PennState
College of Earth
and Mineral Sciences

John and Willie Leone Family
Department of Energy and
Mineral Engineering

Identifying the Links Between Climate Change and Automation

Taimur Zain and Joel R. Landry

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Introduction

Historically, technological change has focused on *labor-augmenting technologies*, such as the computer, which increase the productivity of workers by augmenting or extending their labor capacities. However, recently a new task view of labor has been developed that distinguishes between *labor-augmenting technologies* and *labor-displacing technologies* (Autour, 2015; Acemoglu and Restrepo, 2019), such as the growth in industrial robots, automated processes, artificial intelligence, and machine learning in which *automation* displaces the tasks completed by humans. This task view of labor has been used by labor economists to assess how automation explains the decline in productivity growth and stagnant wage growth for unskilled and medium skilled workers over the past few decades. Climate change also has tremendous potential to alter the distribution of tasks that humans are able to complete. Contemporaneous climate change—reflecting changes in the historical distribution of weather—may in fact partially explain the recent rise in automation and its resulting impacts on productivity and wage growth. Future climate change will also affect the rate of future technological change as a result of automation and potentially have significant implications on future productivity, wage growth and inequality.

Objectives

1. Combine novel automation datasets with historical weather data, to econometrically estimate the historical impact of climate change on automation and labor market outcomes.
2. Using these estimates and future climate projections, assess the potential future implications of climate induced automation on labor market outcomes and broader societal outcomes, such as inequality.

The Current Task View of Labor

In the task view of labor (Autor, 2015; Acemoglu and Restrepo, 2018), a job can best be understood as a discrete collection of tasks, with different jobs requiring different sets of tasks be completed. Some tasks are better performed by humans whereas others could be performed by humans or capital (e.g., robots, industrial automation, artificial intelligence, machine learning). The entire continuum of existing tasks can be sorted from the most to least displaceable by automation (equivalently, from the least to most human-labor requiring; see **Fig. 1**).

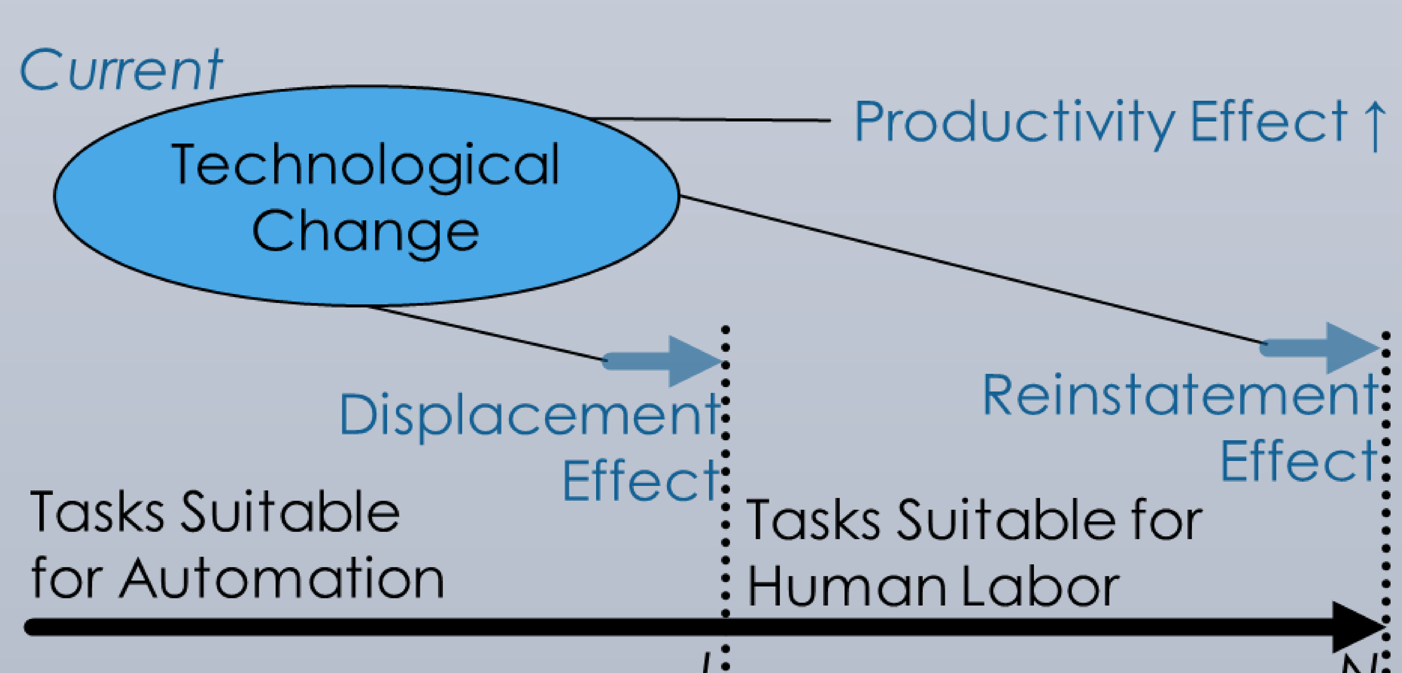

Fig. 1. *The Task View of Labor and Technological Change.*

The Current Task View of Labor (Continued)

An increase in automation technology gives rise to potentially three effects (Acemoglu and Restrepo, 2018):

1. *Displacement Effect*: Automation increases I, reducing the amount of tasks available for human labor, N-I, and potentially displacing the jobs available for humans.
2. *Reinstatement Effect*: Automation may lead to the development of new tasks for humans, or increase N, which can offset the displacement effect.
3. *Productivity Effect*: Automation may lower the costs of production and increase overall productivity.

These three effects alter demand for tasks across the task distribution, causing corresponding changes in the demand for jobs across the job distribution, from low-skilled to highly-skilled, which has implications for the employment level and incomes of different workers.

How Climate Change Affects the Task View of Labor

We intend to examine several relationships between climate change, automation, the distribution of tasks, and labor and energy market outcomes (**Fig. 2**).

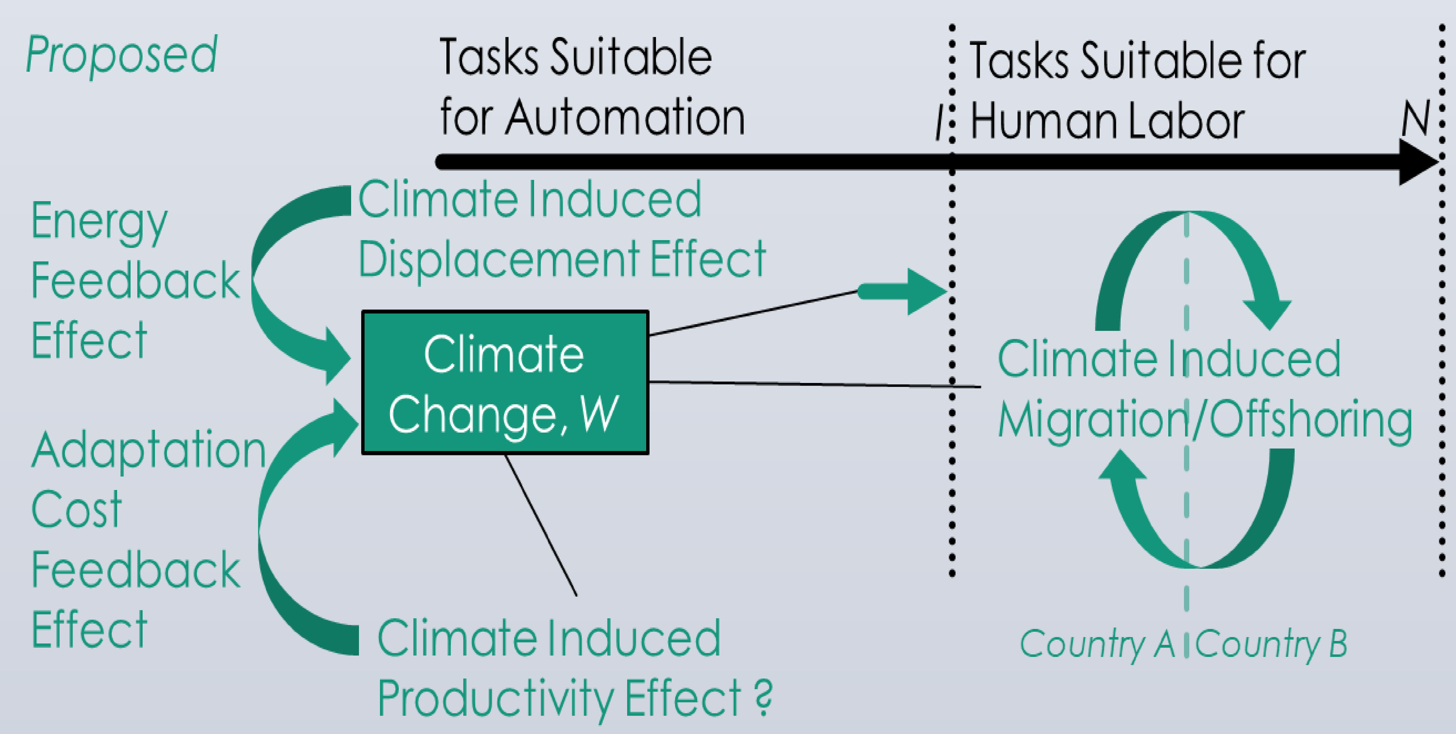

Fig. 2. *The Effect of Climate Change on Tasks and Technological Change.*

We hypothesize several important channels by which climate change is likely to affect the climate suitability of tasks and the pace of automation, as well as feedback effects with respect to adaptation and energy consumption:

1. *Climate Induced Displacement Effect*: Climate change is likely to lower the productivity of climate suitable tasks performed by human labor and therefore raise the returns of replacing those tasks by automation, giving rise to climate induced displacement.
2. *Energy Feedback Effect*: If climate change increases the rate of automation, this may increase energy consumption and possibly GHG emissions, reflecting an energy feedback effect.
3. *Climate Induced Migration and Offshoring*: Human labor in certain countries may be more physiologically adapted to certain climates than in other countries; as climate change alters the spatial distribution of climate suitable tasks, this may lead to climate induced migration and offshoring of tasks performed by human labor across and within countries.
4. *Climate Induced Productivity Effect*: Climate induced automation may accelerate the pace at which automation would otherwise occur, giving rise to a possible climate induced productivity effect from lowering the marginal cost of production.
5. *Adaptation Cost Feedback Effect*: The climate induced automation may lower the private costs of adaptation and increase the pace of automation.

These effects will have complex effects within the U.S. and across countries arising from the nexus of climate change and adaptation. We intend to empirically test for the presence of these effects. Similarly, we do not anticipate that a climate induced reinstatement effect will be likely, but we will test this empirically.

Empirical Strategy

We intend to combine high frequency weather data and state-of-the-art techniques used in the climate economics literature (see, e.g., Dell et al, 2014; Auffhammer, 2018) with novel datasets on automation and tasks used in the automation literature (see, e.g., Acemoglu and Restrepo, 2018, Acemoglu and Restrepo 2019), to econometrically estimate for the first time the linkages between climate change and automation depicted in **Fig. 2** using plausibly exogenous changes in idiosyncratic weather.

The domestic U.S. analysis will combine data from Acemoglu and Restrepo (2020) and (2021), which I collected through the internship, with publicly available weather data. The international analysis will also use data from Graetz and Michaels (2018) which I collected through the internship. The analysis will also incorporate publicly available datasets from the offshoring and migration literatures and data on energy intensity and adaptation costs.

In general, our objective is to estimate:

$$A = \beta W + \gamma X + \varepsilon,$$

Where: A is an automation or automation affected labor market outcome, W is historical weather, and X is a vector of other controls, β identifies the effect of weather on automation, γ are other parameters on the control variables, and ε is the error term.

The collection of data has been done by extracting the datasets used in research papers pertaining to either climate change or automation. The data on automation was obtained, but not all the climate change data was extracted from the papers. Further steps would include the processing of the data through Stata and running regressions to identify potential linkages.

Bibliography

Acemoglu, D., and P. Restrepo. 2018. "The Race between Man and Machine: Implications of Technology for Growth, Factor Shares, and Employment." American Economic Review, 108 (6): 1488-1542.

Acemoglu, D., and P. Restrepo. 2019. "Automation and New Tasks: How Technology Displaces and Reinstates Labor." Journal of Economic Perspectives, 33 (2): 3-30.

Acemoglu, D., and P. Restrepo. 2020. "Robot and Jobs: Evidence from U.S. Labor Markets." Journal of Political Economy, 128 (6): 2188-2244.

Acemoglu, D., and P. Restrepo. 2021. "Demographics and Automation," Boston University - Department of Economics - The Institute for Economic Development Working Papers Series dp-299, Boston University - Department of Economics.

Auffhammer, M.. 2018. "Quantifying Economic Damages from Climate Change." Journal of Economic Perspectives, 32 (4): 33-52.

Autor, D. H. 2015. "Why Are There Still So Many Jobs? The History and Future of Workplace Automation." The Journal of Economic Perspectives, 29 (3): 3-30.

Dell, M., Jones, B.F., and B.A. Olken. 2014. "What Do We Learn from the Weather? The New Climate–Economy Literature" Journal of Economic Literature, 52 (3): 740–798.

Graetz, G. and G. Michaels, 2018. "Robots at Work," The Review of Economics and Statistics, 100 (5): 753-768.

Graff Zivin, J., and M. Neidell. 2014. "Temperature and the Allocation of Time: Implications for Climate Change." Journal of Labor Economics, 32 (1): 1-26.

Hsiang, S., Kopp, R., Jina, A., Rising, J., Delgado, M., Mohan, S., Rasmussen, D. J., Muir-Wood, R., Wilson, P., Oppenheimer, M., Larsen, K., & Houser, T. (2017). Estimating economic damage from climate change in the United States. Science (New York, N.Y.), 356 (6345), 1362–1369.

Peri, G., and C. Sparber. 2009. "Task Specialization, Immigration, and Wages." American Economic Journal: Applied Economics, 1 (3): 135-69.

Deryugina, T. and S. Hsiang, 2017. "The Marginal Product of Climate," NBER Working Papers 24072, National Bureau of Economic Research, Inc.

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