How Have Automation and Trade Affected the Taxable Share of Covered Earnings?

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The taxable share has fallen from 90 percent in 1983 to 83 percent in 2016.

- Behind this decline is the well-documented increase in earnings inequality (Piketty and Saez 2013).

- Inequality matters because earnings above a certain point are exempt from the payroll tax – more earnings growth among very high earners lowers the total share taxed.

- Each year, the cap is adjusted by the Average Wage Index (AWI) and in 2018 stands at $128,400.
Despite not counting for benefits, the share of earnings over the cap affects program finances.

- Program finances are potentially affected in two ways:
  - Earnings above the cap count for the AWI used to inflate benefits for all workers.
  - Holding AWI constant, a lower taxable share means low earners earn less; because benefits are progressive, this could lead to revenues falling by more than benefits.

- A percentage point decline in the taxable share reduces the 75-year actuarial balance by 0.11 percent (Social Security 2018).
The question: how much of the decline in the taxable share is due to automation and trade?

- Skill-biased technical change polarizes the labor market, hurting the very bottom and top of the earnings distribution less than the “middle” (Autor, Katz, and Kearney 2006).

- China’s entry into global trade increased the supply of low-skill labor, decreasing earnings in the bottom of the distribution (Autor, Dorn, and Hansen 2013).
This paper proceeds in three steps to examine the effects of these changes.

• Step 1: Identify measures of exposure to automation and trade that vary across the U.S. and match them to earnings in 1994 and in 2015.

• Step 2: Use the variance in exposure to automation and trade across states to see how the earnings distribution is affected by these factors.

• Step 3: Predict what would have happened to earnings and the taxable share, in the absence of these changes.
Step 1: The paper merges measures of automation and trade with earnings data.

- Automation is measured as industrial robots per 1,000 workers as in Acemoglu and Restrepo (2017).

- Trade is measured through imports from China, as in Autor, Dorn, and Hansen (2013).

- Both measures are calculated at the state level separately in 1994 – the year the tax-max formula was fixed – and 2015.

- Individual wage and salary earnings are taken from the Continuous Work History Sample covering ages 16-70.
Step 2: These measures are placed in a series of quantile earnings regressions.

- Each of the regressions uses the same sample and variables.

- But each one focuses on a different point in the earnings distribution, to estimate the effects of automation and trade on a specific quantile (e.g., the 10\textsuperscript{th} percentile, or the median).

- One such quantile regression is run for each earnings decile up to the 8\textsuperscript{th}, and for each percentile from the 80\textsuperscript{th} to the 99\textsuperscript{th}.
The regressions all have the following form:

- \( Earnings_{q,i,s,t} = \theta_q + \beta_{q,1}Robots_{s,t}^{US} + \beta_{q,2}Imports_{s,t}^{US} + \beta_{q,3}Q_{s,t} + \varepsilon_{q,i,s,t} \)

- \( q \) indicates the quantile, \( i \) the individual, \( s \) the individual’s state, and \( t \) the year of observation (either 1994 or 2015).

- The controls in \( Q \) are:
  - State unionization, share of large firms, and health insurance coverage to capture worker bargaining power;
  - State, year, age, and gender fixed effects.
Step 3: The estimates allow construction of counterfactual earnings distributions.

- For each quantile, the coefficient on automation and trade is multiplied by the change in that factor between 1994 and 2015, $\beta_q \Delta X$.

- This quantity reflects the change in earnings at each point in the distribution due to the change in each factor over time.

- This amount is then subtracted from the 2015 actual earnings distribution to arrive at a counterfactual distribution, $Earnings^F_q - \beta_q \Delta X$. 
The estimated effect of automation is most negative for the 8th to 9th deciles.

Source: Authors’ calculations based on the Continuous Work History Sample, 1994 and 2015.
This accords with the fact that the industries most impacted by automation lost more jobs in those deciles.

1994-2015 Change in the Share Employed in Durables and Vehicle Manufacturing by Earnings Decile

In contrast, trade is most harmful to the lowest earners, as imports substitute for low-skill labor.

Source: Authors’ calculations based on the Continuous Work History Sample, 1994 and 2015.
Trade, rather than automation, contributed most to the changes in the top 1-percent share and the taxable share.

Characteristics of Factual and Counterfactual Earnings Distributions

<table>
<thead>
<tr>
<th></th>
<th>Mean</th>
<th>25th percentile</th>
<th>50th percentile</th>
<th>75th percentile</th>
<th>99th percentile</th>
<th>Top 1-percent share</th>
<th>Taxable share</th>
</tr>
</thead>
<tbody>
<tr>
<td>Factual 1994</td>
<td>$36,978</td>
<td>$9,396</td>
<td>$25,522</td>
<td>$48,430</td>
<td>$358,026</td>
<td>9.7%</td>
<td>88.9%</td>
</tr>
<tr>
<td>Factual 2015</td>
<td>45,412</td>
<td>11,482</td>
<td>28,946</td>
<td>55,439</td>
<td>515,065</td>
<td>11.3</td>
<td>85.6</td>
</tr>
<tr>
<td>Only automation at 1994 level</td>
<td>46,993</td>
<td>11,748</td>
<td>29,866</td>
<td>57,428</td>
<td>531,733</td>
<td>11.3</td>
<td>85.6</td>
</tr>
<tr>
<td>Only trade at 1994 level</td>
<td>45,881</td>
<td>12,119</td>
<td>29,712</td>
<td>55,628</td>
<td>509,674</td>
<td>11.1</td>
<td>85.9</td>
</tr>
<tr>
<td>Both factors at 1994 level</td>
<td>47,423</td>
<td>12,399</td>
<td>30,657</td>
<td>57,624</td>
<td>526,167</td>
<td>11.1</td>
<td>85.9</td>
</tr>
</tbody>
</table>

Notes: All numbers are in 2015 dollars. The 1994 taxable share is calculated using a tax-max equal to the actual cap in 1994 adjusted by CPI to 2015 dollars.

Source: Authors’ calculations based on the Continuous Work History Sample, 1994 and 2015.
A limitation is that the results may not capture the full magnitude of the effects.

- The automation measure counts industrial robots, but cannot capture other skill-biased technical change like information technology or artificial intelligence.

- The trade measure uses Chinese imports.
  - These imports’ growth is plausibly exogenous and driven by China’s entry into world trade.
  - But they only represent 1/5 of total imports.

- Thus, the total effect of automation and trade is likely larger.
And other contributors to the top earners’ share increase have been suggested as well.

- Increasing employer concentration (e.g., Azar, Marinescu, and Steinbaum 2017);
- Declining unions (DiNardo, Fortin, and Lemieux 1996);
- And erosion of norms regarding executive pay (Atkinson, Piketty, and Saez 2011).
However, even with these limits, the estimates inform projections of future trends.

- If industrial automation and trade grow at their historic pace, by 2026 the taxable share will decline by another 0.2 percentage points.

- This would result in a taxable share of 82.5 for all earners, consistent with the Trustees’ intermediate projections.

- Given these factors predict only a small part of the decline to date, the true future decline may be even greater.