Quantifying the impact of AI on productivity and labor demand: evidence from U.S. Census microdata

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Any opinions and conclusions expressed herein are those of the author(s) and do not necessarily represent the views of the U.S. Census Bureau or the National Bureau of Economic Research. All results have been reviewed to ensure that no confidential information is disclosed. The DRB codes for this project are: DRB-H0027-CED-20190205, CBDRB-FY19-414, and CBDRB-FY20-105.
AI as a general purpose technology?

• Many commentators view AI as an emerging general purpose technology...

• Potentially powerful enough to boost productivity growth, addressing one of the American economy’s core challenges.

• It could also eventually generate significant disruption in the labor market.

• We are (probably) at a very early stage in the process of development and diffusion of AI
The need for firm level data...and the challenge of finding it

- The good news: we have some time to get ahead of any AI-driven disruption, putting in place policies that could cushion those displaced by new technology.
- The bad news: we lack basic data on how firms are developing and deploying AI systems.
- Current efforts to survey firms directly are laudable and necessary, but it may take years before these data acquire the panel dimension we need to measure the impacts we seek to quantify.
- Is there anything else we can do?
Our idea: use patent data to map the movement of AI concepts into commercial use...

Using AI to find AI inventions...

1. Label initial set of AI and non-AI patents from US Patent Documents.
2. Train model to predict AI patents.
3. Label patients using trained model.
4. Retrain several models on challenge set and combine models to create ensemble.
5. Compare outputs and identify high discrepancy patients.
6. Label identified patients to create challenge dataset.
7. Train several different ML models.
8. Test models on the challenge dataset and combine them with the ensemble model.
Our methods find far more AI patents than other approaches taken by economists

- Cockburn et al. (2019) take a “standard approach,” focusing on a relatively small set of key words and patent classes.
- This approach identifies fewer than 14,000 patents between 1990 and 2014, and it includes large numbers of “robotics hardware” patents.
- Webb et al. (2019) take a similar, more focused approach, identifying 2,000+ patents related to “machine learning” and 4,000+ related to “neural networks.”
- Our approach identifies 52,896 patents that are AI related with 95% confidence and 146,952 patents that are AI related with 70% confidence.
- We identify most of the AI patents tagged by other economists as “AI patents” but also capture a very large number that traditional techniques omit.
AI patenting has grown rapidly in recent years
AI patenting is widely distributed across patent classes...

Figure 5. AI Patents by USPC Class
And across firms....

Figure 3  AI Patents by Assignee (Patent Owner)
Al patenting is concentrated in a few metro areas within the United States...

Figure 4 Inventor Heat Map of AI Patents in U.S
U.S.-based inventors appear to play a dominant role in this domain.
USPTO Patent to Census Crosswalk – recent work by Graham et al. (2018) generated a patent-to-firm crosswalk for USPTO and Census data. We can apply this crosswalk to the set of AI patents and assess firm performance before and after a firm innovates in AI.

![Graph 1](image1.png)

![Graph 2](image2.png)

*Kernel: Gaussian, Bandwidth=(D)*
AI invention increases employment...

Figure 7. Pre/Post AI Patent Employment Growth
AI invention increases revenue...
AI impact on revenue per employee varies across sectors
AI impact on revenue per employee varies across service subsectors
AI widens within firm earnings inequality
AI invention widens within-firm earnings inequality in the full sample

Table 8: Impact of AI Innovations on 90-10, 90-50 and 50-10 Earnings Ratio, 1997-2016 (full matched set of firms)

<table>
<thead>
<tr>
<th></th>
<th>90-10 Earnings Ratio</th>
<th>90-50 Earnings Ratio</th>
<th>50-10 Earnings Ratio</th>
</tr>
</thead>
<tbody>
<tr>
<td>AI Treatment (1/0)</td>
<td>-0.0377*** (0.00324)</td>
<td>-0.00690** (0.00220)</td>
<td>-0.0213*** (0.00210)</td>
</tr>
<tr>
<td>Post AI Year</td>
<td>-0.00375 (0.00275)</td>
<td>-0.00162 (0.00186)</td>
<td>-0.00477** (0.00178)</td>
</tr>
<tr>
<td>AI Treatment x Post AI Year</td>
<td>0.0108** (0.00349)</td>
<td>0.00321 (0.00237)</td>
<td>0.0142*** (0.00226)</td>
</tr>
<tr>
<td>Ln Employment</td>
<td>0.0537*** (0.00171)</td>
<td>0.0204*** (0.00115)</td>
<td>0.0410*** (0.00111)</td>
</tr>
<tr>
<td>Age</td>
<td>-0.0690*** (0.00282)</td>
<td>-0.0561*** (0.00190)</td>
<td>-0.00927*** (0.00182)</td>
</tr>
<tr>
<td>Multinational Status (1/0)</td>
<td>-0.00884* (0.00367)</td>
<td>-0.00876*** (0.00252)</td>
<td>-0.00538* (0.00239)</td>
</tr>
<tr>
<td>Firm Fixed Effects</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Year Fixed Effects</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Observations</td>
<td>704,000</td>
<td>704,000</td>
<td>704,000</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.712</td>
<td>0.704</td>
<td>0.682</td>
</tr>
</tbody>
</table>

Robust Standard Errors clustered at the 4-digit NAICS industry level. *, ** and *** denotes significance at the 5%, 1% and 0.1% respectively. Each regression includes a constant, which is not displayed here.
AI impact on earnings inequality varies across sectors

90-10 Ratio, Post-Treatment Effect

- All Sectors (Pooled)
- Manufacturing
- Tradable Goods
- Information
- Finance
- Professional Services
- Education
- Healthcare
- Other Services

Post-Treatment
Summary of key findings

• We introduce a new approach to the measurement of firm-level AI invention.
• Our approach suggests that AI invention is far more pervasive than previous analyses indicated.
• We match data on AI inventions to Census microdata on firms and employees.
• We find positive, statistically (and economically) significant associations between AI patenting and proxies for labor productivity.
• We also find positive, statistically (and economically) significant associations between AI patenting and increases in within-firm earning inequality.
Next steps

• We will continue to explore the impact of AI invention, studying both the intensive and extensive margins.
• We also intend to bring into our analyses data on the use of other firms’ AI inventions.
• New census microdata can shed light on firm’s use of AI.
• Firm-level data on the recruitment/employment of specialists with AI-related skills may shed light on AI use within firms.