

# Machine Learning for Textual and Unstructured Data

## Research Applications

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# Introduction

Thanks to Stephen and Yabra you are now all experts in the most advanced machine learning techniques for textual and unstructured data

What happens next?

- What type of applications will you choose?
- How will you translate your findings into research insights?
- How will you organize your work?

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# Today's session

Three recent papers that heavily rely on ML tools

- CEO Behavior and Firm Performance (Bandiera, Hansen, Prat and Sadun, JPE 2020)
- The Demand for Executive Skills (Hansen, Fuller, Ramdas and Sadun, NBER WP 2021)
- Remote Work across Jobs, Companies and Space (Hansen, Lambert, Bloom, Davis and Sadun, NBER WP 2023)

Closely related to the sequence you went through this week...

- Features Count
- Word Embeddings
- Transformer Models

...But with a slightly different perspective: **Applications**

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# Organization of the talk

Approximately 1 hour per paper

For each paper, I will focus on:

- Why and how we applied ML tools
- How we convinced ourselves (and the referees) that ML was a suitable approach
- How we organized the research team

Interactive sessions

- Simple examples to play around with
- Your questions/comments!

ML for Textual and Unstructured Data: Applications

1. Introduction
  2. CEO Behavior and Firm Performance (Features Count)
  3. The Demand for Executive Skills (Word Embeddings)
  4. Remote Work across Jobs, Companies, and Space (Transformer Models)
  5. Conclusions

# What is the role of CEOs for firm performance?

Existing literature on CEOs: mostly indirect evidence

"Morbid" evidence

- Johnson et al (1985): positive abnormal returns after death of a founder CEO, negative returns from non-founder
- Bennedsen et al (2007): decline in profitability after CEO death owners)
- Smith et al. (2019): IRS data, firm (S-corp) performance down after premature death of owner (2509 firms of non-elderly top 1%

"Fixed effects" evidence

- Bertrand and Schoar (2003): SP500 publicly traded US firms (M&A, dividend policy, debt ratios, cost-cutting policies, and firm performance)

# CEO Behavior and Firm Performance

First **direct** evidence on CEO behavior at scale

- Scale up shadowing approaches (Mintzberg 1973) to a sample of 1,114 CEOs in 6 countries
- Machine learning techniques (LDA) to build CEO behavioral "types"
- Match with performance data to study relationship

Analyze the data guided by a simple assignment model

- Estimates of CEO-firm matching frictions and implications for aggregate productivity differences across countries

# Collecting time use data

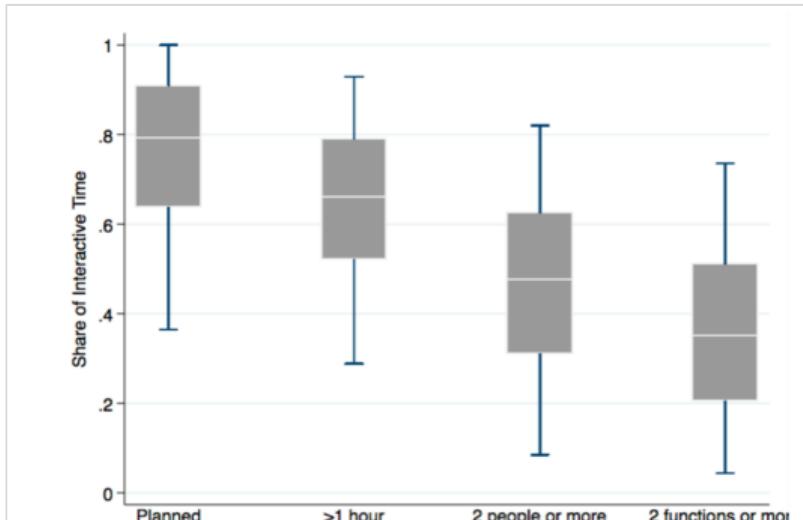
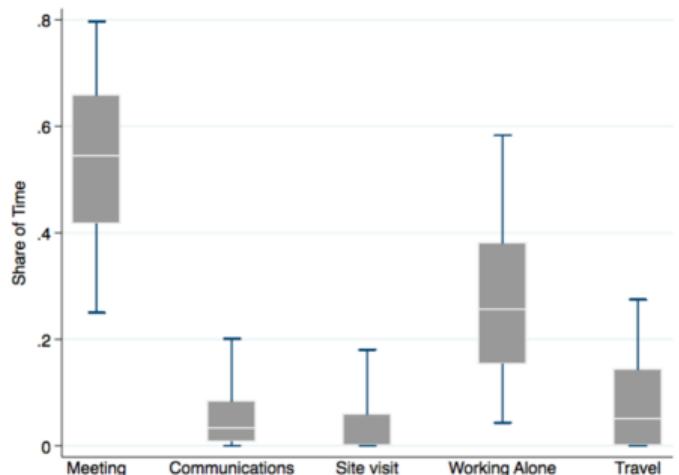
Random sample of 1,114 manufacturing firms drawn from Orbis

- Team of 40 analysts who called the CEO/his PA at the start/end of every day for 1 week (20% response rate; 1500 employees on average, 350 median; CEOs: 51 years old, 10 years tenure, 55% with MBA)

Time diaries

- Code all activities scheduled for that day (start) and those that effectively took place (end). e.g. Meetings; presentations
- Code all available activity features: duration, type and number of participants, location, planning horizon etc
- Record in 15 min chunks of CEO day (225k blocks over 57 hrs)

# What do CEOs do?

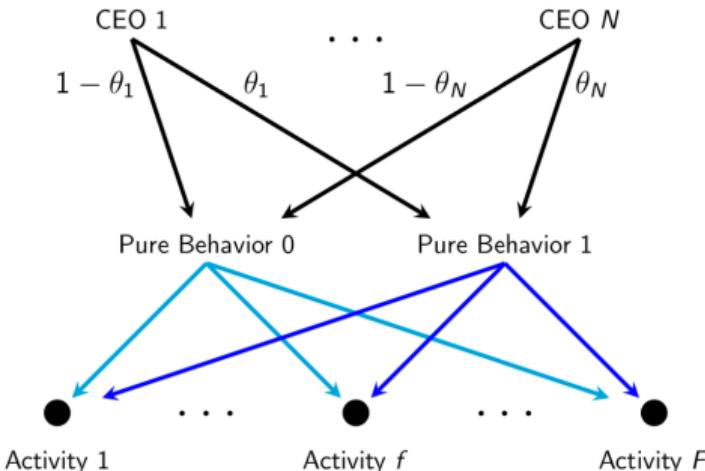


# How Machine Learning helped make sense of the data

Multidimensionality of the data posed a serious challenge

Use an algorithmic approach that projects the high dimensional feature space onto a lower-dimensional type space

- Latent Dirichlet Allocation (Blei, Ng, Jordan 2003)
- 2 styles (robustness with  $N=3, \dots$ )



# Labeling behaviors

What do you see?

# Labeling behaviors

Feature	X times less likely in Behavior 1	Feature	X times more likely in Behavior 1
Plant Visits	0.11	Communications	1.9
Just Outsiders	0.5	Outsiders + Insiders	1.9
Production	0.5	C-suite	34
Suppliers	0.3	Multifunction	1.5

Kotter (1999) emphasizes a behavioral distinction between “managers” and “leaders”

- Management involves monitoring and implementing tasks, i.e. “setting up systems to ensure that plans are implemented precisely and efficiently”
- Leadership aims primarily at the creation of organizational alignment, and involves significant investments in interpersonal communication

We label Behaviour 1 as **Leader** and Behavior 0 as **Manager**

# Labeling behaviors

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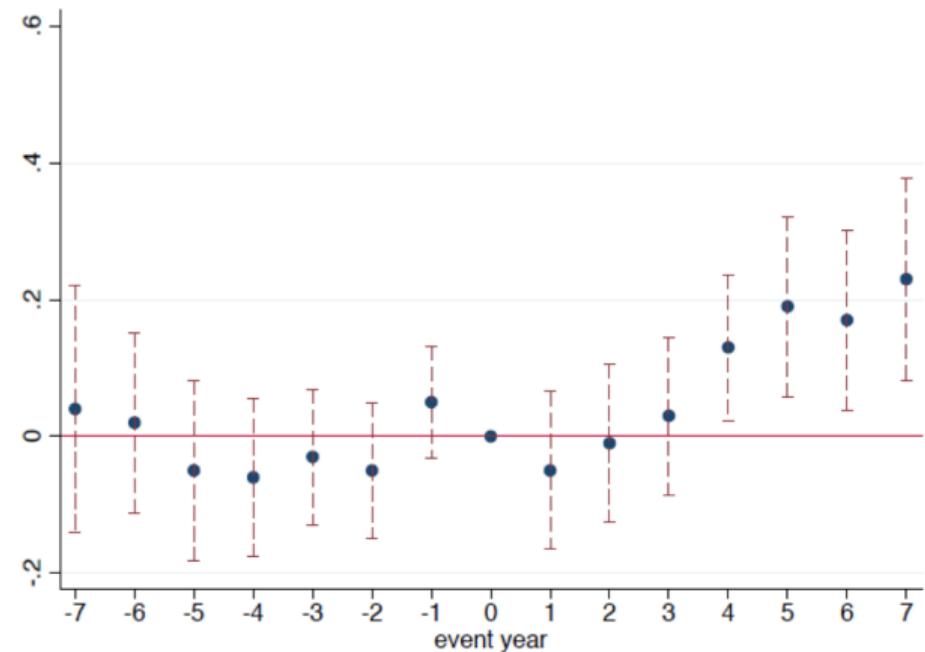
# Behavior correlates with firm performance cross sectionally...

Table 3: CEO Behavior and Firm Performance

Dependent Variable	(1)	(2)	(3)	(4)	(5)	(6)
	Log(sales)				Profits/Emp	
CEO behavior index	0.343*** (0.108)	0.227** (0.111)	0.322*** (0.121)	0.641** (0.278)	0.506** (0.236)	10.029*** (3.456)
log(employment)	0.889*** (0.040)	0.555*** (0.066)	0.346*** (0.099)	0.339** (0.152)	0.784*** (0.090)	-0.284 (0.734)
log(capital)		0.387*** (0.042)	0.188*** (0.056)	0.194* (0.098)		
log(materials)			0.447*** (0.073)	0.421*** (0.109)		
Management					0.179** (0.072)	
Number of observations (firms)	920	618	448	243	156	386
Observations used to compute means	2,202 all	1,519 with k	1,054 with k & m	604 with k & m, listed	383 with management score	1,028 with profits, listed
Sample						

In column 5, a one standard deviation increase in the behavior index (management) increases TFP by 0.16 (0.19) log points. Basic correlation is robust to controls for CEO effort, firm and CEO characteristics. Also robust to different clustering algorithms (k-means, PCA, etc).

...and over time



robust to different trends, different measurement lags

# Why are CEO behavior and firm performance correlated?

Build a simple assignment model with matching frictions to study two possible mechanisms behind the performance correlation

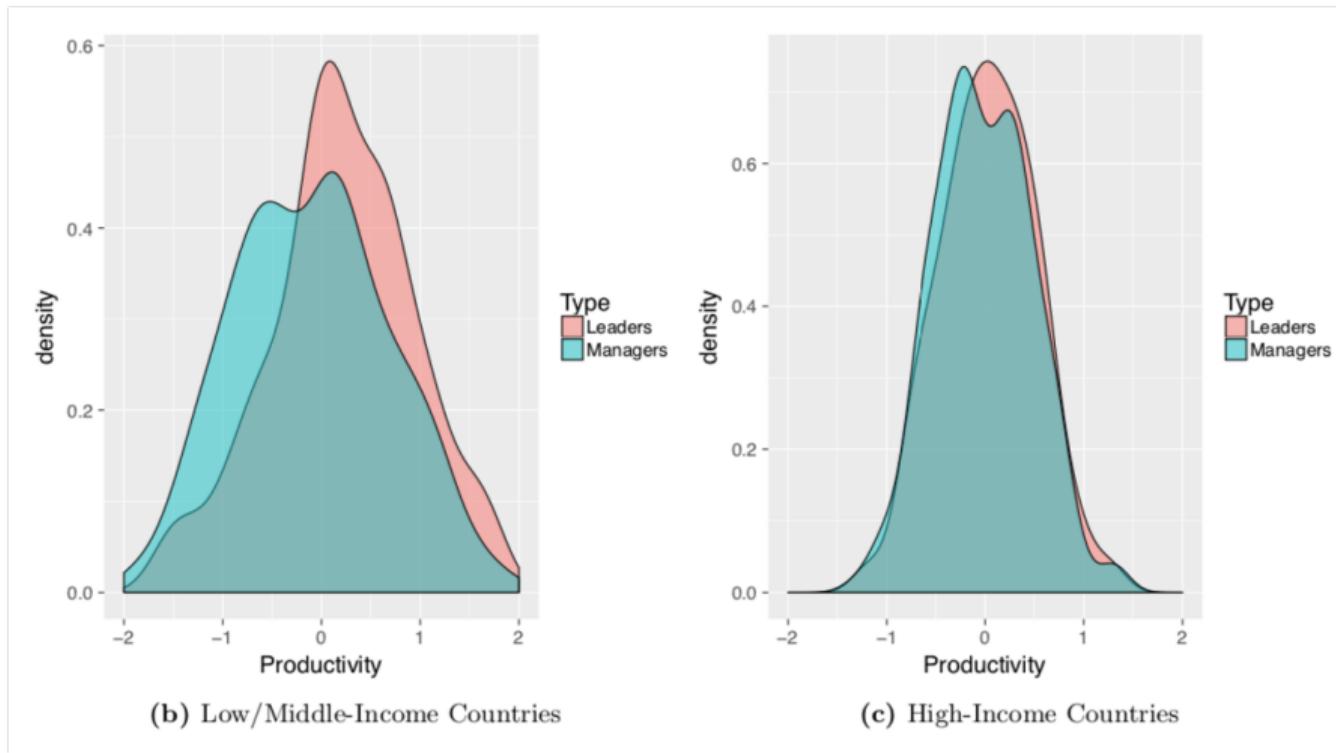
**Horizontal differentiation:** demand for both types of CEOs across different firms, but matching is imperfect

- Some (not all) managers are misallocated
- Distribution of productivity for managers is a mixture of two distributions, one corresponding to inefficient matches (lower mean), one corresponding to efficient matches (higher mean)

**Vertical differentiation:** demand only for leaders (type 1), but they are scarce

- All managers are misallocated
- Distribution of productivity for managers drawn from a single distribution, all inefficient matches

# Non parametric evidence



# Structural estimation

Build a statistical model to infer the most likely parameters generating productivity distributions observed in the data

- Results support horizontal differentiation with assignment frictions

Work out aggregate implications using market clearing conditions

- 17% of mismatched firms (type m CEO in a type l firm)
- Significant productivity losses due to mismatches

Differences across regions and counterfactuals

- If we gave low/middle income countries the same share of misallocated managers as high income countries, 13% of gap in output per worker cross country differences would be closed

## Approach 1: Within sample robustness

- Different numbers of behaviors
- More traditional techniques

## Approach 2: Evidence from different data (new project!)

- Use LASSO to identify which elements of time use are most predictive of the Leader index within the original ETUS sample
- Insert most predictive questions in a different, large scale survey
- Study if similar patterns can be recovered in a *completely different dataset*

# CEO questions most predictive of "Leader" behavior

1. In a typical week, how often does the top manager meet with one or more of the following: Chief Operating Officer (COO), Chief Administrative Officer (CAO), Chief Marketing Officer (CMO), Board members, Business Unit managers, or managers from a parent company?<sup>1</sup>
2. In a typical week, how often does the top manager meet with suppliers?
3. In a typical week, how often does the top manager meet with employees involved in production activities (e.g. plant managers, front line production workers)?
4. In a typical week, how many meetings that involve the top manager include more than one other participant?<sup>2</sup>

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<sup>1</sup>Answer options q1-3: Never, Once a week, 2-4 times a week, Daily, More than once a day

<sup>2</sup>Options q4: Fewer than 5, 5-10, 11-15, 16-20, More than 20.

## Data collection

Measure these four aspects of time use in the [EBRD-EIB-WB Enterprise Surveys \(ES\)](#):

- Unique face-to-face surveys with firm managers
- Information on CEO behavior and firms' characteristics and performance
- 42 economies in Europe, Central Asia and Middle East and North Africa

Final sample of 6,343 firms with at least 50 employees, but we will use around 4500 manufacturing firms as the other sample drops service firms

- Match with Orbis data

## Building the leader index in the EBRD data

We reverse the scale for the questions on the frequency of meetings with suppliers and production/sales employees, as these are activities that Bandiera et al. (2020) find to be characteristic of manager type of CEO

Normalize the scores for each question so that they have a sample mean of 0 and a standard deviation of 1

Create an overall CEO time use index as a sum of the questions and standardize this variable

To create a binary leader variable, we classify CEOs with an index above 0 (the mean in the pooled sample, which is the 46th percentile) as a leader

# Analysis: Steps

1. Quality checks on index
2. Predict which firms "should" have a leader
  - Study matching patterns in US, UK, Germany, France, Italy, Cyprus and Malta (richest 7 countries of both ETUS and ES sample)  $\equiv$  training sample
  - Predict which firms among lower-income countries in ES sample should have leaders based on what observed in ETUS  $\equiv$  testing sample
3. Quantify mismatch: Verify that firms that are matched according to prediction are more productive
4. Study mismatch across firms and countries

# Step 1: Leader share increases with country income

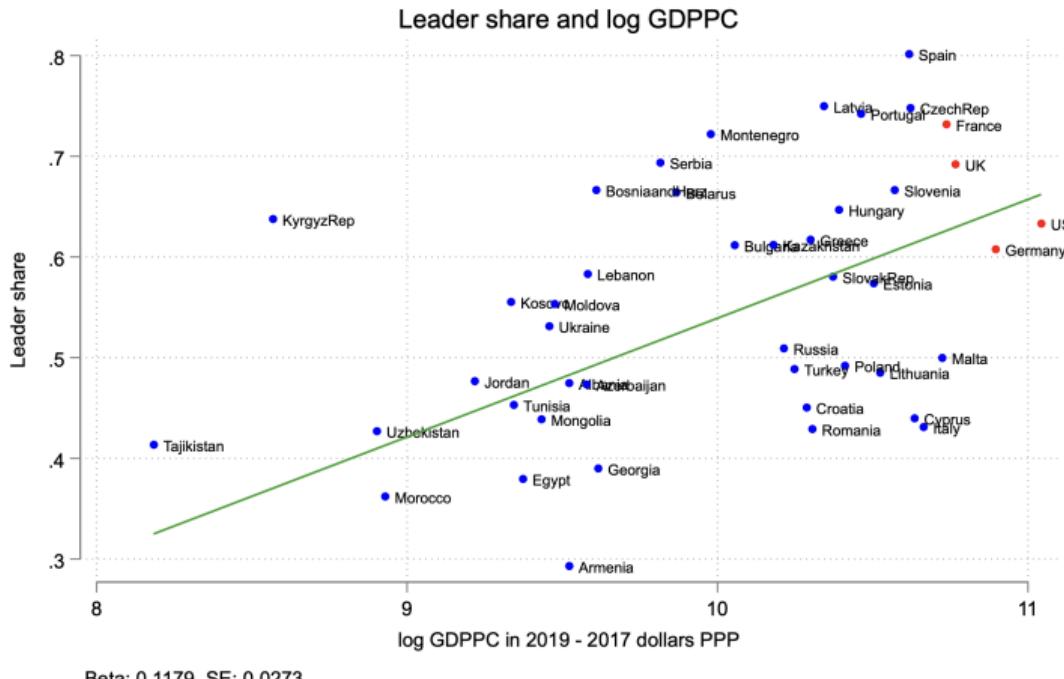


Figure: Red are from the ETUS sample, blue from ES sample.

# Index is correlated with performance within countries

Table: Firm characteristics and Leader status

Dependent variable =	Log(emp)	Log(emp)	Log(sales)	Log(sales)	Log(la.prod)	Log(la.prod)
Leader	0.175*** (0.029)	0.161*** (0.028)	0.279*** (0.047)	0.259*** (0.047)	0.104*** (0.038)	0.098*** (0.038)
Leader * Training Sample	0.131 (0.080)	0.114 (0.078)	0.057 (0.132)	0.044 (0.130)	-0.073 (0.105)	-0.069 (0.105)
Control: Country FE	YES	YES	YES	YES	YES	YES
Control: Industry FE	YES	YES	YES	YES	YES	YES
Control: Listed firm	NO	YES	NO	YES	NO	YES
Control: Family-owned firm	NO	YES	NO	YES	NO	YES
Control: Firm age	NO	YES	NO	YES	NO	YES
Observations	4842	4842	4842	4842	4842	4842
R-squared	0.097	0.154	0.522	0.538	0.665	0.666

Sales are in 2019 USD. Emp = employment, la.prod = labor productivity.

## Step 2: Predicting optimal types

Let LASSO select the coefficients and interactions to be included among all the variables that exist in *both* the ETUS and the ES sample. These are:

- Employment
- Listed firm
- Family-owned firm
- Firm age
- Industry indicators

We then perform the prediction with probit

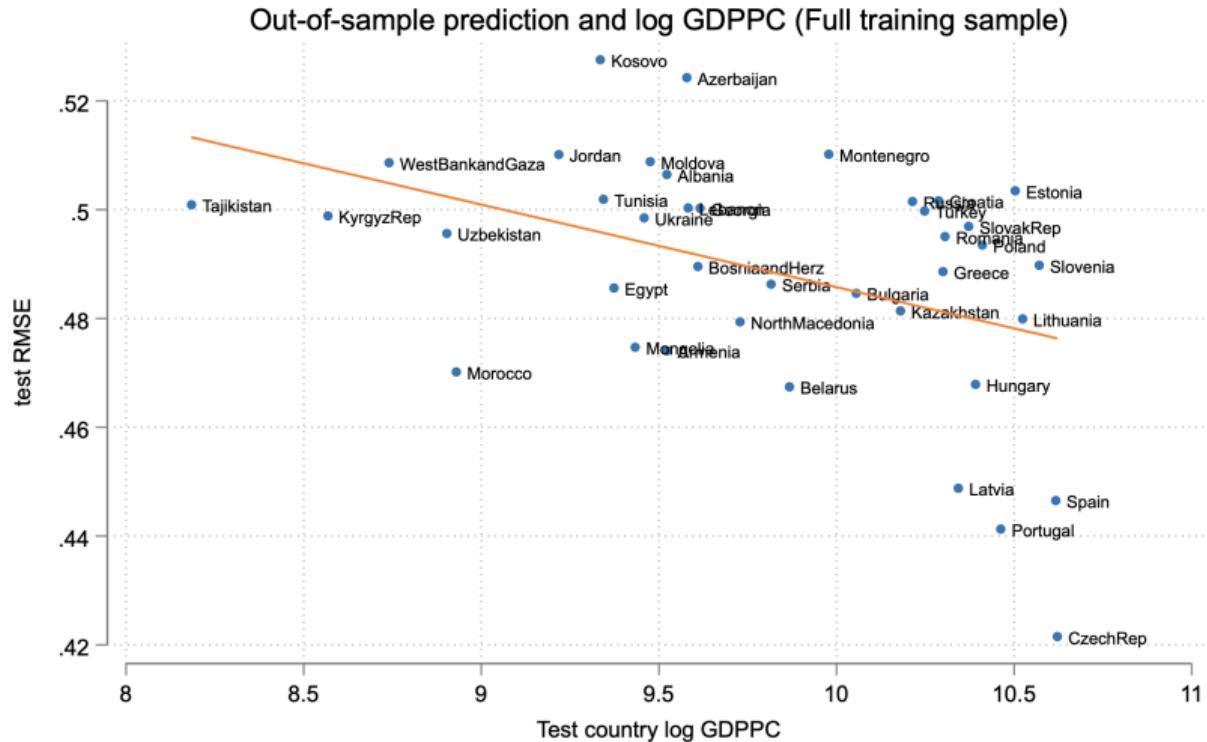
## Step 2: Prediction–Results

Which firms have leaders in rich countries? Selected Average Marginal Effects

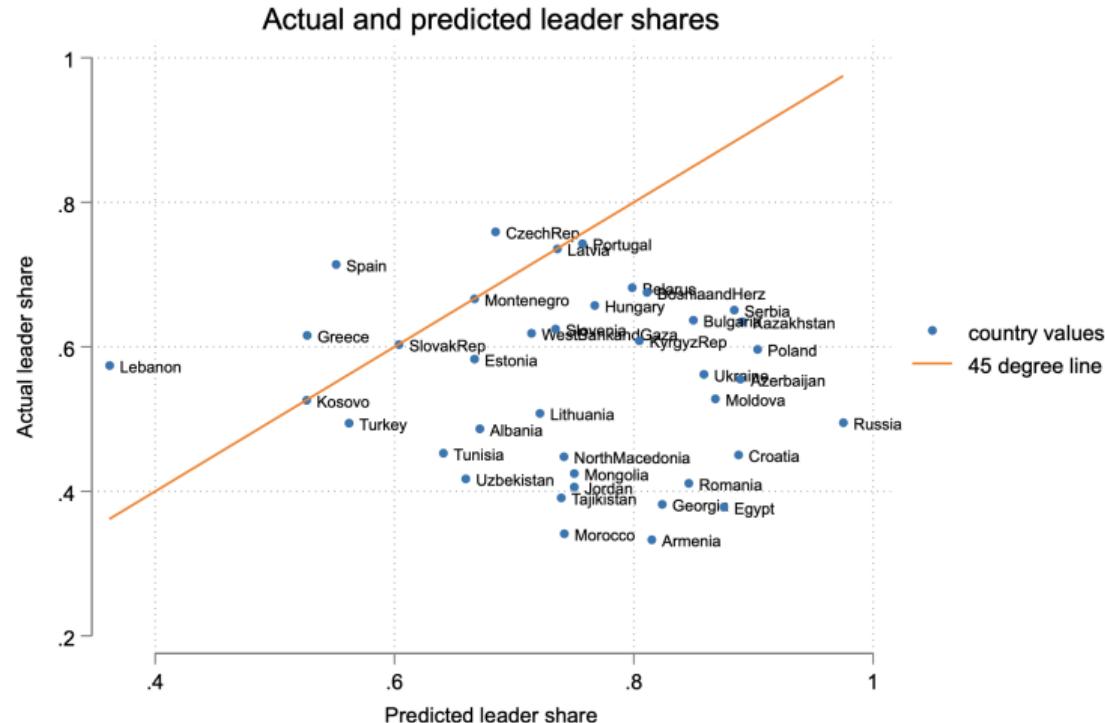
Table: Predicting leader status with firm characteristics - Probit

Dependent variable =	Leader status
Family-owned firm=1	-0.108*** (0.037)
Manufacture of textiles	-0.179* (0.104)
Manufacture of fabricated metal products, except machinery and equipment	0.021 (0.053)
Manufacture of machinery and equipment n.e.c.	0.104** (0.041)
Manufacture of office, accounting and computing machinery	0.237*** (0.060)
Log(emp)	0.079*** (0.018)
Establishment's age	-0.000 (0.000)
Observations	625
Pseudo R-squared	.101

# The prediction does better in higher income countries



# Most countries have a lower leader share than predicted...



Figure

...however, there is also mismatch between firms and CEO types  
*within* countries

We predict which type of CEO each firm should have in the lower income countries

We then study their productivity and other outcomes when they are matched as predicted, or mismatched compared to prediction

# Firms that are better matched are more productive

Table: Productivity and Leader Mismatch

Dependent variable = Log labour productivity	(1)	(2)
Mismatched	-0.131*** (0.039)	
Needs Leader, Gets Manager		-0.154*** (0.039)
Needs Manager, Gets Leader		-0.068 (0.053)
LM-ML p-value		0.164
Control: Country FE	YES	YES
Control: Industry FE	YES	YES
Observations	4209	4209
R-squared	0.375	0.375

# Good matches are also more innovative

Table: Innovation and Leader Mismatch

Dependent variable =	Product Inn.	Product Inn.	Process Inn.	Process Inn.
Mismatched	-0.037*** (0.013)		-0.022* (0.012)	
Needs Leader, Gets Manager		-0.052*** (0.014)		-0.038*** (0.012)
Needs Manager, Gets Leader		0.004 (0.020)		0.020 (0.023)
LM-ML p-value		0.026		0.005
Control: Country FE	YES	YES	YES	YES
Control: Industry FE	YES	YES	YES	YES
Observations	4209	4209	4209	4209
R-squared	0.179	0.180	0.181	0.183

# Intermediate outcomes

Good matches make it more likely that...

- Firm has a business strategy
- Firm is more focused (main product has higher share of sales)

Table: Intermediate Outcomes and Leader Mismatch

Dependent variable =	Business strategy exists	Main product's share
Mismatched	-0.039*** (0.013)	-0.005 (0.005)
Needs Leader, Gets Manager		-0.026* (0.013) 0.005 (0.006)
Needs Manager, Gets Leader		-0.075*** (0.025) -0.031*** (0.010)
LM-ML p-value		0.062 0.000
Control: Country FE	YES	YES YES
Control: Industry FE	YES	YES YES
Observations	4209	4209 4209
R-squared	0.093	0.094 0.065 0.068

# Mechanisms for mismatch

There is less mismatch in:

- Countries with less corruption
- Firms with more foreign private ownership, and that are exposed to more competition (exporters and importers)

# Firm level predictors of mismatched CEO

Table: Leader Mismatch Firm-level Predictors

Dependent variable = Deviation from predicted index	
Exporter or importer	-0.014*** (0.005)
Foreign ownership	-0.019*** (0.005)
Owner largest share	-0.018** (0.007)
Has board	-0.013*** (0.004)
Family management	-0.002 (0.004)
Firm organisation member	-0.008* (0.004)
Credit constrained	0.004 (0.004)
In capital/main business city	-0.008 (0.005)
Sole proprietorship	0.021*** (0.007)
Control: Country FE	YES
Control: Industry FE	YES
Observations	4209
R-squared	0.049

# Reflections

ML gave us a structure to solve a dimensionality reduction problem

- Absolutely necessary with 1st paper
- Instrumental also for 2nd paper

ML on its own would not have led to a publication

- First rejection: referee/editor clearly very suspicious of the new method
- Second submission (acceptance): enthusiastic referee, still required about 1 year of validation with alternative method
- Personally, very reassured to see the mismatch story being replicated in a completely different setting

ML required a very different type of team work

- Different skills in the team: technical, interpretation, execution
- Collaboration had to be much tighter than in previous projects
- Communication was key

# ML for Textual and Unstructured Data: Applications

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2. CEO Behavior and Firm Performance (Features Count)
3. The Demand for Executive Skills (Word Embeddings)
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# Motivation

Top executives matter for organizational performance

But what are the specific **skills** leading to these performance differentials?

More evidence helpful to

- Understand role of top managers in organizations (including matching with firm needs)
- Shape skill formation of future managers

# The Demand for Executive Skills

Large corpus of detailed C-suite job descriptions 2000-2017: **skills explicitly demanded by firms**

New **classification approach** to organize free-text descriptions into well defined categories of skills demanded by firms over time (*transfer learning*)

## Findings

- Wide range of skills demanded, cognitive and non-cognitive
- Wide heterogeneity in the demand for different skills across firms
- **Social** skills gaining relevance over time, especially in larger and more tech intensive firms

# Data

Partnership with a top-5 global executive search firm

- “Corporate headhunters are more powerful than ever” *The Economist, February 2020*
- 80 to 90% of Fortune 250 or FTSE 100 companies pay headhunters to find their C-suite managers, even when the successor is likely to be internal

Search for a C-suite manager takes anywhere from 90 days to a year

- Typically, board forms a committee to oversee the process, works in cooperation with headhunter (even if an internal candidate has been identified)

Board and headhunter craft a **document** describing what company looks for

- Rich and firm-specific description of required competencies to be circulated to viable candidates
- Document has a similar structure, but different language across firms

# Documents

Entire corpus of job descriptions for C-suite searches conducted by the company between 2000 and 2017 (4700 documents, 3846 firms)

- 43% CEO, 35% CFO, 14% CIO, 8% CMO and CHRO
- Large firms: median employment=1500,  $sd=53,000$ ; 26% publicly listed, 59% engaged in M&A activity within period of search
- 60% US firms, 28% Europe; 20% Manufacturing, 40% FIRE, Business and legal services
- 1,483 searches done by the same firm across managerial positions and/or over time (533 firms)

Matched with firm and search-level data

- Firm level: size and public status (Orbis, Capital IQ), M&A activity (Capital IQ), skill demand below the C-suite (Burning Glass)
- Search level: internal appointments

## Documents

Each job description contains sections for (1) company description; (2) responsibilities associated with the position; (3) qualifications expected of the candidate

We combine section (2) and (3) to form the text associated with each document

Standard preprocessing steps to break text into words

Average length is 440 words with standard deviation of 218 words

## Job Descriptions: Examples

*You have the courage of your own convictions even in the face of seemingly insurmountable obstacles*

*You are able to recognize your own biases or preferences and keep these in perspective*

*You have the character to say no but do it in a way that minimizes the damage that might otherwise be caused*

*You demonstrate the following core competencies*

*You can rally all parties towards an effective timely end result*

# The challenge

Classifying free text into meaningful and comparable skills and tasks

# Our approach

**Step 1:** Find a reliable, comprehensive but at the same time manageable classification of the skills and tasks needed to perform the job of the C-suite manager

**Step 2:** Find a robust way to map the text found in the job adverts into these standardized skill categories

## Step 1: Using O\*NET to define C-suite tasks

The O\*NET database is maintained by the US Department of Labor and contains information on around 1,000 occupations covering the entire economy

Each occupation is broken down into potentially dozens of components, each of which has its own descriptor

We take the *Skills*, *Tasks*, and *Work Activities* components of the *Chief Executives* occupation

This yields 68 different components that span a wide range of CEO behaviors and abilities, which we subsequently reduce to 6 clusters (more on this below)

# How to Compute Similarity?

Simplest approach to compute similarity would compare term overlap

But how to deal with ‘talk’ vs. ‘communicate’?

Modern solution uses **word embeddings**: words as vectors whose dimensions encode notion of semantics

# Word Embeddings

An embedding space is a low-dimensional vector space (relative to the total size of the vocabulary) for representing language

- Each term in the vocabulary is represented as a vector in this space: individual vectors are the word embeddings
- Terms with similar meaning have word embeddings that lie close to each other in the vector space

*“You shall know a word by the company it keeps” John R. Firth*

We adopt a popular algorithm for constructing word embeddings

- Word2vec (Mikolov 2013, 16k+ citations)

# Choosing the Training Library

Estimating word embeddings requires a large amount of data: orders of magnitude more than is available in the job ads. So we need a sufficiently large collection of documents to obtain our language model

One approach is to take pre-estimated vectors from standard corpora like Wikipedia, but the meaning of words in general English may differ substantially from that in management

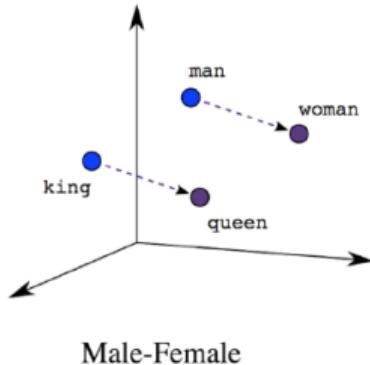
Instead, we build an embedding space constructed with word2vec applied to **Harvard Business Review** corpus

- HBR contains 14,000 articles with 50,000,000 total and 77,000 unique terms, covers period 1922-2019
- Embeddings specific to management rather than generic contexts (of independent interest)
- Validation of the corpus: analogies

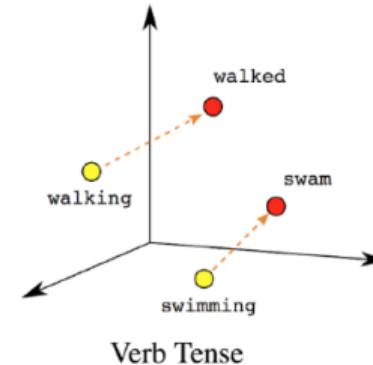
Analogies

Example

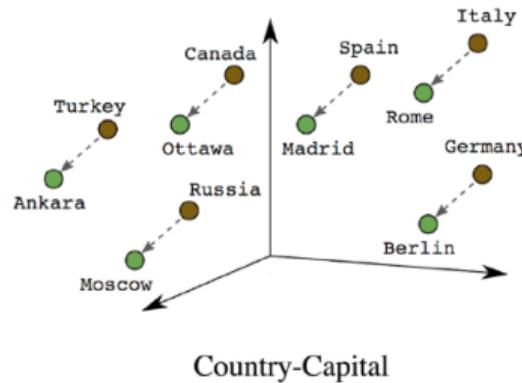
# Validating the approach: Word2vec and Analogies



Male-Female



Verb Tense



Country-Capital

# HBR Analogies between Companies and Products

(1) Company	(2) Product(s)	(3) Company	(4) Closest Vector(s)
General Motors	Automobile/Car	Walt Disney	Bike/Movie/Movies/ Memorabilia/Cinema
Goldman Sachs	Banking	Google	Internet/ World Wide Web Yahoo
Walmart	Retail/Retailing	Intel	Personal Computers /Microprocessor/Optics Computer Industry Manufacturing Semiconductor
Dow	Chemicals	Am Exp	Fin Services

**Notes:** In each row of the above table, we form a vector in an embedding space defined by the embedding vector for the third column plus the (average) embedding vector for the term(s) in the second column minus the embedding vector for the term in the first column. We then rank each term in the HBR vocabulary according to the similarity between its embedding vector and this composite vector.

Approach

# O\*NET Clusters

We project each O\*NET item into an embedding space, and then group O\*NET items into clusters using a k-means clustering algorithm ( $K = 6$ )

## 1. Management of Material and Financial Resources

- "Monitoring and controlling resources and overseeing the spending of money"

## 2. Administrative Tasks

- "Prepare or present reports concerning activities, expenses, budgets, government statutes or rulings, or other items affecting businesses or program services"

## 3. Monitoring of Performance

- "Monitoring/Assessing performance of yourself, other individuals, or organizations to make improvements or take corrective action"

## 4. Information Skills

- "Analyzing information and evaluating results to choose the best solution and solve problems"

## 5. Management of Human Resources

- "Recruiting, interviewing, selecting, hiring, and promoting employees in an organization"

## 6. Social Skills

- "Giving full attention to what other people are saying, taking time to understand the points being made, asking questions as appropriate, and not interrupting at inappropriate times"

# Mapping Job descriptions into O\*NET clusters

We project each document into an embedding space to obtain 6 similarity measures with the O\*NET cluster

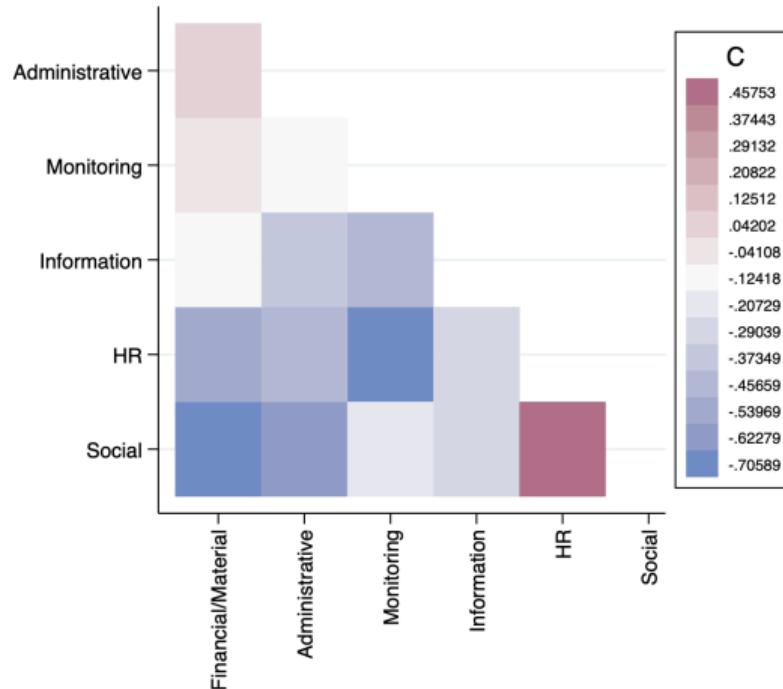
- Control for the average similarity of individual clusters across all documents
- Dummy=1 if the average normalized similarity is greater than the document-specific median similarity

# Exercise: O\*NET skills - Word embeddings

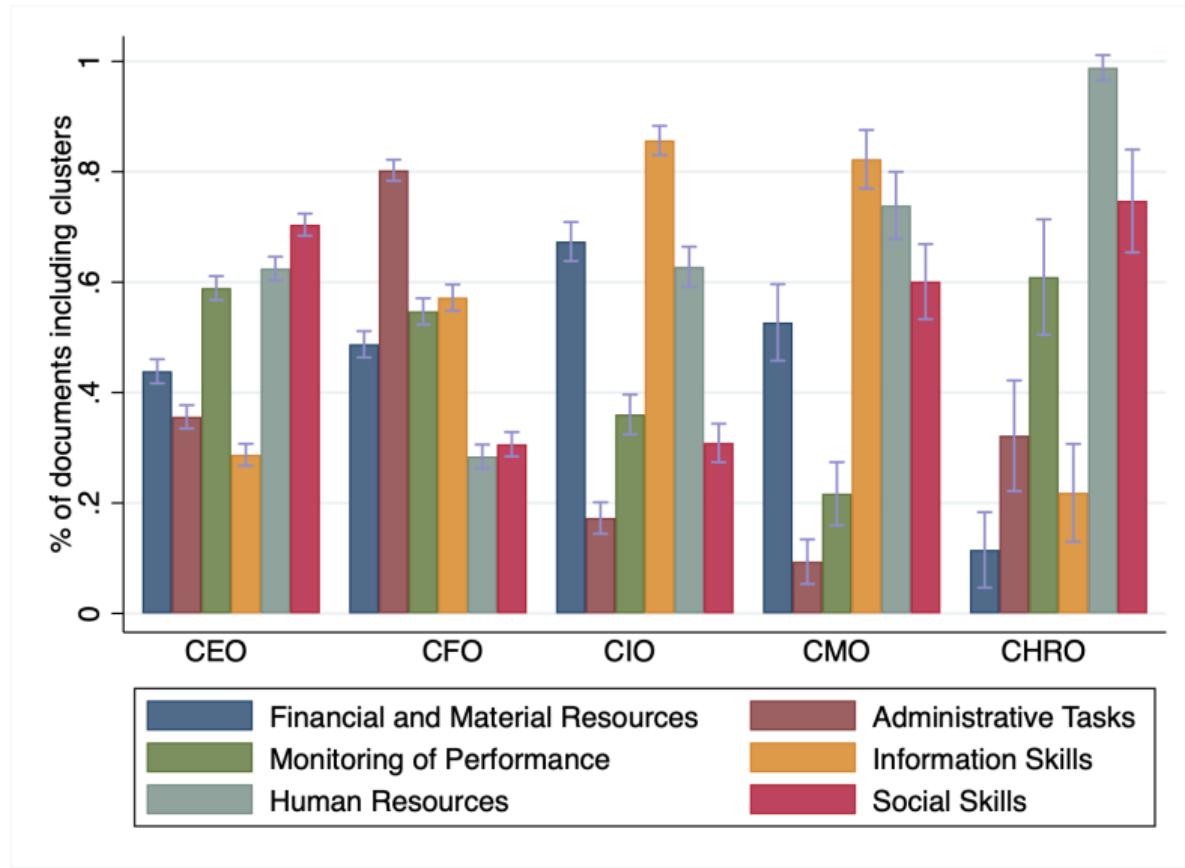
Similarity of job postings to different skill clusters: what do you see?

# Clusters

Clusters are correlated within documents, but not perfectly



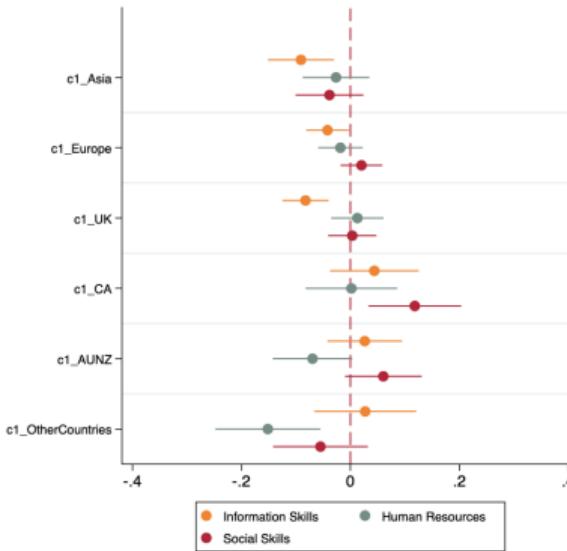
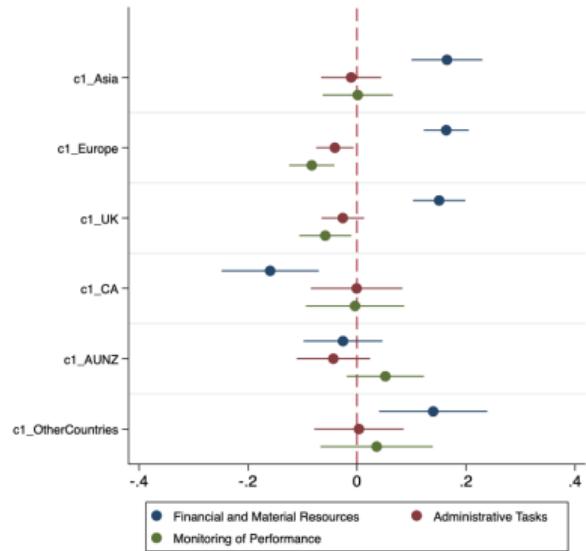
# Skills by C-title



Notes! The bar heights for each job title show the fraction of documents for which our algorithm

# Skills by Country

Variation by CHQ country

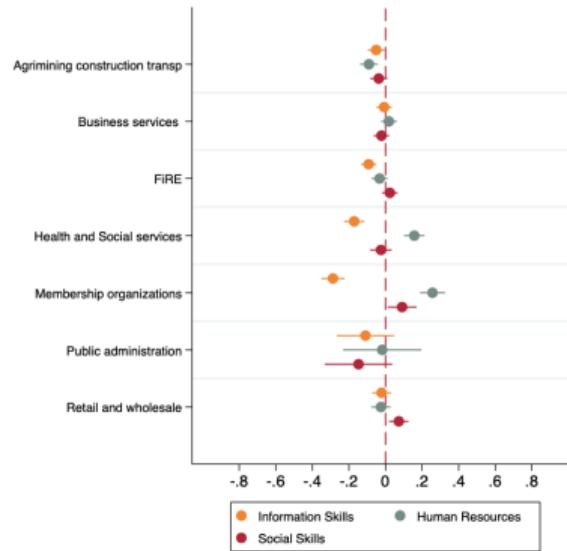
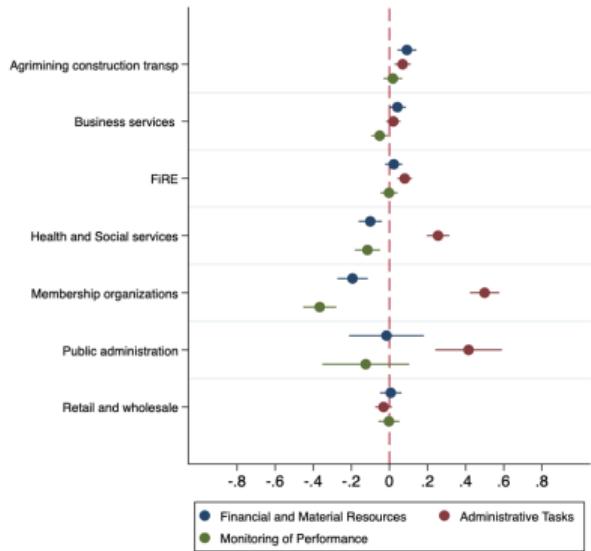


(b) Region Effects

**Notes:** This figure displays point estimates and 95% confidence intervals of regression coefficients from an OLS model of individual skills on region, country, and job title fixed effects. The omitted category for region is USA.

# Skills by Industry

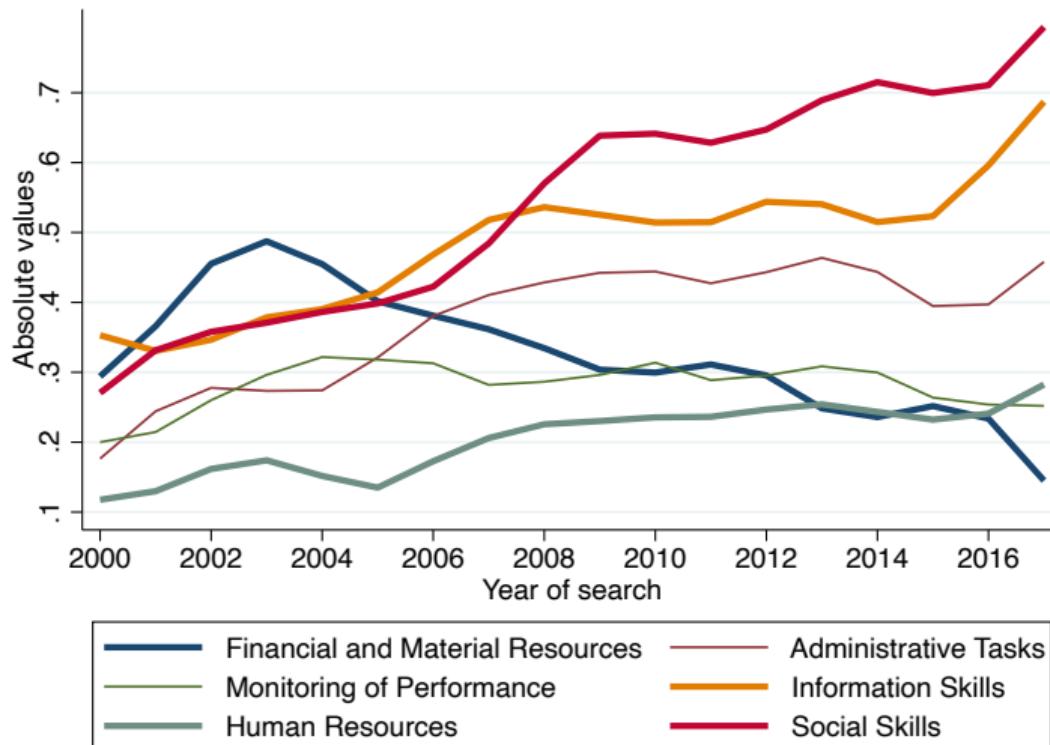
Variation by industry



(a) Industry Effects

**Notes:** This figure displays point estimates and 95% confidence intervals of regression coefficients from an OLS model of individual skills on region, country, and job title fixed effects. The omitted category for industry is manufacturing.

# Skills over Time



# Focus on social skills

What do they capture?

*Human interaction requires a capacity that psychologists call theory of mind—the ability to attribute mental states to others based on their behavior, to "put oneself into another's shoes"* (Deming, 2017)

Three interesting features

- Strong increase over time, even outside the C-suite Deming
- Most demanded in CEO positions
- Very heterogeneous across firms (like other clusters)

# Why would firms value social skills?

In general: example of non-cognitive skill (Heckman et al, 2006)

Specifically: social skills enable more effective communication (within C-suite or between C-suite and workers)

This is especially valuable in team production settings, as they help manage the tradeoff between specialization and coordination

## When are social skills most valuable?

To build basic comparative statics we embed social skills in a basic “management by exception” model (Garicano, 2000)

- Production depends on communication between workers and managers
- Communication needed when problems non-standard enough to require managerial input to be solved
- Managers are subject to a time constraint, which limits ability to achieve optimal output

Other conceptualization possible too, e.g. CEO as a motivator rather than a problem solver

# Communication frictions and Social Skills

Communication costs along the hierarchy depend on managerial social skills, as measured by  $c$  (Deming, 2017)

- C-suite manager needs less time to understand and communicate tacit knowledge

## In which situations are better social skills (reduction in $c$ ) more valuable?

1. More problems to solve (increase in  $N$ ): social skills relax managerial time constraint, allowing managers to focus on more valuable problems at the margin
2. Higher marginal benefit of vertical communication

Develop empirical proxies for these drivers, and test support for these predictions in the data

# Estimation

$$Social_{ft} = \alpha + \beta X_{ft} + \psi_o + \theta_i + \phi_{chq} + \phi_{sl} + \delta_t + \omega_f + \varepsilon_{jt} \quad (1)$$

- $Social_{ft}$ : dummy to denote the relative importance of the *Social* cluster in the job description for firm  $f$  at time  $t$
- $X_{ft}$ : firm characteristics that proxy for the volume of problems in production and value of C-suite expertise
- $\psi_o$  are C-title fixed effects,  $\theta_i$  are industry fixed effects (measured at the SIC 2 level),  $\phi_{chq}$  are fixed effects for the continent in which the firm originating the search is located,  $\phi_{sl}$  are fixed effects for the continent in which the search is launched from
- $\delta_t$ : year of search dummies
- $\omega_f$ : firm fixed effects (used only in some specifications)

# Volume and Scope of Problems

## Empirical proxies

- Size: Firm employment, Sales
- Scope: MNE, diversification, M&A, public status (Bandiera et al, 2020)

# Volume and Scope of Problems

	(1)	(2)	(3)	(4)	(5)
Dependent Variable: Social Skill Cluster					
Log(Employment)	0.014*** (0.003)	0.012*** (0.003)	0.015*** (0.003)	0.012*** (0.003)	0.012*** (0.003)
MNE		0.047*** (0.017)			
Diversified			-0.004 (0.017)		
M&A activity				0.030* (0.016)	
Public					0.030* (0.018)
Observations	4618	4618	4618	4618	4618

**Notes:** \* p<0.1, \*\* p<0.05, \*\*\* p<0.01. All columns are estimated by OLS. Standard errors are clustered at the firm level, in parentheses under the coefficient. The dependent variable across all columns is a dummy denoting an above-the-median similarity with the *Social* O\*NET cluster (where the median is computed using the raw similarity of all clusters in the job description). *MNE*=1 if the firm has operations in more than one country; *Diversified*=1 if the firm has operations in more than one 4 digit SIC sector; *M&A* activity=1 if the firm is involved in M&A activity (as a buyer, target or seller); *Public*=1 if the firm is publicly listed. All independent variables are measured using data in the three years prior to the executive search. All columns control for country of CHQ location, country of search, industry (SIC 2 level), year of search, type of C-suite position advertised.

# Workers' Skills and the demand for Social Skills

Managerial coordination especially valuable when workers are specialized in cognitive-intensive activities

Example: ICT skills

- *[With computerization] more effort is needed to establish the necessary minimum of communications so that we understand each other and know each other's needs, goals, perceptions and ways of doing things. Information does not supply this. Only direct contact, whether by voice or by written word, can communicate... The more we automate information-handling, the more we will have to create opportunities for effective communication Drucker, 1963*

Caveat: ICT skills may proxy for more than technical specialization, and affect benefit of vertical communication in other ways

- Complement to top management decision: e.g. greater benefit of C-suite intervention, faster communication (Guadalupe et al., 2012, Garicano 2000)
- Complement to decentralized decision making, facilitating knowledge acquisition (Bloom et al, 2016)

# Workers' Skills and the demand for Social Skills

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# Measuring ICT skills in the workforce

Burning Glass vacancy data: 703 US based firms with both C-suite and workers' vacancies (5mn job postings)

- Share of vacancies including reference to ICT skills for each firm/year (BG skill families)
- Robustness using principal factor (first factor loading on ICT, design and communication skills) and alternative Deming and Khan (2017) classification approach

# IT and Social Skills?

	(1)	(2)	(3)	(5)	(6)
Dependent Variable: Social Skill Cluster					
Log(Total Vacancies)	0.042*** (0.012)	0.056*** (0.018)	0.061*** (0.018)	0.053*** (0.018)	0.056*** (0.018)
IT Skills (Skill Shares, Burning Glass)	0.680*** (0.241)	0.758*** (0.270)			
IT & Cognitive Skills (Factor, Burning Glass)			0.093*** (0.023)		
IT Skills (Skill Shares, Deming and Khan)				0.285*** (0.098)	
IT & Cognitive Skills (Factor, Deming and Khan)					0.061*** (0.018)
Observations	703	703	703	703	703

**Notes:** \* p<0.1, \*\* p<0.05, \*\*\* p<0.01. All columns are estimated by OLS. Standard errors are clustered at the firm level, in parentheses under the coefficient. The dependent variable across all columns is a dummy denoting an above-the-median similarity with the *Social* O\*NET cluster (where the median is computed using the raw similarity of all clusters in the job description). *IT Skills* measures the average share of job vacancies including reference to the Burning Glass skill categories *Information Technology* or *Analysis*. *IT & Cognitive Skills* is the first principal factor derived from the set of 27 skills categories (factor loadings are presented in Table B.14). The last two rows refer to skill shares and factor built using the alternative Deming and Kahn (2018) classification. All independent variables are measured using data in the three years prior to and following the executive search. All columns control for country of CHQ location, country size, industry (SIC 1-3), industry of CHQ, firm size, and year.

# Robustness: Other clusters

Dependent Variable:	(1) Social (Baseline)	(2) Management of Financial and Material Resources	(3) Administrative Tasks	(4) Monitoring of Perfor- mance	(5) Information Skills	(6) Personnel Manage- ment
Log(Employment)	0.014*** (0.003)	-0.008** (0.003)	-0.005 (0.003)	0.006 (0.003)	-0.002 (0.003)	-0.005 (0.003)
MNE	0.047*** (0.017)	0.003 (0.017)	-0.054*** (0.015)	0.023 (0.017)	0.021 (0.017)	-0.040** (0.017)
Diversified	-0.004 (0.017)	0.009 (0.018)	-0.011 (0.015)	0.016 (0.018)	0.005 (0.017)	-0.015 (0.018)
M&A Activity	0.030* (0.016)	-0.003 (0.016)	-0.060*** (0.013)	0.030* (0.016)	0.009 (0.014)	-0.062*** (0.013)
Public	0.030* (0.018)	-0.038** (0.018)	0.007 (0.016)	-0.062*** (0.019)	0.022 (0.018)	0.040** (0.019)
IT Skills (Shares, Burning Glass)	0.758*** (0.270)	0.177 (0.262)	-0.669*** (0.247)	-0.894*** (0.279)	0.663** (0.260)	-0.036 (0.278)
IT & Cognitive Skills (Factor, Burning Glass)	0.093*** (0.023)	-0.043** (0.022)	-0.050** (0.021)	-0.075*** (0.024)	0.060*** (0.021)	0.014 (0.023)
IT Skills (Shares, Deming & Khan)	0.285*** (0.098)	0.074 (0.096)	-0.259*** (0.086)	-0.163 (0.103)	0.168* (0.099)	-0.105 (0.100)
IT & Cognitive Skills (Factor, Deming & Khan)	0.061*** (0.018)	-0.035* (0.018)	-0.035** (0.016)	-0.027 (0.020)	0.026 (0.019)	0.011 (0.020)

# Robustness: Omitted variables

Differences in document quality correlated with firm characteristics:

- Control for doc length

Consultants pushing for social clusters to cross-sell other services in larger firms

- Study change in social and firm size **within the same firm**

Boards including social language to hire internal candidates

- Study if social skills correlated with internal appointment, control for internal appointments (small sample)

# Robustness

Dependent Variable: Social Cluster	(1)	(2)	(3)	(4)	(5)	(6)
	Baseline	Probit	Control for document length	Within firm	Internal sample	Internal sample, control for internal
Log(Employment)	0.014*** (0.003)	0.001** (0.001)	0.014*** (0.003)	0.080*** (0.029)	0.014** (0.006)	0.016** (0.006)
MNE	0.047*** (0.017)	0.147*** (0.050)	0.048*** (0.017)		0.058* (0.033)	0.061* (0.033)
Diversified	0.030* (0.016)	0.091* (0.054)	0.031* (0.018)		0.008 (0.034)	0.009 (0.034)
MA Activity	-0.004 (0.017)	-0.011 (0.051)	-0.004 (0.017)		0.007 (0.036)	0.011 (0.036)
Public	0.030* (0.018)	0.088* (0.047)	0.030* (0.016)		-0.012 (0.031)	-0.010 (0.031)
IT Skills (Shares, Burning Glass)	0.680*** (0.241)	2.550*** (0.875)	0.763*** (0.271)			
IT & Cognitive Skills (Factor, Burning Glass)	0.093*** (0.023)	0.310*** (0.074)	0.094*** (0.023)			
IT Skills (Shares, Deming & Khan)	0.285*** (0.098)	0.949*** (0.320)	0.288*** (0.098)			
IT & Cognitive Skills (Factor, Deming & Khan)	0.061*** (0.018)	0.210*** (0.060)	0.061*** (0.018)			

**Notes:** Every coefficient corresponds to a different regression.

# External validity?

A comment from the Head-hunting firm

- *The rise of technology, digital, and AI could be driving a doubling down on the distinct nature of executive judgment—creativity, interpersonal insight, empathy, etc.*
- *Outside the firm, there is a growing number of partnerships, alliances, complex supply chains, interactions with regulators and the government, and an increasing role for CEOs to play as social leaders in society.*
- *There is a constellation of issues—ESG, social value, purpose, longtermism, sustainability—that is increasingly being raised by directors. Originally this was because of investor pressure, but increasingly it is because of employee pressure.*

# All this effort for nothing? GPT prompt

YM

Your task is to read the text of job postings and identify the demand for social skills. You should classify a posting as a 1 if it describes explicitly the need for any of the following skills:

- Social Perceptiveness: Being aware of others' reactions and understanding why they react as they do.
- Coordination: Adjusting actions in relation to others' actions.
- Active Listening: Giving full attention to what other people are saying, taking time to understand the points being made, asking questions as appropriate, and not interrupting at inappropriate times.
- Persuasion: Persuading others to change their minds or behavior.
- Negotiation: Bringing others together and trying to reconcile differences.
- Judging the Qualities of Things, Services, or People: Assessing the value, importance, or quality of things or people.
- Resolving Conflicts and Negotiating with Others: Handling complaints, settling disputes, and resolving grievances and conflicts, or otherwise negotiating with others.
- Selling or Influencing Others: Convincing others to buy merchandise/goods or to otherwise change their minds or actions.

If none of the above skills are mentioned you should classify the posting as 0. If classification is unclear, say "Could not classify".

- Text of job posting: • Providing advice to improve the effective use of technology resources and investments.

Please provide the classification and an explanation for your choice in the following format:

- Classification: [1 or 0]
- Explanation: [Explanatory text]

Prompt with  
description of relevant  
skills

Text of job posting

Output format

# GPT-4 classification results: social skills

*" Skills: Managing one's own time and the time of others. Giving full attention to what other people are saying, taking time to understand the points being made, asking questions as appropriate, and not interrupting at inappropriate times. Adjusting actions in relation to others actions. "*



- Classification: 1
- Explanation: The job posting explicitly mentions the need for "Active Listening" (giving full attention to what other people are saying, taking time to understand the points being made, asking questions as appropriate, and not interrupting at inappropriate times) and "Coordination" (adjusting actions in relation to others' actions), which are among the listed social skills. Therefore, the posting can be classified as requiring social skills.

*" Teamwork(Cooperation)-Active participation in, and facilitation of, team effectiveness; taking actions that demonstrate consideration for the feelings and needs of others; being aware of the effect of one's behavior on others. "*



- Classification: 1
- Explanation: The job posting explicitly mentions the need for "Social Perceptiveness" (being aware of the effect of one's behavior on others), and it implies the need for "Coordination" (taking actions that demonstrate consideration for the feelings and needs of others). These are among the listed social skills. Therefore, the posting can be classified as requiring social skills.

# GPT-4 classification results - resource management skills

*"Responsible for being mindful of controlling crew costs including effective use of manpower, proper work methods, amount of trimming, and operation of equipment."*

*"Completes the make-ready process to prepare vacant apartment homes for leasing and new move-ins by completing the pre-move-out inspection, creating a punch list of maintenance work needed, scheduling vendors and contractors as needed, obtaining needed supplies and materials, completing all maintenance tasks, and inspecting completed work."*



- \* Classification: 1
- \* Explanation: The job posting explicitly refers to the need for "Management of Material Resources" through the mention of "effective use of manpower, proper work methods, amount of trimming, and operation of equipment", and possibly "Management of Financial Resources" as inferred by the phrase "mindful of controlling crew costs". Therefore, the posting can be classified as requiring the mentioned skills.



- \* Classification: 1
- \* Explanation: The job posting explicitly refers to the need for several of the specified skills. "Management of Material Resources" is referred to in the mention of "obtaining needed supplies and materials", "Administer programs for selection of sites, construction of buildings, or provision of equipment or supplies" is hinted at in the task of "scheduling vendors and contractors as needed", and "Performing Administrative Activities" is evident in the task of "completing the pre-move-out inspection, creating a punch list of maintenance work needed". Therefore, the posting can be classified as requiring the mentioned skills.

# Conclusions

## Results

- Firms exert effort in specifying what they want in C-suite managers
- Variety of operations, cognitive and interpersonal skills
- Increasing importance of **Social** skills, decline of operational skills
- Demand for social skills correlated with firm size, need for central involvement, IT investments

## Implication and future research

- How easy/hard to find and assess candidates with good Social skills? Possible door for bias?
- Do Social skills matter for managerial compensation?
- Do Social skills matter for firm performance? If so, how can screening be improved?

# Reflections

ML allowed us to classify unstructured text into more manageable categories

- More informative than standard keyword approach given small sample

ML on its own is not leading to a publication

- First rejection: referee/editor clearly very suspicious of the new method
- Now working on a new version of the paper with more explicit identification strategy
- Validation is taking a very long time
- Original method (probably) made obsolete by chat GPT anyways

ML required a very different type of team work

- Partnership with external private firm: needed to align on objectives to get the full dataset
- Several dedicated RAs working full time on cleaning, pre-processing and classifying data
- Documentation is key

# ML for Textual and Unstructured Data: Applications

1. Introduction
2. CEO Behavior and Firm Performance (Features Count)
3. The Demand for Executive Skills (Word Embeddings)
4. Remote Work across Jobs, Companies, and Space (Transformer Models)
5. Conclusions

# Motivation



# Motivation

Remote work adoption greatly accelerated by COVID-19

This shift appears to have a permanent component

- SWAA (Barrero et. al. 2021) suggests 25% of workdays away from the office after pandemic recedes

RW is much more than a simple change in locus of work

- Change in the organization of work (a new ‘technology’)
- Changes in the boundaries of the firm
- Real-estate externalities

# Need for evidence

Various kind of data used to examine RW

- Occupation-level ‘teleworkable’ classifications
- Survey-data collected from workers/firms

These data have limitations

- Limited sample size
- Little pre-pandemic coverage
- Unfeasible to measure RW adoption at scale, at high frequency, and across countries
- Not ideal for firm level analysis

Our goal: To measure RW adoption **at scale** with **high granularity** and substantial  
**pre-pandemic coverage**

# This project

## New data

- Near-universe of **online job vacancy postings** collected since Jan 2014 from Lightcast (formerly Burning Glass): half a billion postings from 50,000+ sources (scraped daily)
- Covers USA, UK, Canada, Australia and New Zealand (... EU next!)

## New classification approach

- LLM application to classify all ads which explicitly offer RW

## New analysis

- Document **variation in the share of RW vacancy postings across time, occupations, cities, countries and firms**

Outputs available on [www.wfhmap.com](http://www.wfhmap.com)

# Literature

## Measurement:

- Dingel and Neiman (2020): 37% of jobs ‘remotable’
- Brynjolfsson et al. (2020): Survey 25,000 in April 2020,  $\approx$  30% RW
- Barrero et al. (2021) survey 5,000pm from May 2020, 25% full days

## Productivity Impact:

- Bloom et al. (2014); Emanuel and Harrington (2021): 10% increase for teleworkers
- Choudhury et al. (2021): 4.4% increase for US Patent examiners
- Kunn et al. (2021) Negative impact on professional chess players
- Gibbs et al. (2022) Negative impact on grad teams in Asian IT firm (but no clean counter-factual)
- Etheridge et al. (2020); Barrero et al. (2021); Aksoy et al. (2022): Self-reported worker productivity increased

## Migration and Cities:

- Coven et al., 2021; Delventhal et al., 2020; Althoff et al., 2020; Ramani and Bloom, 2021: Residents moved out of city centers

# Data

## Lightcast Data

- Near universe of online job vacancies (50,000+ sources scraped daily)
- USA, UK, Canada, Australia and New Zealand
- Jan 2014 - Feb 2023 (updated in real time)

## Each vacancy contains

- Structured metadata on occupation, location, firm, posting date
- Unstructured text data describing relevant aspects of position

## Sample

- Sample begins in 2014, updated monthly
- English-speaking countries: USA, UK, Canada, A/NZ
- 5% random sample from each country taken through 2018

# Measurement challenges

Common approach: Dictionary method

- Adrjan et. al. (2021) uses this approach to measure remote work adoption with cross-country Indeed.com data
- Draca et. al. (2022) uses it on our same UK Lightcast data sample

We ‘quickly’ (3 months) realized this was not going to be a good fit for our project

- False positives due to breaks in the structure of the ads during the pandemic and negation
- False negatives due to semantic variations around the concept of RW

## False positives

- The Senior BA will be regularly placed in situations where there is pressure to produce tangible results in response to unplanned events or situations. These situations sometimes have the additional stress of working with remote teams in different geographies.
- This role will be part of the homebased programme so the successful applicant will need a current first aid certificate. The nanny will have the support of a registered teacher.
- Business Development Manager AN UNNAMED COMPANY, Yorkton, SK, CANADA RAM Industries Inc., a design and manufacturer of custom designed hydraulic cylinders, is seeking a new full time Business Development Manager. This position is located at home office in Yorkton, Saskatchewan.

## False negatives

- Key Requirements: -Compliance experience within financial services  
-An ability to get the job done from home and maintain the work  
-Keeping up with the derivatives market and the relevant regulations  
-A previous relationship with the FMA
- We require some of the work to be done in our office in Chatswood, Sydney. Other work can be done at home. Applications close 5pm, February 16th
- Candidate can live anywhere within the US We are hiring in over 20 states including California, Indiana, Illinois, Georgia, Michigan, Texas, New York, Rhode Island, Pennsylvania, Virginia, Tennessee, Colorado and Oregon.

# Enter WHAM: Work from Home Algorithmic Measure

A fine-tuned large language model (BERT)

- We select 10,000 sequences of job posting text with mix of (dictionary terms from existing literature, negated dictionary terms, generic keywords, random sample)
- Each passage is labeled by three workers on Amazon Mechanical Turk: 30,000 human-based classifications (identify remote work at least one day per week)
- Agreement rate is above 90%



# Measurement Caveats

Online job ads not perfectly representative of the whole economy

Since we use text offer must be explicit: a commitment Only covers RW adoption for new hires

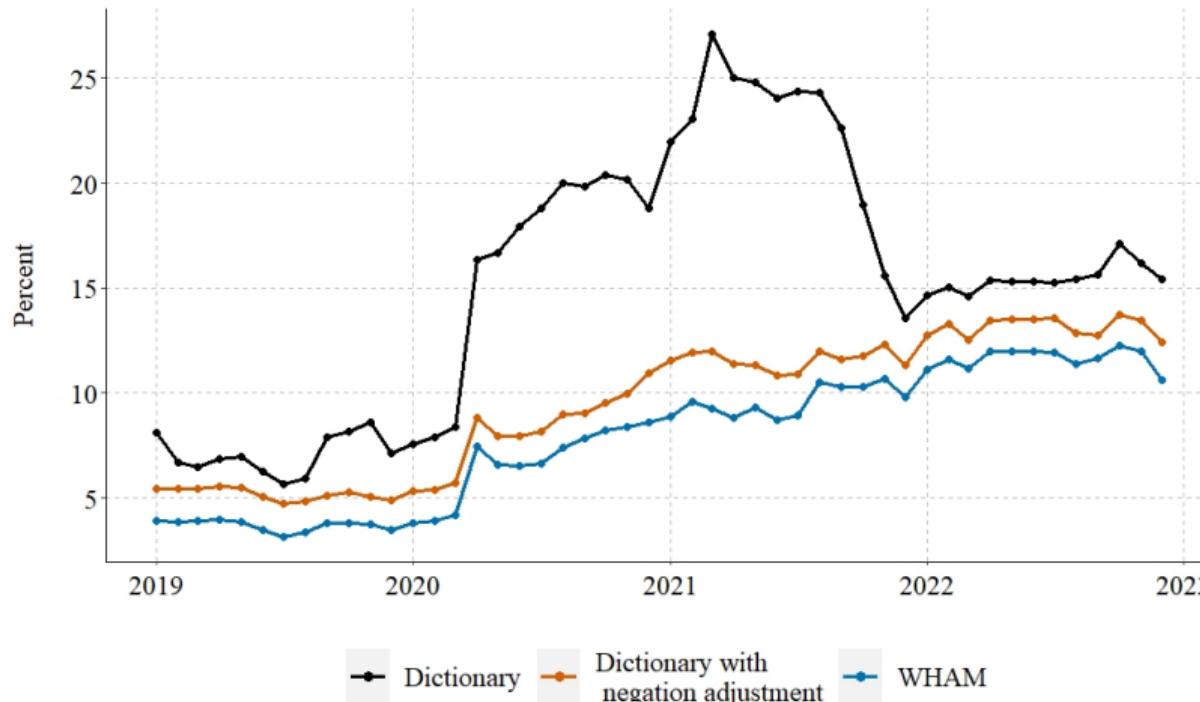
**...so after all this effort, what did we find?**

# Some case studies

Comparisons across methods: what do you see?

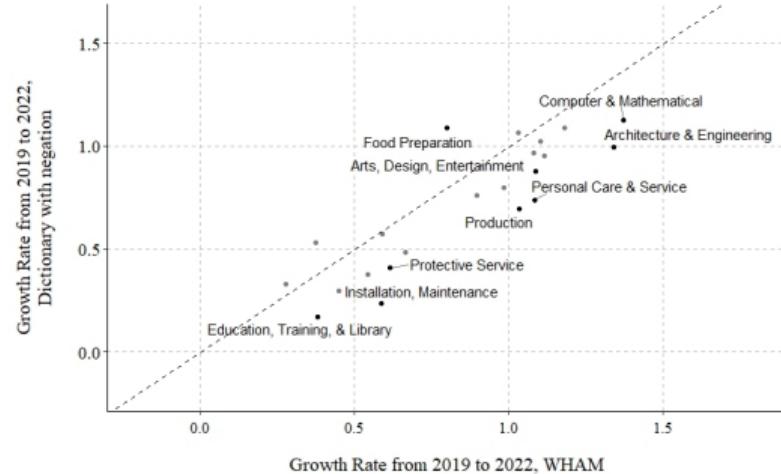
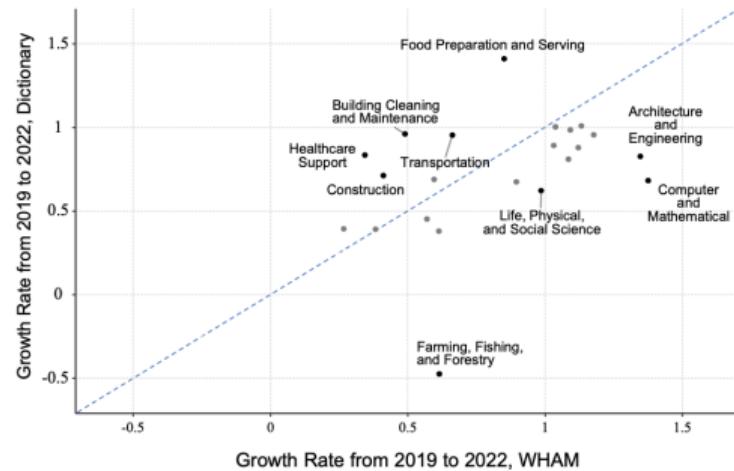
# WHAM vs. Dictionary and Negated Dictionary: Time series

Postings Classified as Hybrid or Fully Remote Work, U.S. Vacancy Postings



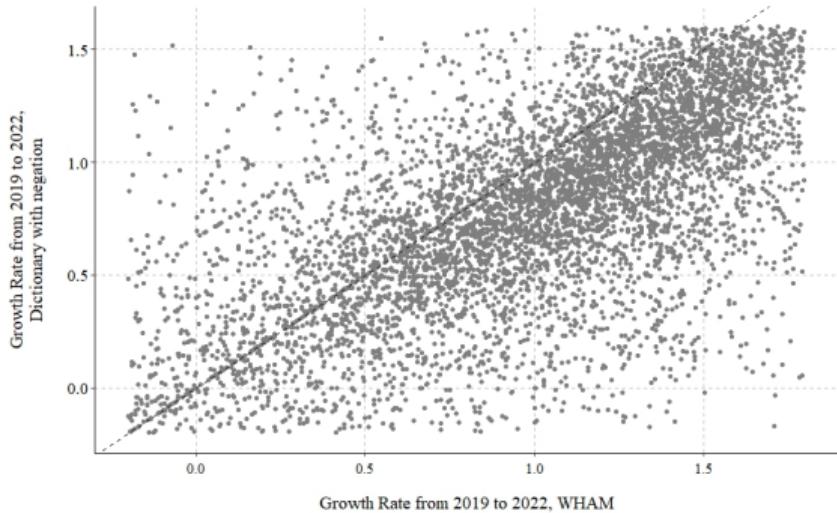
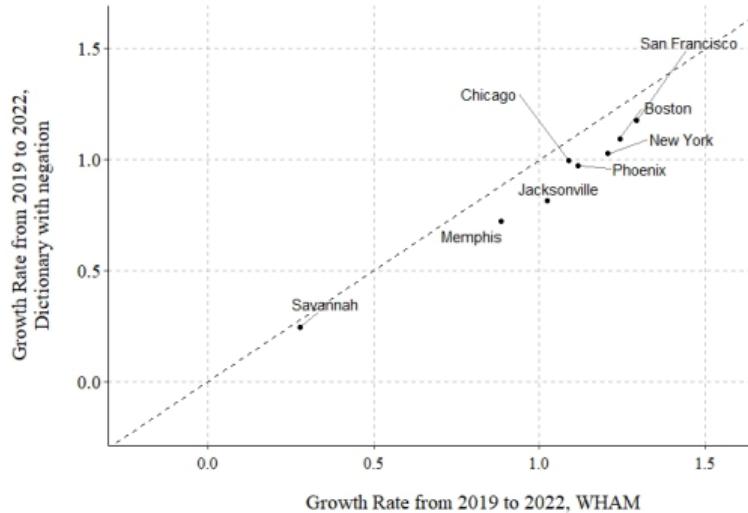
# WHAM vs. Dictionary and Negated Dictionary: Occupations

**Figure:** Share of U.S. Postings that Allow Some Remote Work, Growth Rate by Two-Digit Occupations, WHAM Compared to Dictionary Method



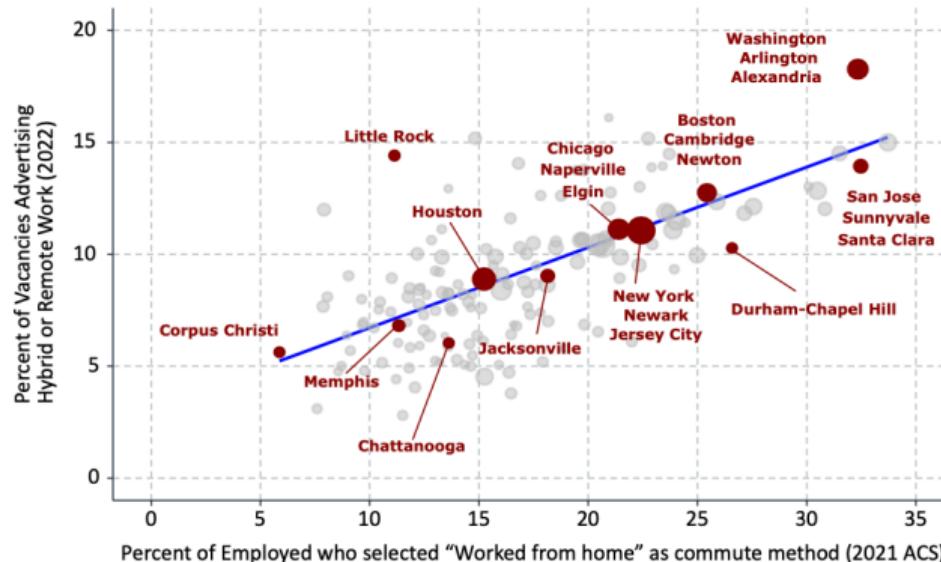
**Note:** We sort postings into Standard Occupational Classifications (SOC) at the two-digit level and calculate the share of postings that say the job allows for one or more days per week of remote work in 2019 and 2022. We then calculate the DHS growth rate from 2019 to 2022 as  $(X_{2022} - X_{2019}) / 0.5 * (X_{2019} + X_{2022})$ . For the dictionary method, we use the keywords in Adrjan et al. (2021). The blue-dashed line shows a 45 degree line.

# WHAM vs. Negated Dictionary: Cities



# WHAM vs. ACS

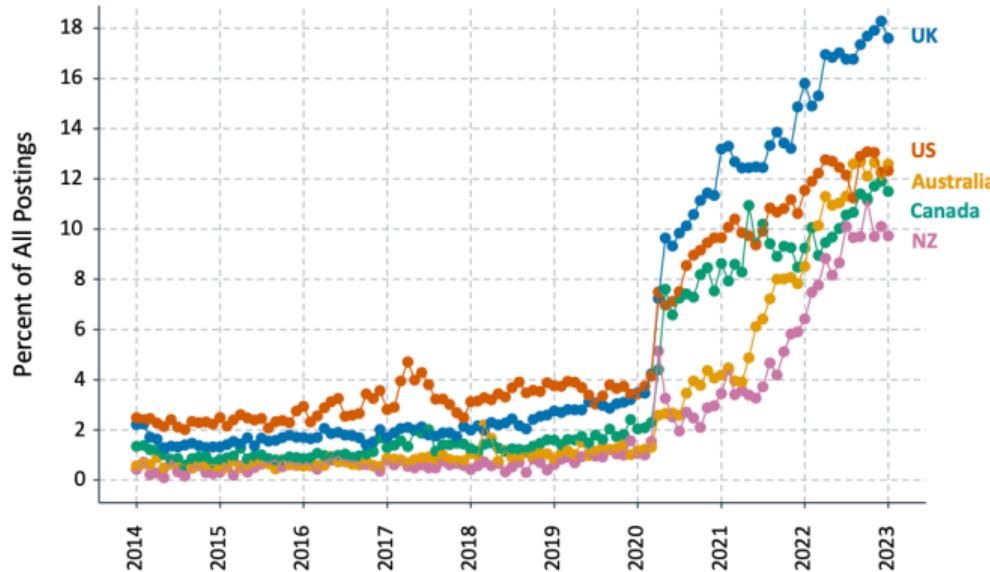
**Figure:** Share of Vacancy Postings Offering Hybrid or Fully Remote Work Compared to Share of Employed that Designate "Worked from home" as commute method, U.S. Metropolitan Statistical Areas



**Note:** The vertical scale is the percent of postings in 2022 that say the job allows one or more remote workdays per week (i.e. both hybrid and fully-remote). The horizontal scale is the percent of employees who select "Worked from home" as their commute method in 2021 in the American Communities Survey (ACS). ACS respondents are instructed to "Mark (X) ONE box for the method of transportation used for most of the distance," which suggests that only those who work in a fully-remote capacity should select this box. (Persons with 1+ days of commute per week have more mileage from that commute mode.) The line shows the unweighted OLS fit:  $\log(y) = 3.12 + 0.36 \log(x)$ , which has an  $R^2$  value of 0.55. The regression includes one observation that is outside the plotted axes.

# RW Adoption Across Countries

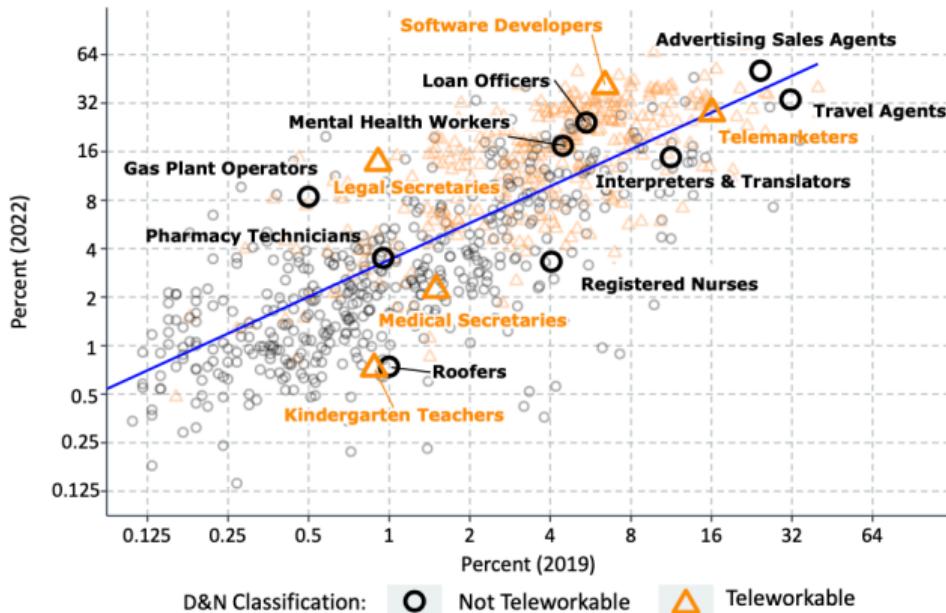
**Figure:** Vacancy Postings that Explicitly Offer Hybrid or Fully Remote Work Rose Sharply in All Five Countries from 2020



**Note:** This figure shows the percent of vacancy postings that say the job allows one or more remote workdays per week, encompassing both hybrid and fully-remote working arrangements. We compute these monthly, country-level shares as the weighted mean of the own-country occupation-level shares, with weights given by the U.S. vacancy distribution in 2019. Our occupation-level granularity is roughly equivalent to six-digit SOC codes. See Appendix B for the corresponding raw series and series based on alternative weighting schemes.

# RW Growth Across Occupation Groups

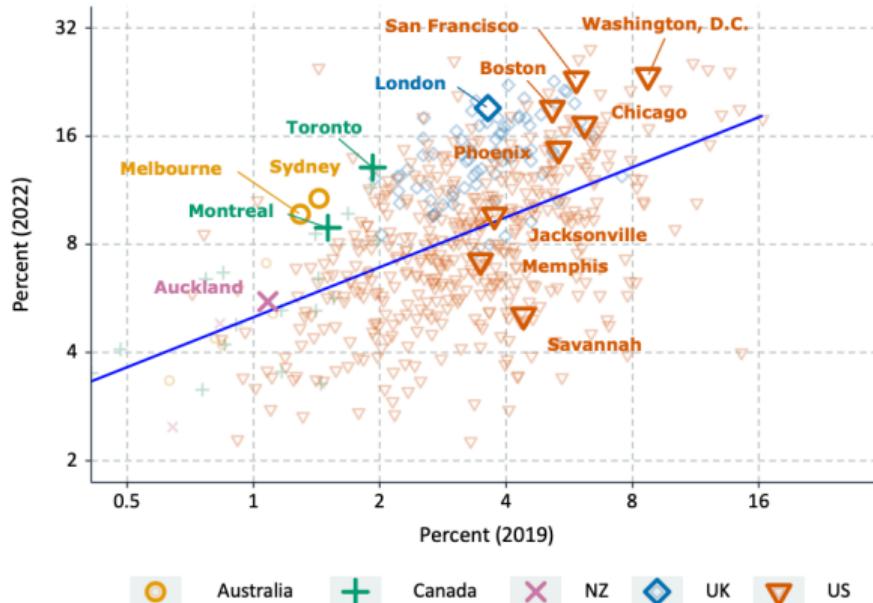
**Figure:** The Share of Vacancy Postings that Explicitly Offer Hybrid or Fully Remote Work Rose in Almost Every Occupation, U.S. Data



**Note:** This figure plots the percent of postings that say the job allows one or more remote workdays per week for 875 occupations in 2019 and 2022. We define occupations by ONET codes, dropping those with fewer than 250 posting in 2019. The line shows the unweighted OLS fit:  $\log(y) = 1.22 + 0.76 \log(x)$ , which has an  $R^2$  value of 0.63. The color and shape denote whether Dingle & Neiman (2020) classify the occupation as feasible for fully remote working.

# RW Growth Across Cities

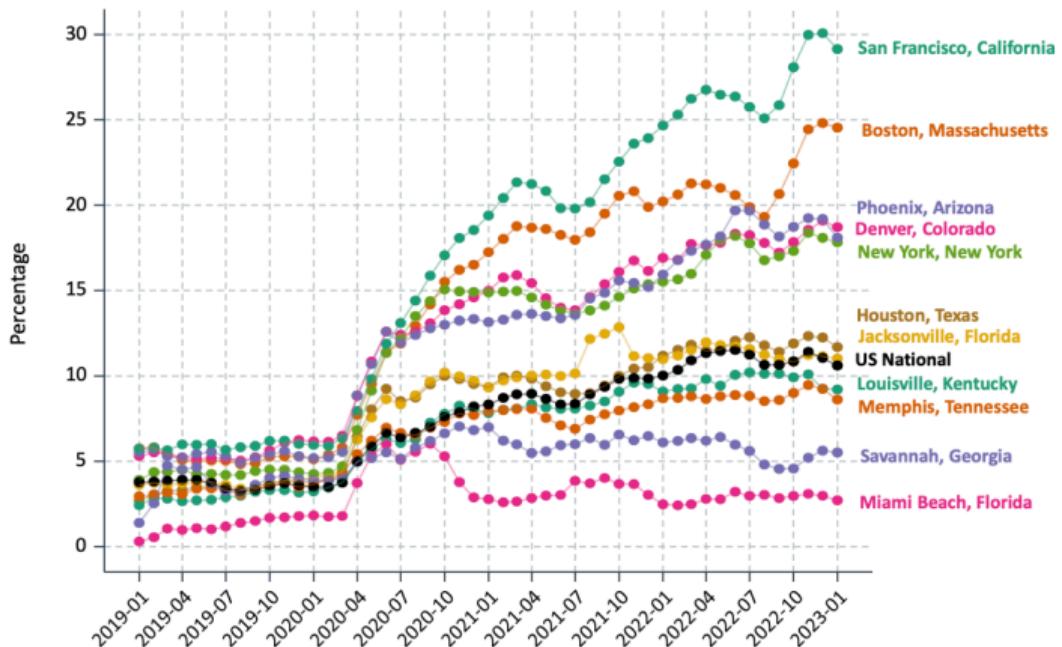
**Figure:** The Share of Vacancy Postings that Explicitly Offer Hybrid or Fully Remote Work Grew at Different Rates across Cities since the Pandemic



**Note:** This figure plots the city-level percent of postings that say the job allows one or more remote workdays per week in 2019 and 2022. "City" refers to the location of the establishment or firm that is hiring. The line shows the unweighted OLS fit:  $\log(y) = 1.61 + 0.46 \log(x)$ , which has an  $R^2$  value of 0.28.

# RW Growth Across Cities

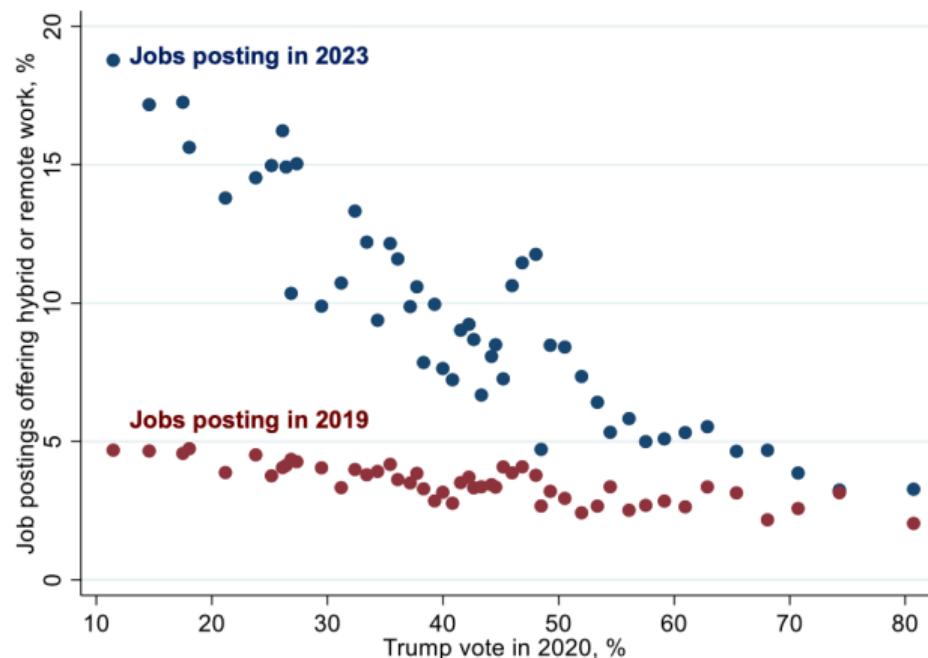
**Figure:** Share of Postings Offering Hybrid or Fully Remote Work vary across US cities



**Note:** We calculate the monthly share of all new job vacancy postings which explicitly advertise remote working arrangements (i.e. both hybrid and fully-remote), by selected cities. Prior to aggregation at the monthly level, we employ a jackknife filter to remove a small number of outlier days (see Appendix A: Data for further details). This figure shows the 3-month moving average. Cities chosen above are selected examples to illustrate the wide cross-city spread.

# RW Adoption and Ideology

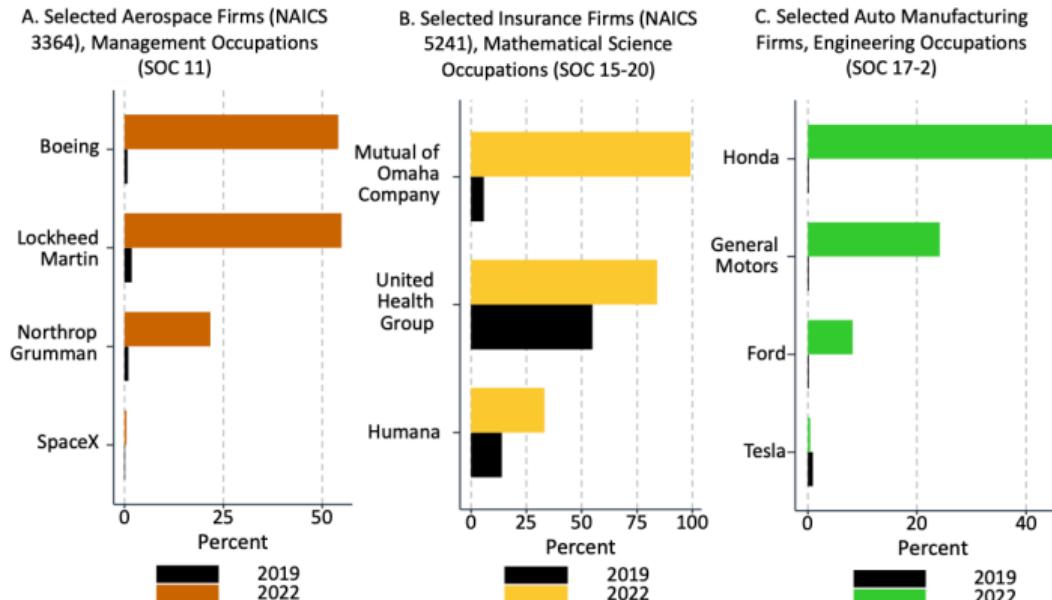
WFH grew most post-pandemic in non-Trump voting parts of the US



**Notes:** US county level binscatter of share of vacancy postings offering a job that allows 1+ days remote working per week vs Trump 2020 Presidential Vote Share. Weighting by county size. 50 bins. Source [www.wfhmap.com](http://www.wfhmap.com)

# RW Adoption Across Firms

**Figure:** The Prevalence of Postings that Allow Hybrid or Fully-Remote Work Varies Greatly, even among Same-Industry Firms Recruiting in the Same Occupational Category



**Note:** For each firm, year and indicated occupation, we report the percent of U.S. postings that say the job allows one or more remote workdays per week.

# Where to next?

Measurement:

- Expanding measurement to 27 EU countries
- Expanding measurement to distinguish WFH vs WFA
- Link employers to canonical firm-level data

Study causes of remote work adoption:

- Geographic: Infrastructure, Commuting Habits, COVID-severity (disease and policy)

Firm level focus

- Which firms adopt RW?
- Do firms spread RW?

# Conclusion

We develop a new measurement approach using online job vacancies, capable of near-human classification accuracy at very large scale

Share of vacancy postings offering RW increased

- 3x (US), 5x (UK), 9x (Canada)

But growth in RW adoption is heterogeneous across organizations, even within narrow industry/occupation groups

- Causes and consequences of heterogeneous RW adoption?

WFH Map

Measuring remote work across space and time, using job ads.

[Home](#) [Team](#) [Data](#) [Method](#) [Partnerships](#) [Contact](#) [Media](#)

Data

We encourage other researchers and interested parties to explore our dataset, and utilise it in their own work.

Please cite our working paper when using these data: "Remote Work across Jobs, Companies, and Space" (Hansen, Lambert, Bloom, Davis, Sadun & Taska, 2023).

## Data Categories

#### **Category A: Readily Available!**

- Monthly country-level statistics for United States, United Kingdom, Australia, Canada, and New Zealand
  - Monthly occupation-level statistics (2-digit US SOC) for the United States

[Download here](#)

**Category B: Readily Available (with sign-up)**

- Monthly Industry-level statistics (NAICS 2-digit sector) for the United States
  - Monthly occupation-level statistics (2-digit US SOC) for the United States
  - **NEW!** Monthly city-level statistics (for **150+** cities) for the United States
  - **NEW!** Monthly city-level statistics (for **40+** cities) for the United Kingdom

**Sign-in** to access these data

# Reflections

ML allowed us to classify an enormous corpus in real time

- Much more precise than standard dictionary method

A different kind of output

- Academic publication: WHAM not enough on its own
- Public good: WHAM already been adopted in media and research

ML required a very different level of resources and organization

- External partnership
- An ARMY of CS specialists and RAs (pre-processing, labeling, iterating, etc.)
- An even more intense organizational/managerial challenge: constant Human-AI interaction

# ML for Textual and Unstructured Data: Applications

1. Introduction
2. CEO Behavior and Firm Performance (Features Count)
3. The Demand for Executive Skills (Word Embeddings)
4. Remote Work across Jobs, Companies, and Space (Transformer Models)
5. Conclusions

# Conclusions

Overview of three different applications of ML models in economics research

ML provides new and exciting research opportunities

- ML especially suited for research questions that benefit from use of **complex and/or unstructured** data
- All papers discussed today fit into this category (Organizational economics)

But ML also poses new challenges for researchers

- "Black-box" nature of the techniques require caution and additional effort to validate results: ML alone not sufficient to publish
- While access to generic tools is low, tailoring these approaches to specific RQ imposes very high costs in terms of time and resources
- ML-intensive projects require also a much more collaborative, extensive and (ideally) transparent team-work: key role for management of large teams and Human-AI interaction

# Conclusions

Overview of three different applications of ML models in economics research

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THANK YOU  
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# Background

Increasing importance of ICTs and intangible capital in production (Corrado et al, 2005, Haskel and Westlake, 2018)

- Computerized information, IP, organizational competencies

Contemporaneous changes in task content and requirements of jobs

- Decline in routine jobs, increasing share of employment and wages for jobs with **high cognitive content** (Autor et al, 2003)
- But also increasing importance of **coordination skills**, as many forms of intangibles complement knowledge-intensive, collaborative, networked activities (e.g. process redesign, creative activities; Deming and Khan, 2018, Deming 2017)

*Human interaction requires a capacity that psychologists call theory of mind—the ability to attribute mental states to others based on their behavior, to "put oneself into another's shoes" (Deming, 2017)*

# Increasing importance of social skills in the U.S. labor market (Deming 2017)

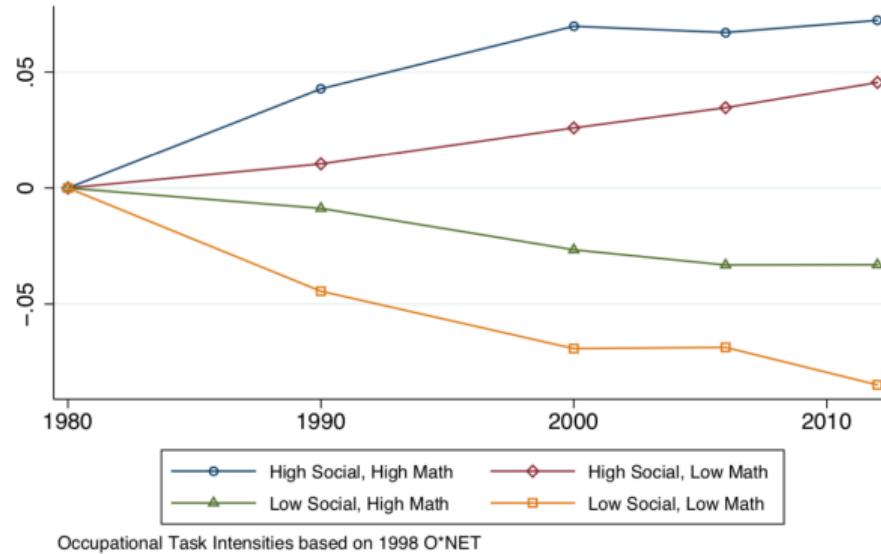
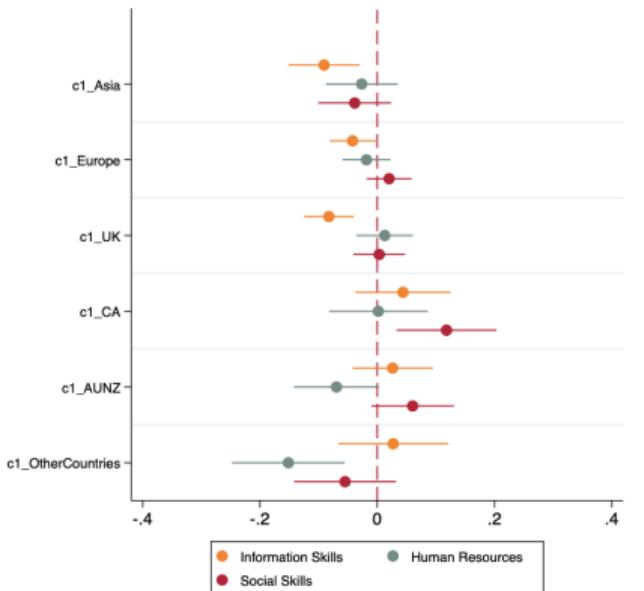
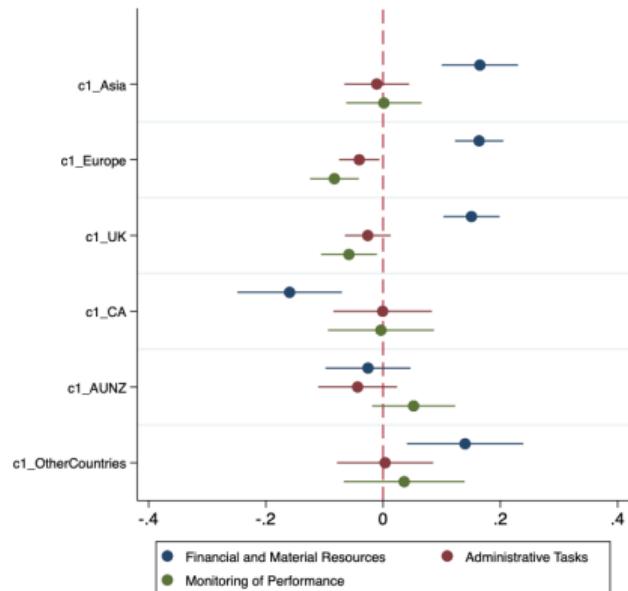


FIGURE IV  
Cumulative Changes in Employment Share by Occupation Task Intensity,  
1980–2012

# Variation in demand for social skills across countries

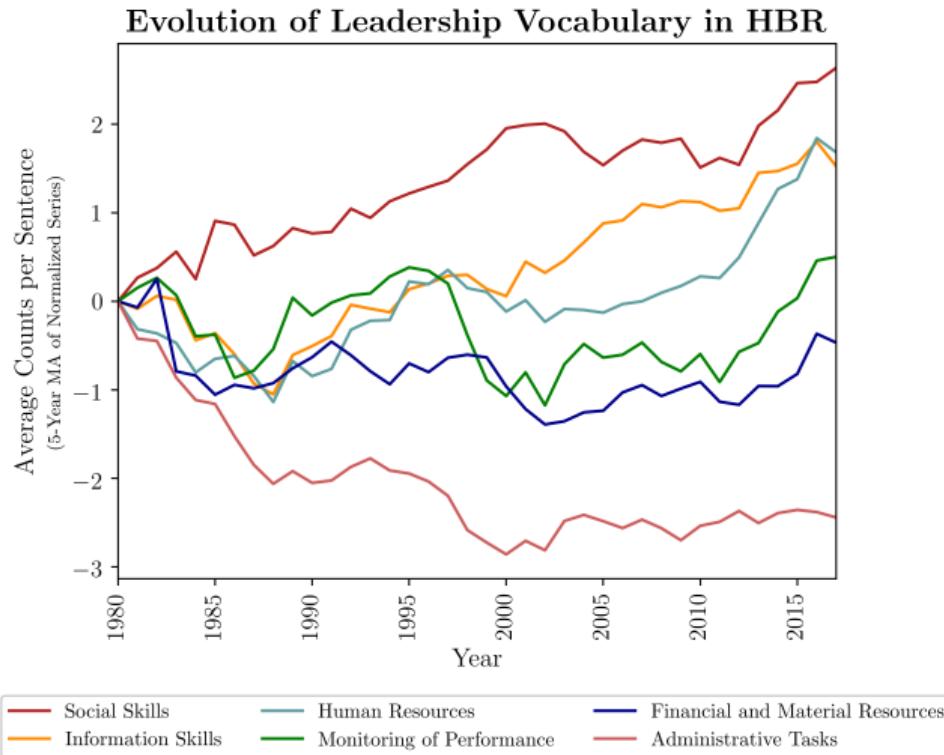
Variation by CHQ country



(b) Region Effects

**Notes:** The graph shows the results of an OLS regression of the social skills cluster dummy on a set of country fixed effects (USA being the reference level). Each dot represents a different coefficient. Errors clustered at the firm level.

# Trends in Harvard Business Review Language



**Notes:** We extract every sentence in the Harvard Business Review that contains the string 'leader', and compute for each year from 1980 the average word counts per sentence (for 25,996 sentences) from six dictionaries that capture particular skill clusters. The above plots a five-year moving average of the normalized average count time series.