jobs using vacancy posts from India's largest jobs website.
  - ⇒ Measure establishment-level demand for ML skills and document a rapid take-off in ML demand from 2015.
  - ⇒ Exploit plausibly exogenous variation in exposure to advances in key AI technologies to examine the impacts of ML adoption on non-ML jobs.
- **What we find:**
  - ⇒ $\uparrow$1% in the ML vacancy growth rate ⇒ $\downarrow$3.6pp in establishment non-ML vacancy growth + $\downarrow$2.6pp in non-ML median wage offers over time.
  - ⇒ These negative effects on wage growth appear across the wage distribution.
- **Clarifications:** (i) ML, (ii) job-level exposure & adoption, not broader systems; (iii) 'posts/wage offers' not 'hiring/wages'; (iv) direct establishment-level effects.

Overview of the paper

- **What we do:**
  - ⇒ Investigate the impact of AI on service sector jobs using vacancy posts from India's largest jobs website.
  - ⇒ Measure establishment-level demand for ML skills and document a rapid take-off in ML demand from 2015.
  - ⇒ Exploit plausibly exogenous variation in exposure to advances in key AI technologies to examine the impacts of ML adoption on non-ML jobs.
- **What we find:**
  - ⇒ $\uparrow$1% in the ML vacancy growth rate ⇒ $\downarrow$3.6pp in establishment non-ML vacancy growth + $\downarrow$2.6pp in non-ML median wage offers over time.
  - ⇒ These negative effects on wage growth appear across the wage distribution.
- **Clarifications:** (i) ML, (ii) job-level exposure & adoption, not broader systems; (iii) 'posts/wage offers' not 'hiring/wages'; (iv) direct establishment-level effects.

Overview of the paper

- **What we do:**
  - ⇒ Investigate the impact of AI on service sector jobs using vacancy posts from India's largest jobs website.
  - ⇒ Measure establishment-level demand for ML skills and document a rapid take-off in ML demand from 2015.
  - ⇒ Exploit plausibly exogenous variation in exposure to advances in key AI technologies to examine the impacts of ML adoption on non-ML jobs.
- **What we find:**
  - ⇒ $\uparrow$1% in the ML vacancy growth rate ⇒ $\downarrow$3.6pp in establishment non-ML vacancy growth + $\downarrow$2.6pp in non-ML median wage offers over time.
  - ⇒ These negative effects on wage growth appear across the wage distribution.
- **Clarifications:** (i) ML, (ii) job-level exposure & adoption, not broader systems; (iii) 'posts/wage offers' not 'hiring/wages'; (iv) direct establishment-level effects.

Overview of the paper

- **What we do:**
  - ⇒ Investigate the impact of AI on service sector jobs using vacancy posts from India's largest jobs website.
  - ⇒ Measure establishment-level demand for ML skills and document a rapid take-off in ML demand from 2015.
  - ⇒ Exploit plausibly exogenous variation in exposure to advances in key AI technologies to examine the impacts of ML adoption on non-ML jobs.
- **What we find:**
  - ⇒ $\uparrow$1% in the ML vacancy growth rate ⇒ $\downarrow$3.6pp in establishment non-ML vacancy growth + $\downarrow$2.6pp in non-ML median wage offers over time.
  - ⇒ These negative effects on wage growth appear across the wage distribution.
- **Clarifications:** (i) ML, (ii) job-level exposure & adoption, not broader systems; (iii) 'posts/wage offers' not 'hiring/wages'; (iv) direct establishment-level effects.

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

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.

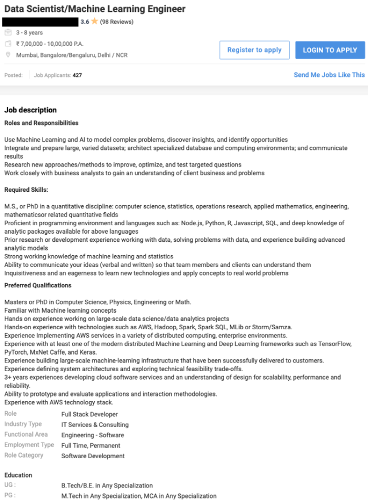
Role	Full Stack Developer
Industry Type	IT Services & Consulting
Functional Area	Engineering - Software
Employment Type	Full Time, Permanent
Role Category	Software Development

Education

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

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.

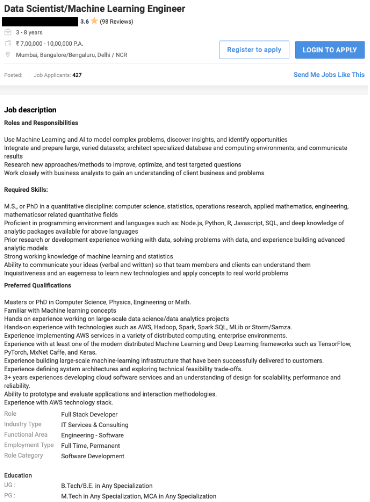
Role	Full Stack Developer
Industry Type	IT Services & Consulting
Functional Area	Engineering - Software
Employment Type	Full Time, Permanent
Role Category	Software Development

Education

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

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

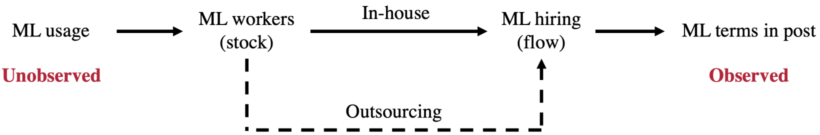
Masters or PhD in Computer Science, Physics, Engineering or Math.
Familiar with Machine learning concepts
Hands on experience working on large-scale data science/data analytics projects
Hands-on experience with technologies such as AWS, Hadoop, Spark, Spark SQL, MLib or Storm/Samza.
Experience Implementing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

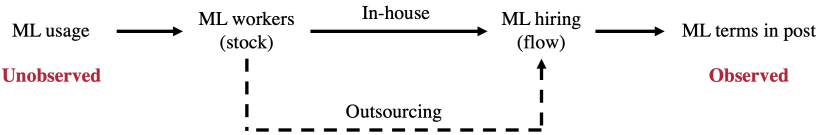
UG :	B.Tech/B.E. in Any Specialization
PG :	M.Tech in Any Specialization, MCA in Any Specialization

Measuring demand for machine learning skills



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

Measuring demand for machine learning skills

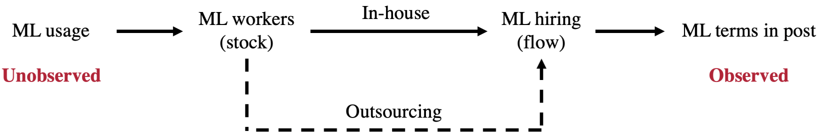


- Classify a post as an ML vacancy if it includes words from list of specific ML terms (Acemoglu et al. 2021)

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

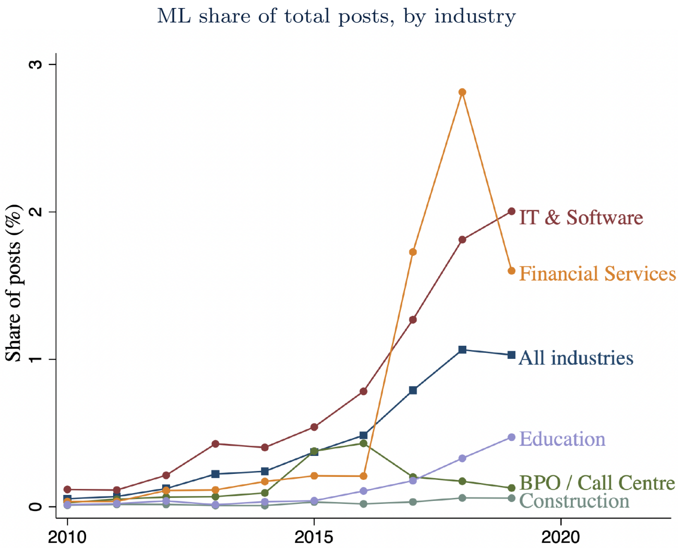
- Exploit that primary method for sourcing ML capabilities is external hiring
  (McKinsey Global Institute 2019)

Measuring demand for machine learning skills

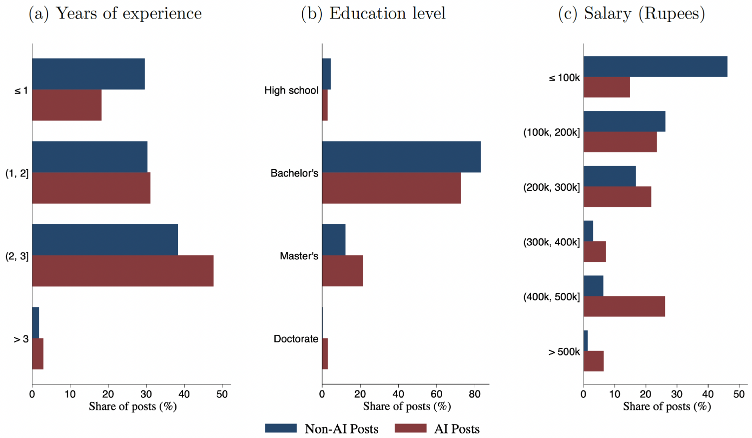


- Classify a post as an ML vacancy if it includes words from list of specific ML terms (Acemoglu et al. 2021)
- Use demand for ML skills in vacancies to proxy for ML usage (Rock 2019, Benzell et al. 2019, Acemoglu et al. 2021, Stapleton 2021)
- Exploit that primary method for sourcing ML capabilities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

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



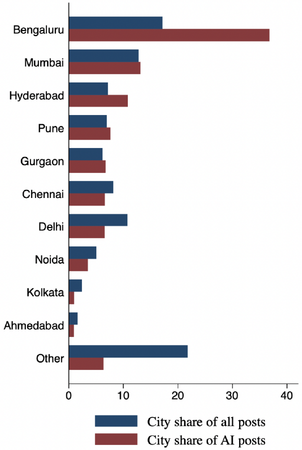
2. ML roles require more education, but offer substantially higher wages than other white-collar services jobs



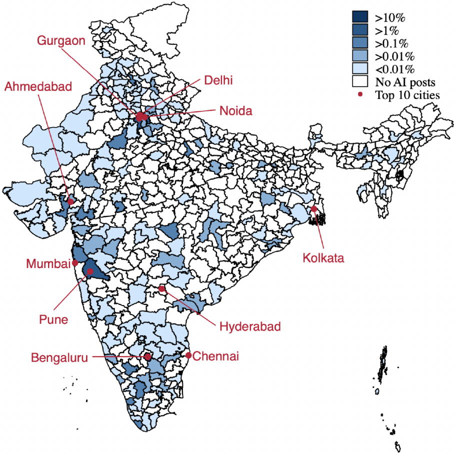
⇒ ML posts pay a 13% salary premium, even after controlling for education, experience, and detailed fixed effects (industry-region, industry-year, region-year, firm, occupation).

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

(a) Shares of posts across cities

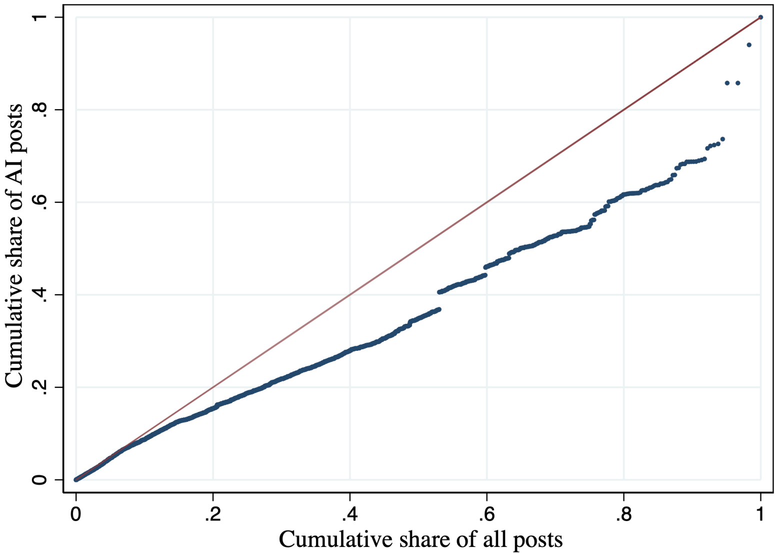


(b) Share of all AI posts, by city, 2010-2019

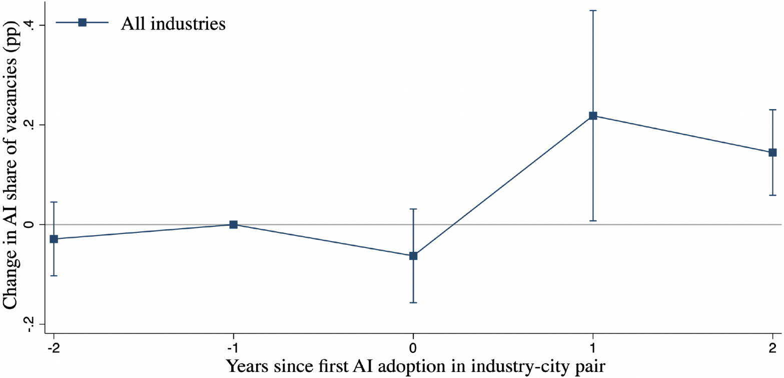


4. ML roles are highly concentrated in the largest ‘superstar’ firms

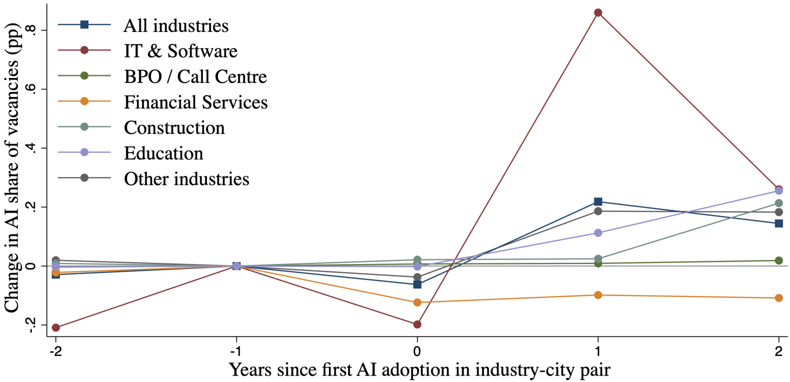
Distribution of ML posts across all firms, 2010-2019



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



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



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

First stage:

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

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

Second stage:

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

- 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 ML 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: *ML exposure* ⇒ *ML adoption* ⇒ *#Posts + Wage offers*

First stage:

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

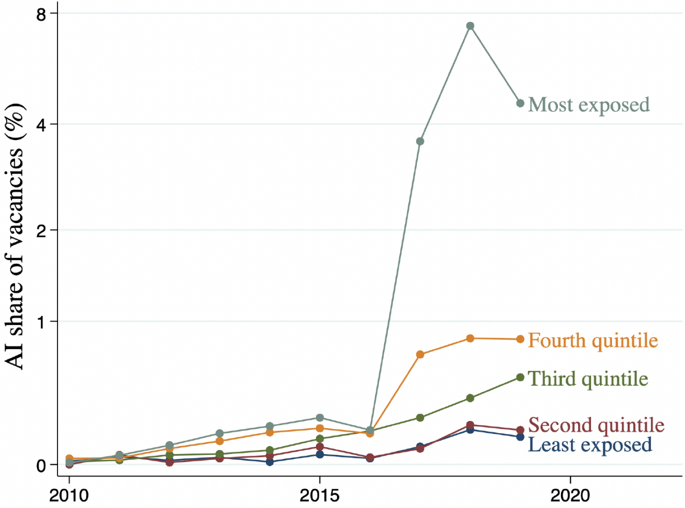
- We instrument demand for ML skills (our proxy for adoption) with Webb (2020) AI exposure measure

Second stage:

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

- 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 ML 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: ML exposure predicts ML demand



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

Second stage: ML demand lowers growth in non-ML demand

	Growth in Non-AI Vacancies			Growth in Total Vacancies		
	(1)	(2)	(3)	(4)	(5)	(6)
Growth in AI Vacancies	-5.942***	-3.605***	-9.944*	-5.909***	-3.566***	-9.923*
	(-3.66)	(-3.16)	(-1.84)	(-3.64)	(-3.14)	(-1.84)
Fixed Effects:						
– Region	✓	✓	✓	✓	✓	✓
– Firm Decile	✓	✓		✓	✓	
– Industry		✓			✓	
– Firm			✓			✓
First Stage F-Stat	26.31	27.17	4.185	26.31	27.17	4.185
Observations	22,251	22,251	19,383	22,251	22,251	19,383

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

Second stage: ML demand lowers growth in non-ML demand

	Growth in Non-AI Vacancies			Growth in Total Vacancies		
	(1)	(2)	(3)	(4)	(5)	(6)
Growth in AI Vacancies	-5.942***	$\boxed{-3.605^{***}}$	-9.944*	-5.909***	$\boxed{-3.566^{***}}$	-9.923*
	(-3.66)	$\boxed{(-3.16)}$	(-1.84)	(-3.64)	$\boxed{(-3.14)}$	(-1.84)
Fixed Effects:						
– Region	✓	✓	✓	✓	✓	✓
– Firm Decile	✓	✓		✓	✓	
– Industry		✓			✓	
– Firm			✓			✓
First Stage F-Stat	26.31	27.17	4.185	26.31	27.17	4.185
Observations	22,251	22,251	19,383	22,251	22,251	19,383

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

Second stage: ML demand lowers non-ML wage growth

	Growth in Non-AI Median Wage			Growth in Overall Median Wage		
	(1)	(2)	(3)	(4)	(5)	(6)
Growth in AI Vacancies	-3.101***	-2.599***	-5.973*	-3.017***	-2.527***	-5.696*
	(-3.47)	(-3.43)	(-1.83)	(-3.50)	(-3.46)	(-1.87)
Fixed Effects:						
– Region	✓	✓	✓	✓	✓	✓
– Firm Decile	✓	✓		✓	✓	
– Industry		✓			✓	
– Firm			✓			✓
First Stage F-Stat	25.64	26.39	4.294	26.84	27.71	4.602
Observations	22,064	22,064	19,217	22,071	22,071	19,223

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

Second stage: ML demand lowers non-ML wage growth

	Growth in Non-AI Median Wage			Growth in Overall Median Wage		
	(1)	(2)	(3)	(4)	(5)	(6)
Growth in AI Vacancies	-3.101***	-2.599***	-5.973*	-3.017***	-2.527***	-5.696*
	(-3.47)	(-3.43)	(-1.83)	(-3.50)	(-3.46)	(-1.87)
Fixed Effects:						
– Region	✓	✓	✓	✓	✓	✓
– Firm Decile	✓	✓		✓	✓	
– Industry		✓			✓	
– Firm			✓			✓
First Stage F-Stat	25.64	26.39	4.294	26.84	27.71	4.602
Observations	22,064	22,064	19,217	22,071	22,071	19,223

Again, the negative effects are hardly changed when considering all posts (inclusive of ML-posts).

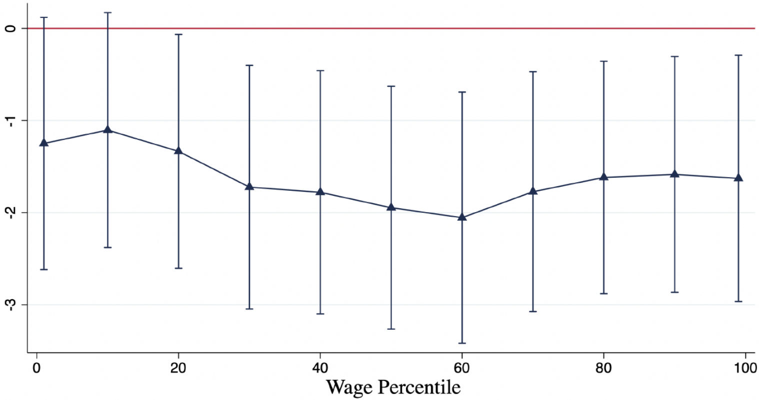
Second stage: ML demand lowers non-ML wage growth

	Growth in Non-AI Median Wage			Growth in Overall Median Wage		
	(1)	(2)	(3)	(4)	(5)	(6)
Growth in AI Vacancies	-3.101***	-2.599***	-5.973*	-3.017***	-2.527***	-5.696*
	(-3.47)	(-3.43)	(-1.83)	(-3.50)	(-3.46)	(-1.87)
Fixed Effects:						
– Region	✓	✓	✓	✓	✓	✓
– Firm Decile	✓	✓		✓	✓	
– Industry		✓			✓	
– Firm			✓			✓
First Stage F-Stat	25.64	26.39	4.294	26.84	27.71	4.602
Observations	22,064	22,064	19,217	22,071	22,071	19,223

✓ Robust to changes in education and experience profiles (-1.933***, -1.891***)

Second stage: ML demand lowers non-ML wage growth

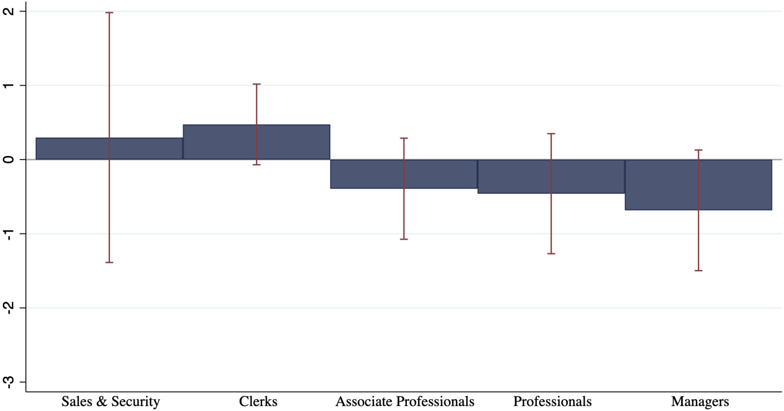
Impact of 1% higher establishment ML demand on non-ML wage growth:



The reduction in the growth rate of non-ML wage offers in response to increased ML demand occurs across the wage offer distribution ($p < 0.05$ from 20^{th} pctile).

Second stage: Wage effects driven by high-skill occupations (early)

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



Re-run for wage offers within broad occupational categories: smaller samples → not significant, but effects focused in high-skill boccupation categories.

Results are robust to:

1. Alternative exposure measure (Felten et al. 2018) ✓
2. Alternative baseline period ✓
3. Weighting by baseline establishment size ✓
4. Alternative data sources (NSS/PLFS, Prowess) ✓

Conclusion

Our paper:

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

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

⇒ Incumbent establishments that adopt ML disproportionately lower their number of non-ML posts + the associated wage offers

⇒ Early evidence that these displacement effects are driven by high-skilled occupations

Key open questions:

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

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

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

Conclusion

Our paper:

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

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

⇒ Incumbent establishments that adopt ML disproportionately lower their number of non-ML posts + the associated wage offers

⇒ Early evidence that these displacement effects are driven by high-skilled occupations

Key open questions:

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

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

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

Conclusion

Our paper:

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

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

⇒ Incumbent establishments that adopt ML disproportionately lower their number of non-ML posts + the associated wage offers

⇒ Early evidence that these displacement effects are driven by high-skilled occupations

Key open questions:

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

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

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

Conclusion

Our paper:

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

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

⇒ Incumbent establishments that adopt ML disproportionately lower their number of non-ML posts + the associated wage offers

⇒ Early evidence that these displacement effects are driven by high-skilled occupations

Key open questions:

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

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

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

Conclusion

Our paper:

- ⇒ Rich new data on ML demand and wage offers in a developing country
- ⇒ ML jobs pay a substantial wage premium, but they are highly concentrated in certain industries, cities and firms.
- ⇒ Incumbent establishments that adopt ML disproportionately lower their number of non-ML posts + the associated wage offers
- ⇒ Early evidence that these displacement effects are driven by high-skilled occupations

Key open questions:

- ⇒ To what extent does ML adoption generate new tasks &/or firms?
- ⇒ How do ‘creative’ vs ‘destructive’ effects compare?
- ⇒ GE: is overall ‘creation’ > ‘destruction’?

Conclusion

Our paper:

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

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

⇒ Incumbent establishments that adopt ML disproportionately lower their number of non-ML posts + the associated wage offers

⇒ Early evidence that these displacement effects are driven by high-skilled occupations

Key open questions:

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

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

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

Conclusion

Our paper:

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

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

⇒ Incumbent establishments that adopt ML disproportionately lower their number of non-ML posts + the associated wage offers

⇒ Early evidence that these displacement effects are driven by high-skilled occupations

Key open questions:

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

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

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

AI, firms and wages: Evidence from India

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

December 19, 2021

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

Classifying ML posts

Back

Posts are categorised as ML-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)