

# The Concentration of Technical Skills and Superstars

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April 23, 2024

## This Project in One Quote

“The **secret of my success** is that we have gone to exceptional lengths  
**to hire the best people** in the world.”

*Steve Jobs, Chairman, CEO and co-founder of Apple.  
≈ 20-25% global smartphone market*

Can **concentration in technical labour markets** explain rising **output market concentration**?

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# Introduction

Can concentration in technical labour markets explain rising output market concentration?

- ▶ Since 1980s, advanced economies have seen **rising concentration** in output markets
  - ▶ rise of the “superstar” firm Autor-Dorn-Katz-Peterson-VanReenen ('22)
- ▶ Concurrently: *extraordinary* transformation associated with digital technologies.
  - ▶ Tech has never been as powerful as it is today
  - ▶ Tech has never been as cheap as it is today
- ▶ Adoption of these technologies in the production process has been
  - ▶ **slow** Acemoglu et al ('22,'23), Zolas et al ('22), Digit DPaW ('23)
  - ▶ **concentrated** in the **largest**, most established firms Tambe-Hitt-Rock-Brynjolfsson ('20), Digit DPaW ('23)
- ▶ Why do we care? Implications for **Inequality**, both functional and within-labour income

# This Project

Can concentration in technical labour markets explain rising output market concentration?

Suppose that

1. modern technologies and technical labour are strongly complementary
2. human capital is expensive to hire and retain

Then

1. to get something out of digital tech, need to hire technical talent
2. the “true cost” of technology adoption: equipment cost + human capital investments
3. 2nd component can dominate!  $\implies$  adoption concentrated at large firms

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# Contribution

## 1. Modern/Digital Technology Adoption, Productivity and Labour Markets:

Katz-Murphy '92, Krusell-Ohanian-RiosRull-Violante '00, Autor-Levy-Murnane '03, Bartel-Ichniowski-Shaw '07, Tambe-Hitt '12, Michaels-Natraj-Van Reenen '14, Tambe '14, Acemoglu-Autor '11, Ayyagari et al '18, Acemoglu-Restrepo '18, Calligaris et al '18, Bessen-Righi '19, Dillender-Forsythe '19, Rock '19, Bessen '20, McElheran et al '21, Zolas et al '21, Acemoglu et al '22, '23, Kariel '23

- ▶ empirically disciplinable explanation for slow adoption

## 2. Intangibles, Fixed Costs and Superstar Firms:

Corrado et al '09,'10,'22, Crouzet-Eberly '19, Lashkari et al '19, Koh et al '20, Andrews et al '16, Haskel-Westlake '18, 2022, Korinek-Ng '19, ADKPV '20, Akcigit-Ates '21, Ding et al '22, OlmsteadRumsey '22, Chiavari-Goraya '23, Kariel-Savagar '23, de Ridder '24

- ▶ one explicit measure of intangible capital and a microfoundation for higher returns to scale

## 3. Labour Market Power:

Card-Cardoso-Heining-Kline '18, Rossi-Hansberg-Sarte-Trachter '18, Abel-Tenreyro-Thwaites '20, Prager-Schmitt '21, Azar-Marinescu-Steinbaum-Taska '22, Benmelech-Bergman-Kim '22, Handwerker-Dey '22, Manning-Petrongolo '22, Rinz '22, Yeh-Macaluso-Hershbein '22, Berger-Herkenhoff-Mongey '23, Caldwell-Danieli '24, CMA '24, Jarosch-Nimczik-Sorkin '24

- ▶ Focus on interactions between labour market & product market power

# Outline

- ▶ Data
- ▶ Some Motivating Facts
- ▶ Stylised Facts About Technical Talent
- ▶ Outlining a Model
- ▶ Policies to Evaluate

# Data

1. Data on Tech adoption: Harte-Hanks-Aberdeen CiTDB
2. Data on Vacancies: Lightcast.io

# Dataset 1: Technology Usage: Harte-Hanks-Aberdeen CiTDB

- ▶ Establishment-level data on use of ICT across mainland US establishments
- ▶ Previous versions widely used in literature on 3rd Industrial Revolution

Bresnahan, Brynjolfsson, Hitt (2002), Forman-Goldfarb-Greenstein (2002, '12), Bloom-Draca-van Reenen (2007), ...

- ▶ **An observation** contains the following info:

In 2016,      the Coupa Cafe at the GSB      used      Intuit Quickbooks      to maintain its general ledger.  
Year      Establishment (identity + address + sector)      Manufacturer + Model      Brief description of use case

- ▶ 2.8-3 million estabs per year after basic cleaning, panel of  $\approx 550,000$  observed 2010-19.
- ▶ Weights: match state-year-NAICS3 estab. counts from US Stats of US Businesses

$$\omega_{it} = \frac{N_{state(i),ind(i),t}^{SUSB}}{N_{state(i),ind(i),t}^{CiTDB}}$$

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# Dataset 1: Technology Usage: Harte-Hanks-Aberdeen CiTDB

## ▶ **What's awesome:**

- ▶ 2.8 - 3 mn establishments per year after basic cleaning
- ▶ can consistently define a measure of ICT intensity, *PCs/Employee*, at establishment level
- ▶ dataset includes estimates of IT budgets, indicators for presence of software, ...
- ▶ detailed industry, geographic information about each establishment

## ▶ **What's not awesome:**

- ▶ no occupational information (earlier years: white-collar vs blue-collar employees)
- ▶ limited information on quantities (early years: measure of quantity as well)
- ▶ limited documentation

▶ Aside: Data for UK & Europe exists for 2000-2007.

Bloom-Draca-van Reenen (2012)

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# Dataset 1: Technology Usage: Harte-Hanks-Aberdeen CiTDB

- ▶ Data I use from Harte-Hanks:
  - ▶ Number of PCs installed at the establishment
  - ▶ Number of employees, and number of IT employees (binned)
  - ▶ IT budget and estimated establishment revenue
- ▶ Data contains indicators for the presence of certain technologies

## Dataset 2: Labour Market Concentration - Lightcast

- ▶ Universe of online job vacancies in the US, 2010-2019
- ▶ Tracks aggregate trends well, oversamples managerial/professional/technical talent

▶ Coverage: Aggregate Trends

▶ Coverage: Industry

▶ Coverage: Occupation

- ▶ Construct measures of concentration of *new vacancy creation*

Azar et al (2020)

- ▶ On agenda: study concentration of stocks of employed workers too.

Lightcast/LinkedIn/Revelio Labs

- ▶ Today:
  - ▶ Analysis at *commuting zone* level
  - ▶ Concentration measures: CR(4) and HHI

## Dataset 2: Labour Market Concentration - Lightcast

- ▶ For each vacancy we have a vector of *skills* associated with the job
- ▶ Today: Let's consider four sets of skills
  - ▶ **Coding**: Does job require knowledge of coding?
  - ▶ **Programming Languages**: Does job require any specific programming language?
  - ▶ **Database Management Skills**: Does job require knowledge of RDBMS, big data, data management/stewardship?
  - ▶ **AI Skills**: Does job require any AI skills (Lightcast-classified)?
- ▶ In progress: specific software packages that are particularly highly in demand
  - ▶ MySQL, ERP Programs like SAP's offerings matched to Harte-Hanks technologies

# Motivation

1. Concentration in US Output Markets
2. Slow Technology Adoption
3. Concentrated Technology Adoption
4. What People Say



# Setting the Stage

1. Concentration in US Output Markets
2. Slow Technology Adoption
3. Concentrated Technology Adoption
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# 1. Concentration in US Output Markets

- ▶ *Extensively* documented with a wide range of datasets, methods

..., Gutiérrez-Philippon ('16, '18), Grullon et al ('19), ADKPV ('20), Covarrubias et al ('20), ...

- ▶ Today: the share of NAICS 2-digit output accounted for by top 4 (public) firms

# 1. Concentration in US Output Markets

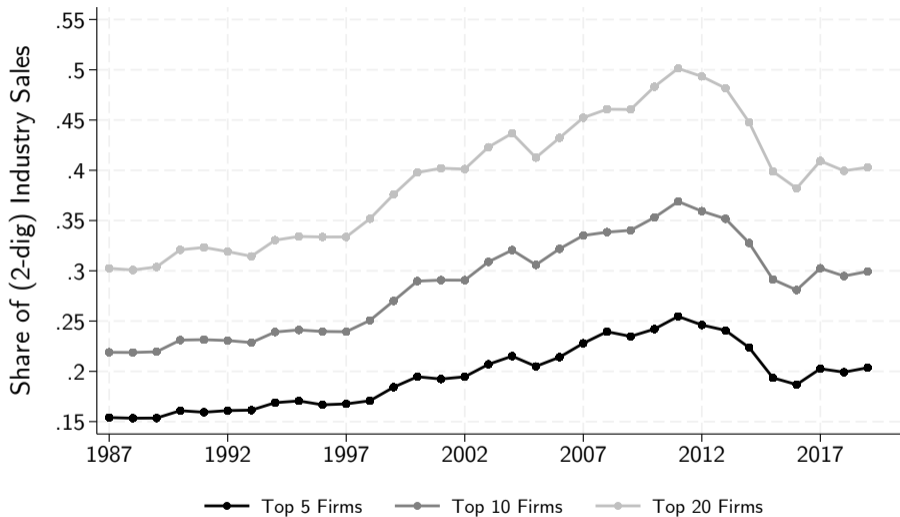


Figure: Share of 2-digit industry gross output accounted for by top firms in Compustat Fundamentals, gross-output-weighted mean across sectors. Sectoral Output from Bureau of Economic Analysis Industry output statistics (archived 2020 data).

# Setting the Stage

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## 2. Slow Technology Adoption

- ▶ Aggregate reported tech used to four kinds of technologies I can identify clearly:

### Business Process Software



### Enterprise Resource Planning Software



### Database Management Software



### Software as a Service (SaaS)



## 2. Slow Technology Adoption

- ▶ For each technology  $i$ , define adoption indicators for site  $s$  and year  $t$  as

$$Adoption_{i,s,t} = \mathbf{1}(\text{tech } i \text{ was present at site } s \text{ at any } \tau \leq t)$$

- ▶ Addresses issue that as technologies become ubiquitous
  - ▶ firms may stop reporting use
  - ▶ Harte-Hanks/Aberdeen may stop recording use
  - ▶ When did you last *report* using MS Excel, or require it of an applicant?

## 2. Slow Technology Adoption

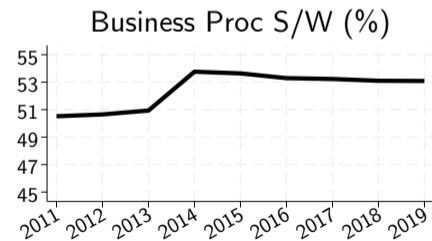
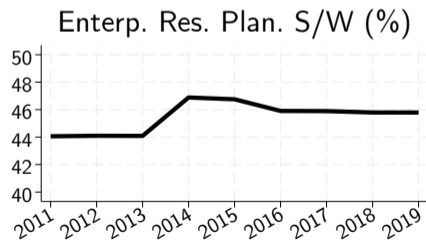
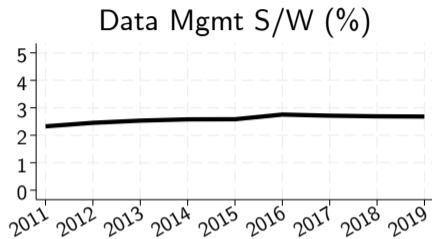
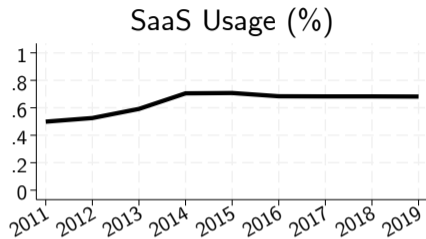


Figure: Share of establishments reporting usage of different digital technologies. Data from the Harte-Hanks-Aberdeen CiTDB, 2010-2019 extracts. Only includes observations observed in all 10 years ( $\approx 25\%$ ). Observations weighted to match commuting zone  $\times$  year  $\times$  NAICS3 establishment counts from US Census Business Dynamics Statistics. Data Mgmt software include RDBMS, Data Warehousing, Data Science. I thank Nick Bloom for data access.

## 2. Slow Technology Adoption

- ▶ Levels of adoption comparable to results from US Census ABS
  - ▶ usage of “specialized software”  $\approx$  40.2%, 2016-18.
- ▶ Also comparable to Bloom et al (2023) using Lightcast/Earnings Calls/Patenting
- ▶ Given the maturity of these technologies, shocking how few firms report using them!
- ▶ Next: which firms are/are not using these technologies?

Acemoglu et al. '23



# Setting the Stage

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### 3. Tech Adoption is Concentrated in Large Firms

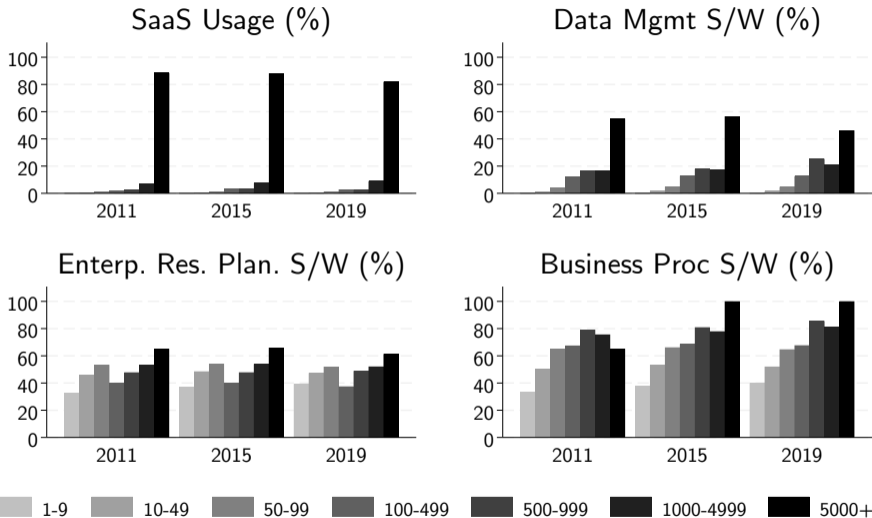


Figure: Share of establishments by employment level reporting usage of digital technologies. Data from the Harte-Hanks-Aberdeen CiTDB, 2010-2019 extracts. Only includes observations observed in all 10 years ( $\approx 25\%$ ). Observations weighted to match commuting zone  $\times$  year  $\times$  NAICS3 establishment counts from US Census Business Dynamics Statistics. I thank Nick Bloom for data access.

### 3. Tech Adoption is Concentrated in Large Firms

- ▶ Large firms overwhelmingly more likely to have adopted
- ▶ Vast heterogeneity, rises with establishment size
- ▶ This is consistent with many IT installation projects failing to generate results

▶ Scatter

# Concentration of Technology Adoption: The UK is No Different

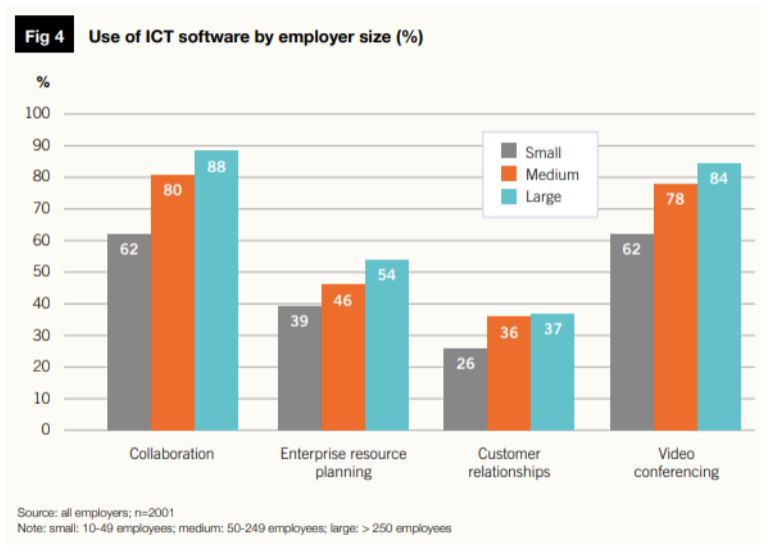


Figure: Digit Centre's Employer's Digital Practices at Work Survey, 2023, for the period 2021-22.

# Setting the Stage

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## Share of CIOs reporting talent shortages are holding back adoption

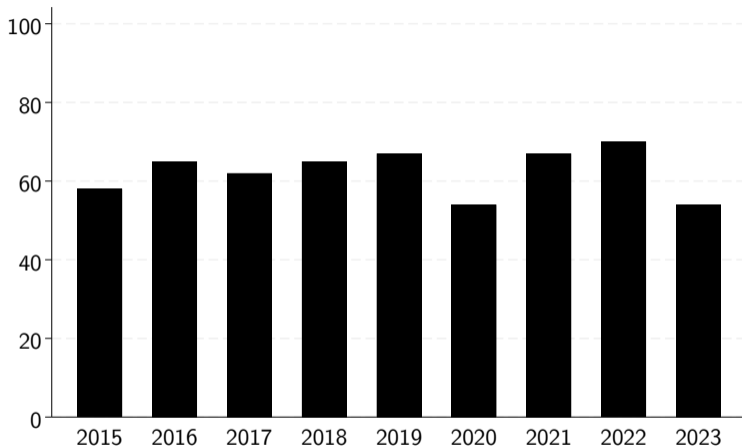


Figure: Share of CIOs responding "Yes" to "Does a skills shortage prevent your organization from keeping up with the pace of change?", NashSquared Digital Leadership Report 2023. Survey of 1,785 digital leaders from 82 countries in July-Oct 2023.

# What People Say



## IT depts struggle with skills shortages despite Big Tech layoffs

### THE IT SKILLS GAP IS ONLY GETTING WIDER IN 2024

02 February 2024

LEADERSHIP | November 9, 2021 | updated 23 Jun 2022 5:06am

## Tech skills shortages delay two-thirds of digital transformation projects

NEWS

### Tech skills shortage still a problem for employers

Many organisations have struggled to find tech talent over the past year, leading them to consider alternative ways to attract skilled workers

By Chris McDonald, Business Editor | Published: 17 Jun 2023 10:28

Almost 96% of employers looking for tech talent have encountered a skills shortage over the past year, according to Hays.

In a survey of 13,000 employers and workers in the UK, 1,400 of which were in fact, the recruitment and HR firm found 94% faced a lack of talent last year, up from 89% the year before.

Events - Training - News - Import / Export - Economic development - Research

### The UK's IT skills shortage - addressing and combatting the crisis

February 21, 2024 | by Robin Parkinson, Evolve IMS

DIGITAL TRANSFORMATION

## Why the skills gap is stopping businesses from achieving agility

Severe shortages of IT professionals and agile coaches mean that businesses need to put real effort into recruiting and retaining the talent required to reach agility

## MAJORITY OF UK TECH PROFESSIONALS BELIEVE TECH TALENT SHORTAGE IS WORSENING, REPORT FINDS

20 September 2023

Over half of tech professionals across the UK (57%) say that the tech talent shortage has increased compared to last year, according to a new survey by Stamford, Conn., March 7, 2023



### Do Recent Layoffs Mean the Tech Talent Crunch Is Over?

Q&A with Mbula Schoen

Following numerous announcements of layoffs across the tech industry, many industry leaders have concluded that the tech talent crunch is over. However, appearances can be deceiving, as demand for tech talent still significantly exceeds supply. In fact, a survey conducted in November and December 2022, 86% of CIOs reported facing more qualified candidates and 73% were worried about IT talent attrition.

FORBES > LEADERSHIP > EDUCATION

## The Biggest Tech Talent Gap Can Be Found In The SAP Ecosystem

Ryan Craig Senior Contributor @

Follow

Jan 1, 2024, 11:07am EST

## DSIT must prioritise fixing the UK's tech talent shortage

Debate Topics SPOTLIGHT TOPICS INDUSTRIES MORE FROM DELLOITTE INSIGHTS

Article

Estimate read: 14 August 2023

### Tech talent is still hard to find, despite layoffs in the sector

Tech industry execs face multiple workforce challenges as they work to fill critical gaps and address the needs of younger workers.

# Five Facts

- a. tech talent associated with more productive ICT within the firm
- b. tech talent is expensive to hire relative to tech purchases
- c. higher availability of tech talent associated with higher technology adoption rates
- d. tech talent vacancies are more concentrated than general vacancy postings
- e. tech talent vacancy concentration and adoption concentration appear linked



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## Tech talent associated with more productive ICT within the firm

- ▶ Idea: test if **revenue** elasticity of ICT is higher if a firm has more IT employees/worker
- ▶ By year and industry, split sample into above/below mean IT employment/worker
  - ▶ results robust to using medians
  - ▶ call firms above the mean “tech intensive”

$$\log\left(\frac{Revenue_{it}}{Employees_{it}}\right) = \beta_0 + \log\left(\frac{PCs_{it}}{Employees_{it}}\right) \left[\beta_1 + \gamma_1 \mathbf{1}(TechIntensive_{it})\right] + \delta_c + \delta_{it} + \delta_{st} + \varepsilon_{it}$$

- ▶  $\gamma_1 > 0$ : revenue elasticity of PCs higher when more IT employees/employee
- ▶ Caveats galore, most important: does not control for employees' own IT skills

## Tech talent associated with more productive ICT within the firm

Higher tech talent within an establishment  $\implies$  higher output elasticity of ICT

	(1)	(2)	(3)
	log (Revenue/Employee)		
log(PCs/Employee)	0.55*** (0.002)	0.55*** (0.002)	0.54*** (0.002)
log(PCs/Employee) $\times$ Tech Talent per Employee $\geq$ Mean	0.063*** (0.001)	0.063*** (0.001)	0.10*** (0.001)
<i>N</i>	22,921,403		
Year FE	Yes	No	No
Year $\times$ Czone FE	No	Yes	Yes
Year $\times$ NAICS3 FE	No	No	Yes

Table: Data from Harte-Hanks-Aberdeen CiTDB, 2010-2019. Robust standard errors in parentheses. An observation is an establishment-year combination, weighted to replicate SUSB establishment counts by state  $\times$  NAICS 3 industry. All regressions include site fixed effects.

# Tech talent associated with more productive ICT within the firm

- ▶ Results qualitatively similar to only including establishments in the panel
- ▶ Effects of tech intensity on elasticities are larger for large firms Lashkari et al (2019)
- ▶ (In progress) IV strategies to identify elasticities
  - ▶ PC import price shock IVs based on exchange rate shocks Berlingieri et al (2022)
  - ▶ Rigorous production function estimation: challenge is that capital stock is not observed
- ▶ Key message: sign unlikely to reverse

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# Tech talent is expensive relative to tech budgets

▶ IT Budgets per IT Employee

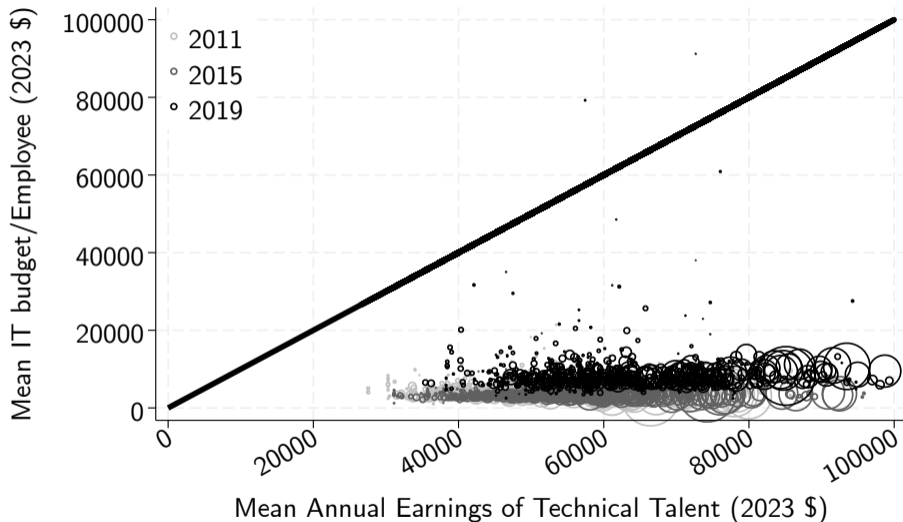


Figure: Observations: czone x year. Areas proportional to commuting zone workforce. Technical talent incomes are total annual earned wage incomes for workers in OCC1990 44-83 and 203-235 from the IPUMS ACS, weighted following Autor-Dorn (2019). IT budget data and establishment-level employment from Harte-Hanks-Aberdeen CiTDB, aggregated to czone-level using weights to match SUSB state x NAICS3 estab. counts.

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## Higher availability of tech talent associated with higher tech adoption

More IT talent in the firm  $\implies$  Higher likelihood of adoption

$$Adoption_{it} = \beta_0 + \beta_1 ITEmpl/Worker_{it} + \delta_i + \varepsilon_{it}$$

	(1) SaaS	(2) DBMS	(3) ICT H/W	(4) ERP S/W	(5) Busi. S/W
IT Employees per Worker	0.004*** (0.001)	0.009*** (0.002)	0.0115*** (0.002)	0.185*** (0.035)	0.153*** (0.029)
<i>N</i>	26,111,595				
Year FE	Yes	Yes	Yes	Yes	Yes
Site FE	Yes	Yes	Yes	Yes	Yes

Table: Outcome variable is an indicator for presence of a technology at a given establishment, cumulated over time. An observation is an establishment-year. Observations weighted to match SUSB distribution of establishments by year-state-NAICS 3-digit sector. Robust standard errors in parentheses. Data from Harte-Hanks-Aberdeen CiTDB.



## Higher availability of tech talent associated with higher adoption

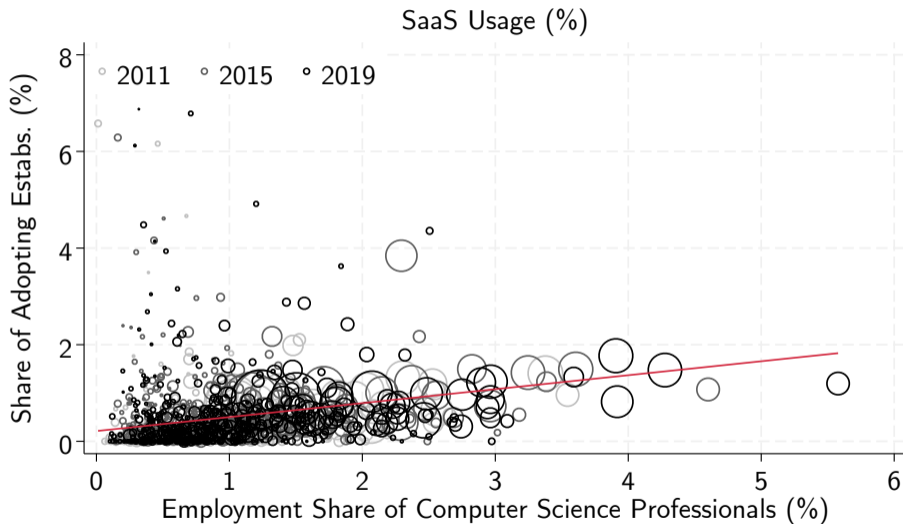


Figure: Data from American Community Survey and Harte-Hanks-Aberdeen CiTDB. An observation is a czone-year, circles weighted by number of establishments in that czone-year.  
CS Professionals: OCC 64,229

# Higher availability of tech talent associated with higher adoption

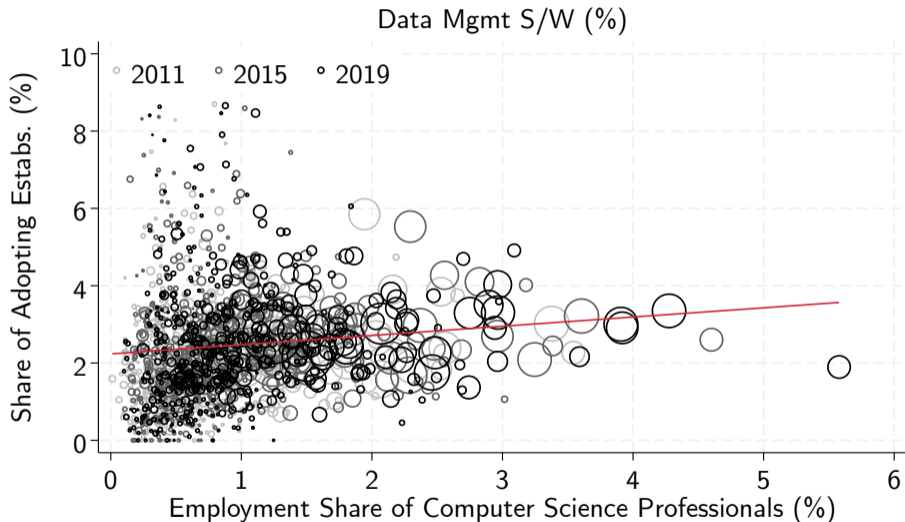


Figure: Data from American Community Survey and Harte-Hanks-Aberdeen CiTDB. An observation is a czone-year, circles weighted by number of establishments in that czone-year. CS Professionals: OCC 64,229

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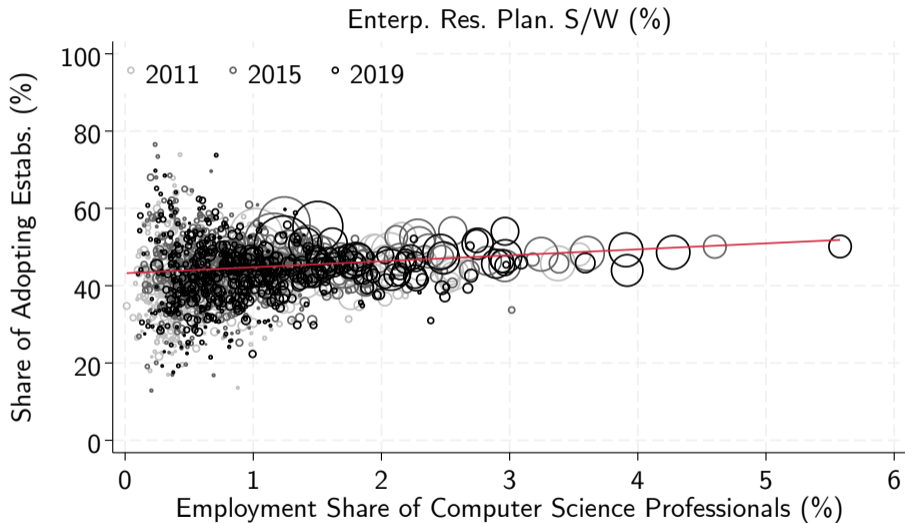


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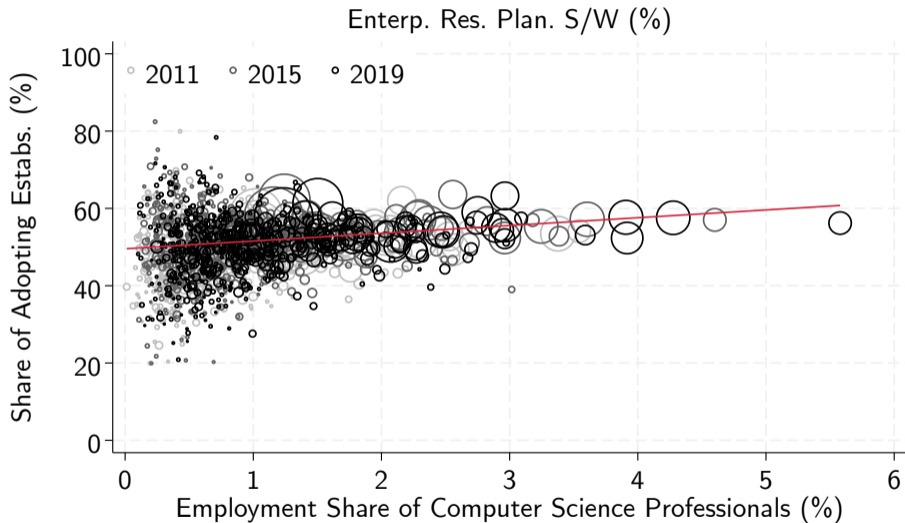


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## Five Facts

- a. tech talent associated with more productive ICT within the firm
- b. tech talent is expensive to hire relative to tech purchases
- c. higher availability of tech talent associated with higher technology adoption rates
- d. tech talent vacancies are more concentrated than general vacancy postings**
- e. tech talent vacancy concentration and adoption concentration appear linked

## Tech talent vacancies more concentrated than all vacancy postings

- ▶ Plots of mean concentration across commuting zones over time
- ▶ To construct the series by skill, identify postings with a specific set of skills
  - ▶ *Understates* concentration in skills: does not account for “how important” skill is for job
- ▶ First, consider IT Employment (SOC 15-1000: “Computer” Occupations)
- ▶ Second, let’s consider four sets of skills
  - ▶ **Coding**: Does your job require knowledge of coding?
  - ▶ **Programming Languages**: Does your job require any specific programming language?
  - ▶ **Database Management Skills**: Does your job require knowledge of RDBMS, big data, data management/stewardship?
  - ▶ **AI Skills**: Does your job require any AI skills (Lightcast-classified)?
- ▶ Contrast the plotted series against concentration for all jobs

# Tech talent vacancies more concentrated than all vacancy postings ► Herfindahl

## Concentration of Postings involving IT Occupations vs All Postings

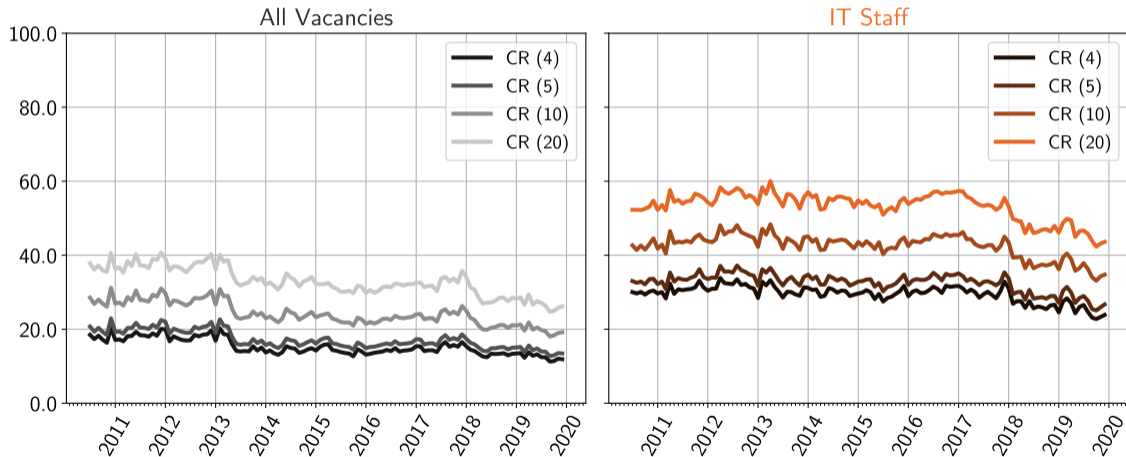


Figure: Data from Lightcast.io, 2010-2019 US extracts. A labour market is a commuting zone in a given month.

# Tech talent vacancies more concentrated than all vacancy postings Herfindahl

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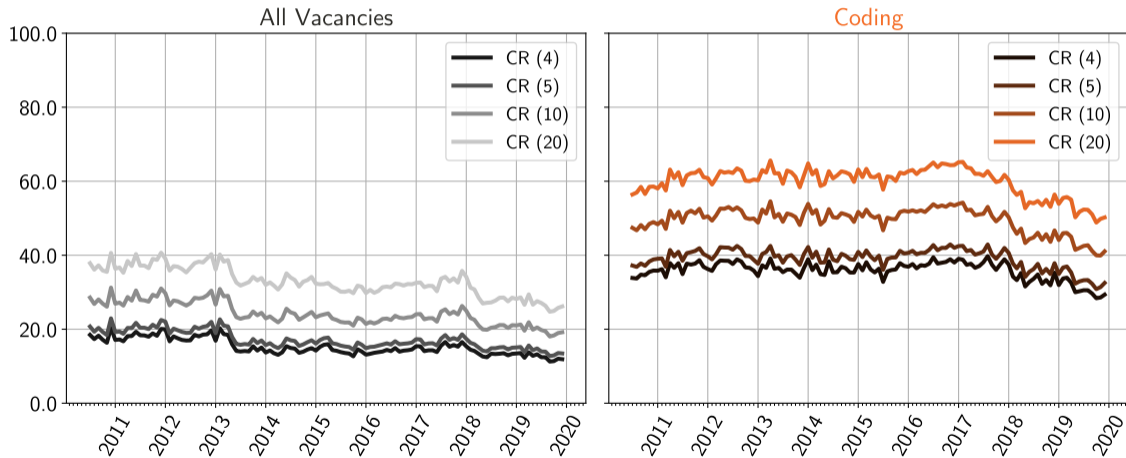


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Concentration of Postings involving **knowing Programming Languages** vs All Postings

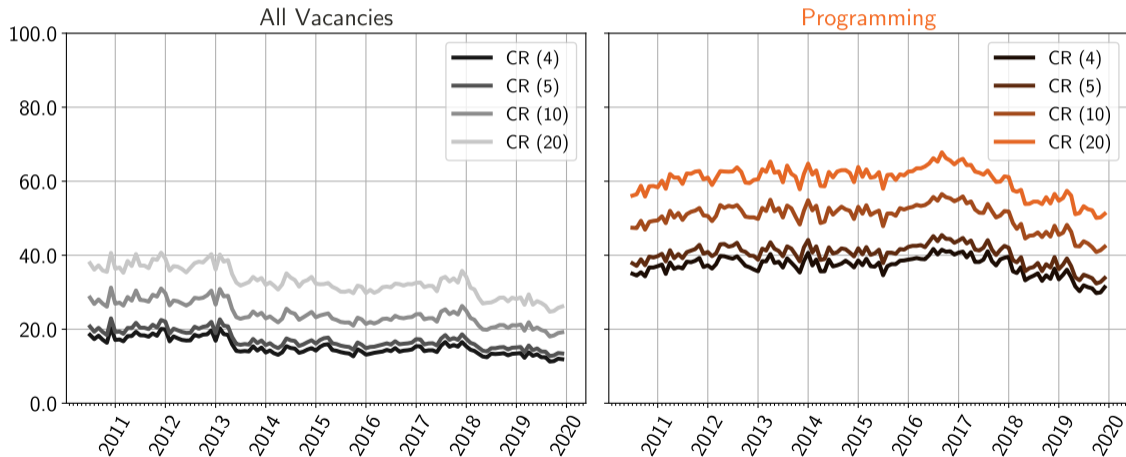


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## Concentration of Postings involving Database Mgmt Skills vs All Postings

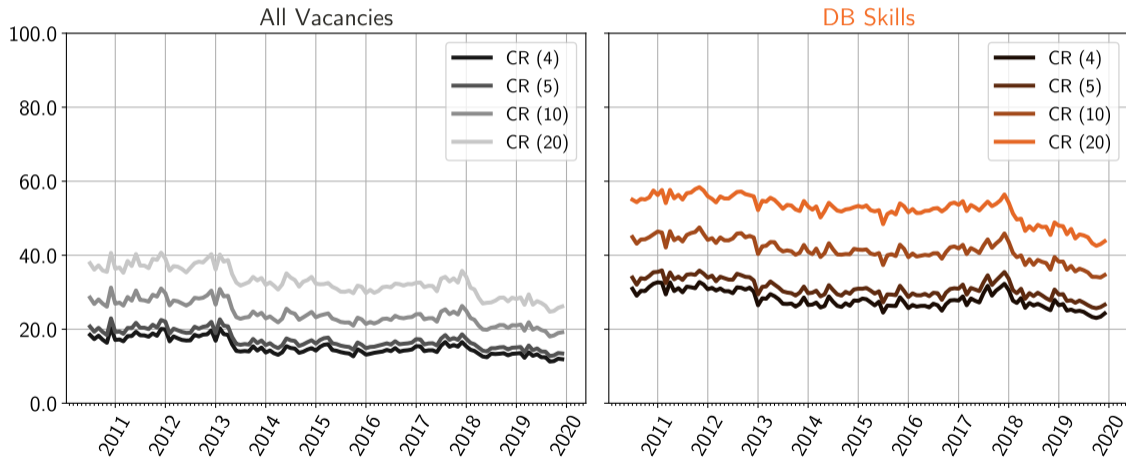


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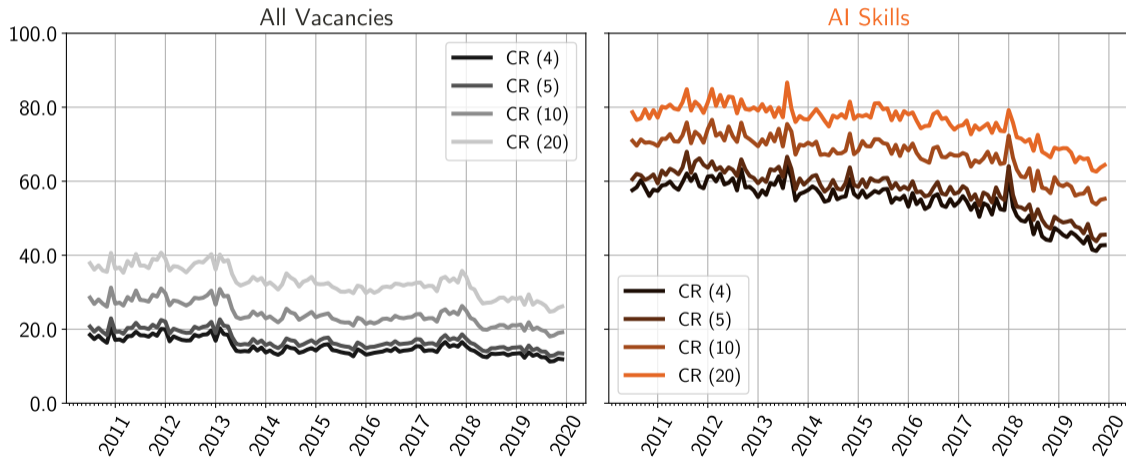


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## Tech talent vacancy concentration ↑ with concentration of IT intensity

	(1)	CR (4), PCs (2)	(3)
CR (4), Coding Skills	0.0944*** (0.0223)		
CR (4), Programming Languages		0.138*** (0.0349)	
CR (4), Database Management			0.0544*** (0.0175)
<i>N</i>	5470	5470	5470

Table: An Observation is a comm. zone x year, 2010-19. Data from Lightcast and Harte-Hanks-Aberdeen. All regressions contain czone and year fixed effects. Observations weighted by number of vacancies in czone-year. Robust standard errors in parentheses. \*  $p < 0.05$ , \*\*  $p < 0.01$ , \*\*\*  $p < 0.001$

## Conclusion: Why do we care?

- ▶ Policymakers who care about **productivity**
  - ▶ growth from experimentation weaker if adoption slower
  - ▶ over some range, concentration can ↓ firm incentives to innovate
- ▶ Policymakers who care about **concentration**
  - ▶ labour market concentration typically concern from workers' point of view ("markdowns")
  - ▶ most literature: markups/markdowns driven by independent elasticities of substitution
  - ▶ this project: labour market conc. might **directly** raise output market concentration!
- ▶ Policymakers who care about **inequality**
  - ▶ functional and within-worker inequality
  - ▶ power in the macroeconomy

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# Conclusion

- ▶ Technical skill concentration is **high** and **increasing**.
- ▶ With 1) technology-skill complementarities and 2) high recruitment and retention costs, this can create **increasing returns to scale!**

⇒ If policymakers want ↑ tech adoption (eg “to raise productivity”), should consider:

- ▶ whether SMEs have access to technical talent
- ▶ whether money spent subsidising software purchases is better spent on easing this access (training programs, “human capital allowances”, ...)

⇒ If policymakers are concerned about concentration, they should (probably) consider:

- ▶ how skill concentration feeds into output market concentration
- ▶ eg how does a merger impact other firms’ access to particularly scarce technical talent?

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# Thank You!

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# Coverage of Lightcast Data: Aggregate Trends [▶ Back](#)

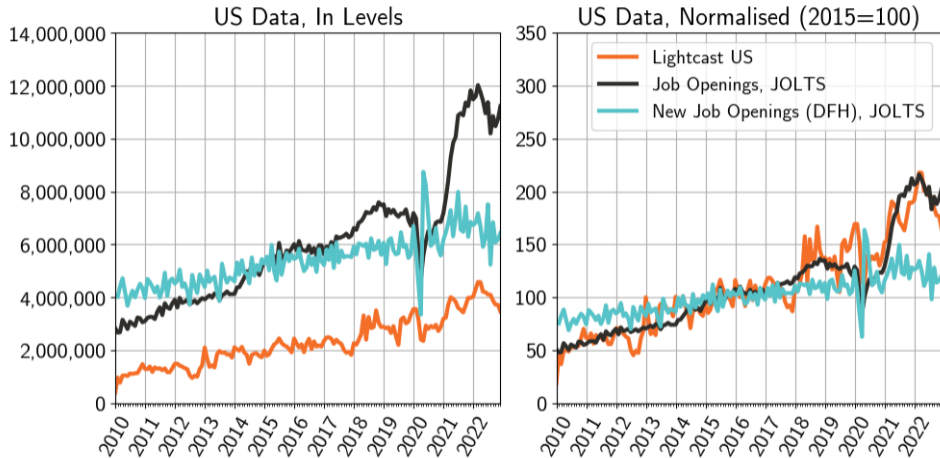


Figure: Lightcast data on US vacancies vs JOLTS data. Lightcast: seasonally adjusted three-month centred moving average of number of job postings in a given month. JOLTS: seasonally adjusted raw number of job openings. New openings: monthly flow of new job openings constructed using Davis, Faberman and Haltiwanger (2013)'s methodology using seasonally unadjusted raw data, deseasonalized ex-post.

# Coverage of Lightcast Data: Industries

▶ Back

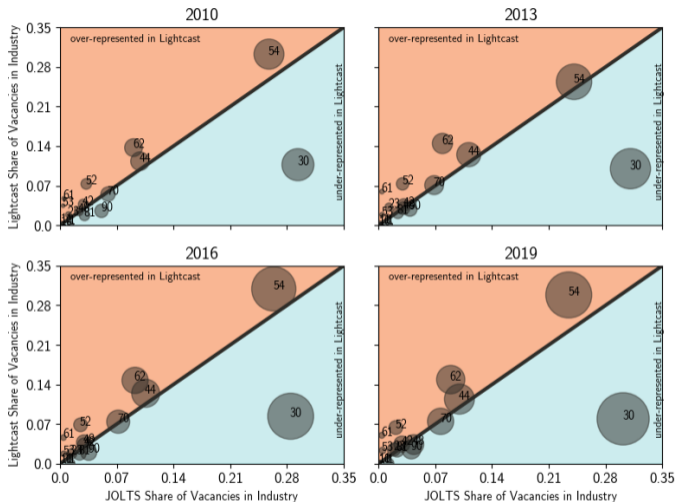


Figure: Benchmarking Lightcast US against JOLTS data by Industry. JOLTS data are the shares of (seasonally adjusted) job openings reported in a given year by industry. Lightcast data report the share of all vacancies by industries in the same year, reclassified to be consistent with the JOLTS classification.

# Coverage of Lightcast Data: Occupations [▶ Back](#)

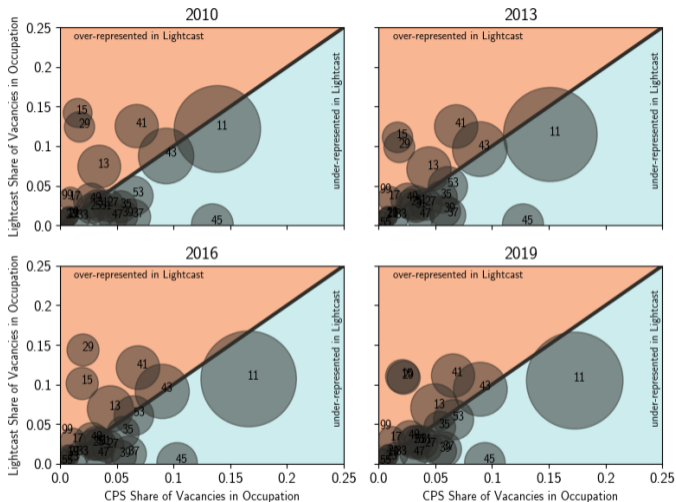


Figure: Benchmarking Lightcast US against CPS data on new vacancy creation by occupation. CPS data are the shares of all new job openings reported in a given year by occupation (2-digit SOC 2010 codes), computed using information on worker flows across sectors adjusted for flows in/out of employment. Lightcast data report the share of all vacancies by occupation opened in the same year.

# Tech talent is expensive relative to tech budgets [▶ Back](#)

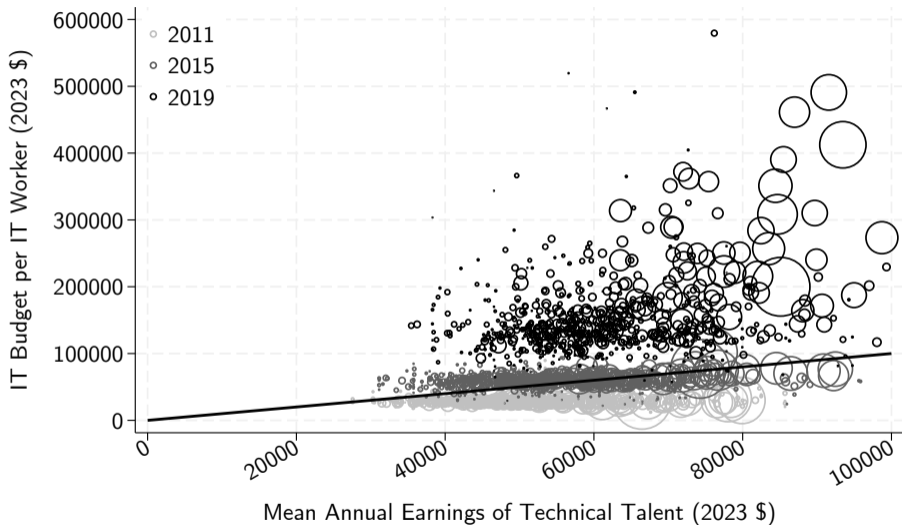


Figure: Observations: czone x year. Areas proportional to commuting zone workforce. Technical talent incomes are total annual earned wage incomes for workers in OCC1990 44-83 and 203-235 from the IPUMS ACS, weighted following Autor-Dorn (2019). IT budget data and establishment-level employment from Harte-Hanks-Aberdeen CiTDB, aggregated to czone-level using weights to match SUSB state x NAICS3 estab. counts.



# Tech talent vacancies more concentrated than all vacancy postings [▶ Back](#)

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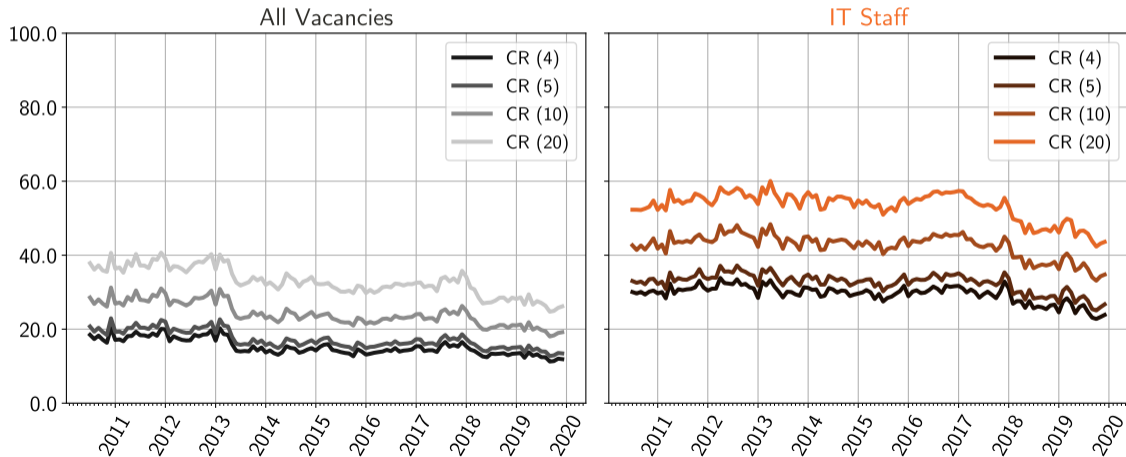


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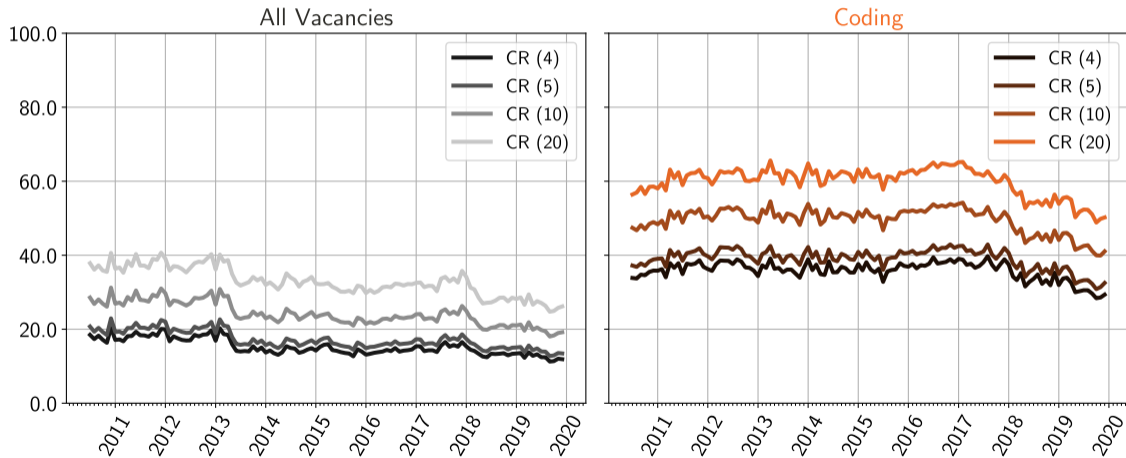


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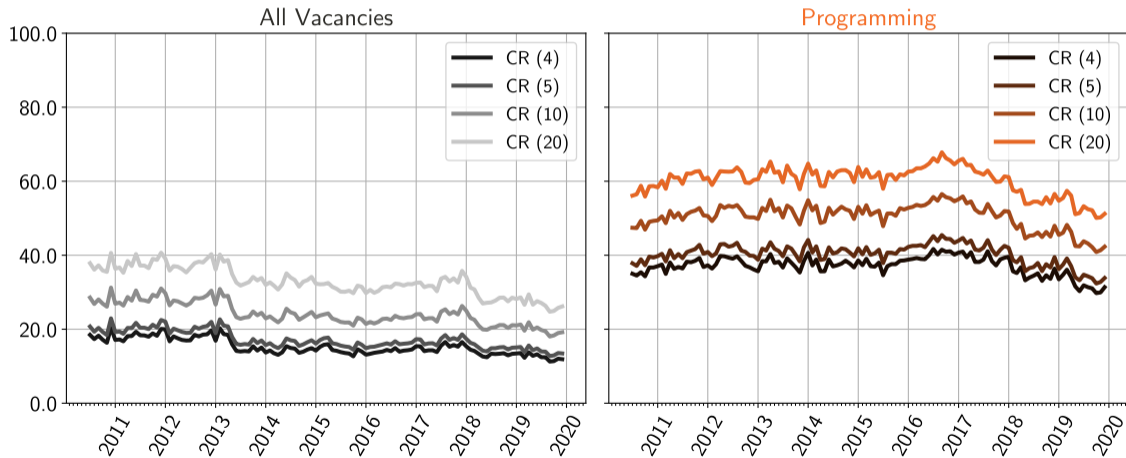


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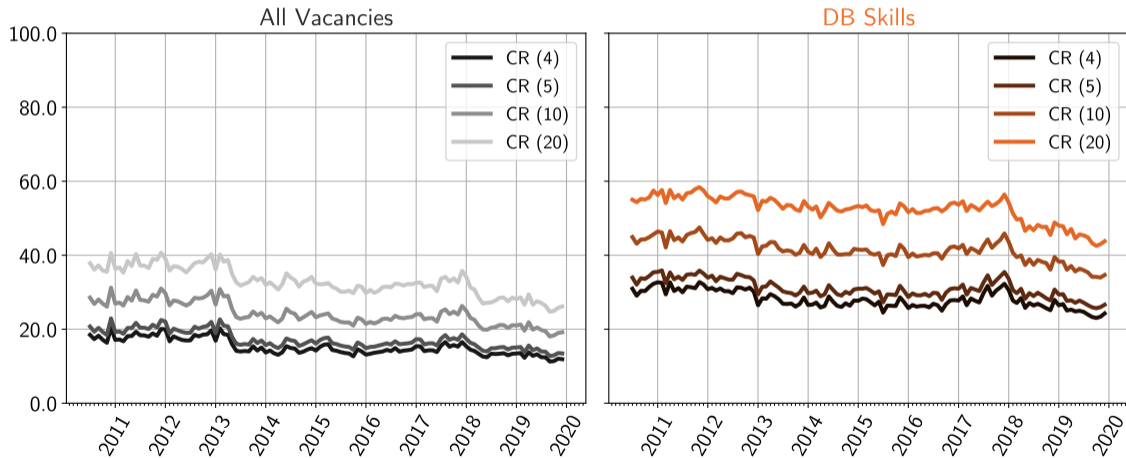


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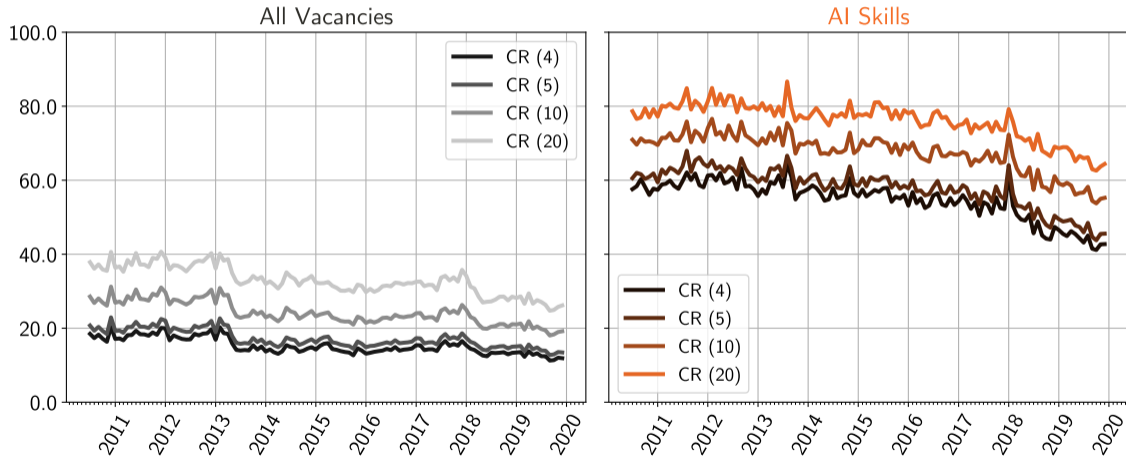


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