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ECONOMIC Synopses

The Impact of Automation on Inequality

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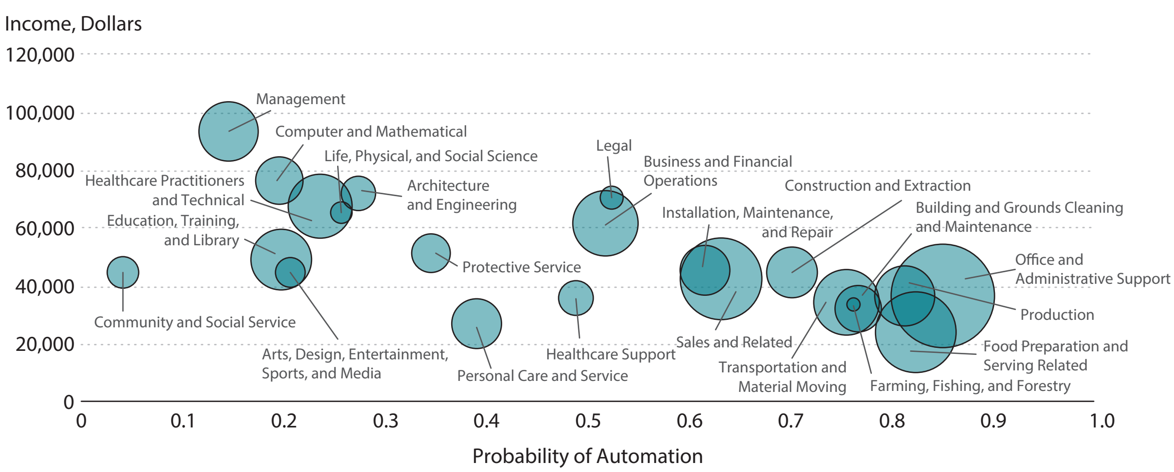
We see the changes brought by automation and computerization everywhere, from autonomous, self-driving cars to self-checkout machines in grocery stores. This essay looks at how the advancing wave of automation might affect employment and income inequality.

> Occupations with large employment and low income have a higher automation probability.

We use estimates from Frey and Osborne (2017) of how likely automation is to affect occupations. They first identify the tasks of each occupation that may become automated: perception and manipulation tasks, creative intelligence tasks, and social intelligence tasks. Then they use a machine learning algorithm to calculate the probabilities of computerization. We merge their estimates with MSA-level occupational employment and wages from the 2017 Occupational Employment Statistics (OES, from the Bureau of Labor Statistics). The figure shows the probability of automation for each occupation on the horizontal axis, the annual income for each occupation on the vertical axis, and the employment in each occupation by the size of the bubble. Low-paid occupations, such as office and food service jobs, are the most likely to be automated. These occupations also have large employment.

Next, we study the effect of automation on income inequality in hypothetical scenarios. We measure income inequality in the table with the Gini coefficient and two percentile ratios. A Gini coefficient measures income inequality in a population. A coefficient of 1 represents a perfectly unequal distribution (that is, one person has all of the income), while a Gini coefficient of zero represents perfectly equal incomes. The 90-50 ratio is the ratio of the income of the 90th percentile to the 50th percentile, and the 50-10 ratio is of the 50th percentile to the 10th percentile. Unlike the Gini coefficient, these ratios can be any number greater than or equal to 1. Higher ratios indicate more concentration of wealth in the higher end of the income distribution relative to the middle or lower end—in other words, higher income inequality. We calculate Gini coefficients and percentile ratios assuming that if an occupation has a 60 percent chance of automation, 60 per-

Probability of Automation and Annual Income by Occupation



NOTE: Data are for 2017.
SOURCE: OES, Frey and Osborne (2017), and authors' calculations.

Income Inequality Scenarios

Scenario	Gini coefficient	90-50 ratio	50-10 ratio
Pre automation	0.31	2.34	1.74
Post automation, become unemployed (Income = 0)	0.70	—	—
Post automation, earn minimum wage	0.43	5.58	1.00
Post automation, receive a 20% pay cut	0.35	2.67	1.80

SOURCE: OES, Frey and Osborne (2017), and authors' calculations.

cent of the employees get one of three hypothetical, alternative labor market outcomes after automation:

- Affected employees become unemployed and earn zero income.
- Affected employees earn the minimum wage, $15,080 per year.
- Affected employees take a 20 percent pay cut on their original income.

As the table shows, automation increases inequality in every scenario because it tends to displace the lowest-paid workers. For the first (and most extreme) scenario, when all affected employees become unemployed, the Gini coefficient goes from 0.31 to 0.70—it more than doubles. However, this scenario is very extreme; it is used here only as an exercise to understand where automation will most impact the income distribution. The percentile ratios for the case in which workers become unemployed are not provided in the table because the entire bottom half of the distribution would earn zero income, so the 90-50 and 50-10 ratios cannot be calculated. It is more likely that affected employees would earn the minimum wage or take a 20 percent pay cut; but these scenarios are still based on strong assumptions. The Gini coefficient is high in the minimum-wage scenario: 0.43. The 50-10 ratio of 1 for the minimum-wage scenario means that the bottom half of the distribution would earn minimum wage. The scenario that is probably closest to reality, and most useful in this case, is that the affected employees take a 20 percent wage cut. The Gini coefficient increases to 0.35, and the 90-50 ratio increases more than the 50-10 ratio, indicating that income becomes more concentrated at the top of the distribution.

We need to be careful when interpreting these numbers. Several factors influence the impact of automation. For example, the three scenarios do not consider the costs of R&D expenditures for automation. If the costs of automation are high enough, it will instead be more profitable to keep using human labor. And while these numbers suggest some effects of automation in the future, they do not convey exactly when and how it would happen. Lastly, the analysis above does not consider how the labor market would adjust to automation. There will be changes not only in wages, but also in employment flows across industries, creation of new industries, etc. This topic deserves more attention from policymakers and researchers. ■

Reference

Frey, Carl Benedikt and Osborne, Michael A. "The Future of Employment: How Susceptible Are Jobs to Computerisation?" *Technological Forecasting and Social Change*, January 2017, *114*, pp. 254-80; https://doi.org/10.1016/j.techfore.2016.08.019.

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