"Firm Investments in Artificial Intelligence Technologies and Changes in Workforce Composition"

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OUTLINE

1. **Introduction/Summary**
2. Conceptual Issues
3. Data Issues
4. Econometric Issues

Introduction

- Important Q: What is the effect of AI on skills and organizational structure of firms?

- Database combining:
  - **Compustat**: accounts of US publicly listed firms
  - **BGT**: Online ads for jobs with AI-related tasks
  - **Cognism** resume data: 535 million individuals globally (54% of US workforce in 2018)
  - 1,218 firms between 2010-2018, focus on US workers

- Data used in authors' earlier papers, but not yet focused on the key outcomes examined here

Some Key Findings

- Growth of AI higher when large initial % of STEM and PhD employees

- Higher growth of AI associated with:
  - Faster change towards **flatter hierarchies** measured by % of workers in junior (vs more senior) managerial positions
  - Larger fall in **unskilled** (% workers without college degree) & faster rise in average years of education
  - Bigger increase in **STEM qualified workers** (relative to e.g. social science qualification)

Assessment

- Nice data – hard to get firm-level panel data on technology and skill mix, especially in US

- Simple, transparent approaches

- Evidence on impact on organizational form particularly interesting

- Results seem sensible and robust to controls for many initial firm characteristics

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Conceptual Issues

1. **Risk of a mechanical relationship?**

2. **Issues with measuring AI by labor**

3. **A framework?**

Conceptual Issues

1. **Risk of a mechanical relationships?**
   - AI adoption measured by online postings on labor hiring (BGT) & outcomes are also based on employment (Cognism). Better than regressing BGT employment on BGT AI data, but still risks a mechanical relationship
   - **Example:** if all AI done by STEM workers then unsurprising more “AI” postings (right hand side variable) means more STEM workers (left hand side variable)

Conceptual Issues

2. Issues with measuring AI by labor (related to last point)

- Much AI is embodied in capital/software <u>not</u> labor. **Examples:** Enterprise Resource Planning: SAP module with predictive analytics for demand management; cyber-security apps from Palantir. These big “AI” spend will not be reflected in BGT hirings. Indeed – may need *less* AI-related workers hiring as it is all done “in the box”
- Broader ICT literature uses employer surveys (e.g. Harte-Hanks use of ERP in Bloom, Garicano, Sadun & Van Reenen, 2014 or spending cumulated into ICT stock). Can we compare these surveys with your BGT type measure?

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- Analogy with measuring software expenditure by “own account” (in-house labor) & “shrink wrapped” (bought-in)
- Issue extends to measuring hierarchies. How does your labor measure of “flattening” compare to Rajan & Wulf (2006) type data based on org charts or WMS/MOPS measures?
- NB: This is a general issue in literature!

Conceptual Issues

3. **Possible framework**
   - Production (or Cost) function with multiple labor types, AI and ORG as intangible capital inputs
   - Derived labor demand has the kind of regressions you run
   - Could also estimate the primitives: i.e. production or cost function. This design would exploit your (largely unused) Compustat

- **Examples of modelling productivity:**
  - as function of AI interacted with STEM (plus linear terms)
  - expand to include ORG to address big picture question of whether failures to change ORG is a reason for only small impact of AI on productivity

BACK TO BASICS: THE PRIMITIVES

Output, Q, function of efficiency (A), vector of labor of skill type j, AI capital, organizational hierarchy (ORG) & other inputs X.

$$Q = AF(L^j, AI, ORG, X)$$

Assume labor flexible supplied at wage W^j, but other intangible capitals are quasi-fixed

Consider two types of labor high skill (H) and low skill (L), abstract from ORG and X. Short-run cost function is:

$$CV(W^H, W^L; AI, Q)$$

SHORT-RUN FACTOR DEMAND EQUATION

Approximate Cost function by flexible 2nd order form (translog) & by Shephard's Lemma, can derive $SHARE^H$ of high skilled labor in total labor costs:

$$SHARE^H = \alpha ln\left(\frac{W^H}{W^L}\right) + \beta AI + \gamma lnQ$$

Write relative wages as composed of time dummies, firm *i* fixed effect & idiosyncratic shock. Take differences:

$$\Delta SHARE^H_{it} = \beta\Delta AI_{it} + \gamma\Delta lnQ_{it} + \tau_t + \Delta u_{it}$$

Hypothesis of skill-AI complementarity is β > 0 (related to Hicks-Allen elasticity of complementarity)

SHORT-RUN FACTOR DEMAND EQUATION

Further assuming homotheticity $\gamma = 0$

$$\Delta SHARE_{it}^{H} = \beta\Delta AI_{it} + \tau_t + \Delta u_{it}$$

Which is essentially what you estimate as one long difference.

Could also consider *ORG* and other factors and have multiple skill groups:

$$\Delta SHARE_{it}^{j} = \beta\Delta AI_{it} + \theta\Delta ORG_{it} + \delta\Delta X_{it} + \tau_t + \Delta u_{it}$$

RETURNING TO THE PRIMITIVE PRODUCTION FUNCTION

Direct Estimation using a first order approximation

$$\Delta lnQ_{it} = \beta_{AI}\Delta lnAI_{it} + \beta_H \Delta lnL_{it}^H + \beta_L\, \Delta lnL_{it}^L$$
$$+\rho_{AI,H}\Delta[lnAI_{it} * lnL_{it}^H] + \rho_{AI,L}\Delta[lnAI_{it} * lnL_{it}^L] + \epsilon \Delta lnX_{it}$$

Test of complementarity between high skilled workers and AI: $\rho_{AI,H} > \rho_{AI,L}$

Easy to expand with ORG linear & interactions; more skill groups; more higher order terms, etc.

Can stack in system and estimate jointly

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Data Issues

1. **What fraction of employees in each Compustat firm is in Cognism ("coverage rate")?**
   – This is what you should be weighting by. Simply weighting with #Cognism workers conflates with size
   – Worry that coverage low because Compustat firms dominated by multinationals with many workers outside the US (and matching imperfect). Better to use all global workers to boost coverage?
   – Note: Compustat values are global consolidated (e.g. R&D, etc.)

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2. Why not ditch Compustat entirely and just do a Cognism-BGT match?

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3. **Change/level (?) of AI seems like a trivially small share**. Problem of looking for needle in haystack issue?

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Econometrics

- Your previous work emphasized AI predicts employment growth, so could we just be picking up a growth effect?
  – Faster growing firms will tend to expand lower level workers in managerial hierarchy as (e.g.) adjustment costs lower
  – Not necessarily part of mechanism: growing firms adopt more AI and expand junior managers, but no effect of AI directly on organization (or skills)

- Would be good to think of some designs to get closer to causality
  – IVs like your "university connections with firms", a Bartik style exposure measure (maybe from Mike Webb's approach), etc.
  – Event studies
  – Split years into 2 long differences to look at pre-trends

Other Questions/Comments

- Any information on wages? Wage bill shares attractive summary measure as "price weights" the job quantities and maps back into theory
- Would be good to have some more visualizations (e.g. scatterplots of change in skills on change in AI)
- You mention quality of Cognism by 2018, but what about coverage over time. Like BGT isn't it becoming increasingly better & therefore more selected
- How would Cognism coverage compare to LinkedIn?
- What about AI which uses outsourced workers?
- BGT is flow whereas you really want the stock
- On positive job effects of technology see https://economics.mit.edu/files/22239 & the classic http://cep.lse.ac.uk/textonly/people/vanreenen/papers/jole_emp.pdf
- Note that Caliendo et al hierarchy measure includes production workers: flatter structure means more lowest level vs. next lowest level. You have excluded these workers to just look at managerial levels.
- Conceptual framework I sketch is based on see Bond and Van Reenen (2001) Handbook of Econometrics and Caroli and Van Reenen (2001) as well as my lecture notes
- P.3 "flatten" not "flatter"; p.5 "investments" not "investmetns"

Other Questions/Comments

- Would be good to compare the hierarchy measures with direct firm surveys (e.g. WMS https://worldmanagementsurvey.org/ or MOPS)
- Caliendo et al emphasize that only a big positive shocks mean adding layer to hierarchy. Maybe compare across technology shocks (e.g. AI vs software vs robots?)
- What are the results like if you do not standardize AI
- Do you have anything on wages?
- Given small shares do you check for outliers/winsorize?
- You should look at the data in Rajan and Wulf (2006); Guadalupe and Wulf (2010) and Lerner and Wulf (2007) from Howitt – also looks at delayering in Compustat firms.
- How does Figure 5 compare with aggregate ACS data? Same question for some of other figures.
- Table 3 needs levels (mean & median) as well as changes
- How do you decide on CZ for Compustat firms which covers multiple CZs (and multiple countries), e.g. Wal-Mart
- Add mean of change and level of dependent variables in tables (e.g. 6)
- Fall of share medical qualifications a bit weird in Table 8

Conclusion

- Great paper and well worth reading!
- Lots of possible extensions
- Look forward to next version