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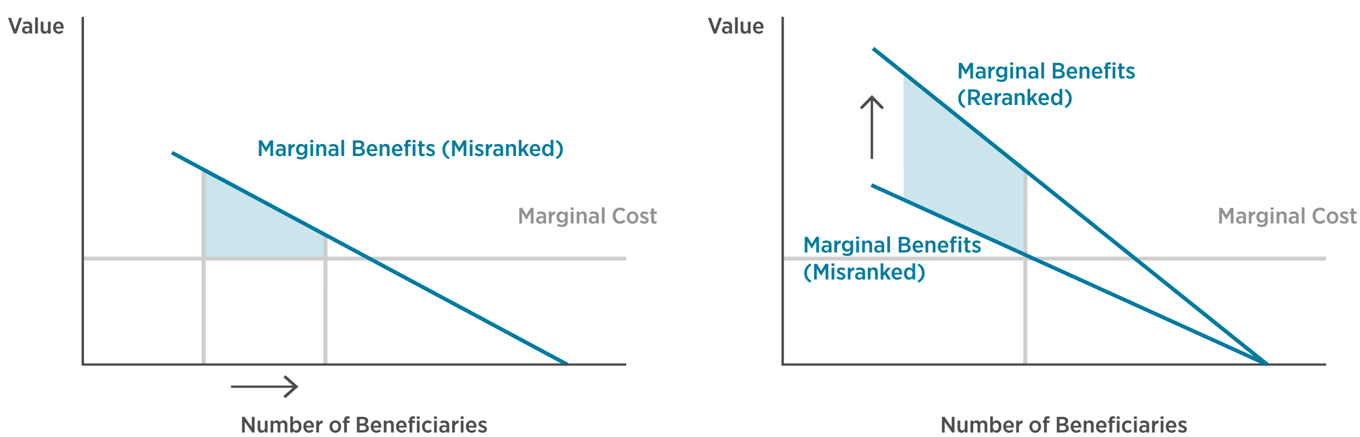
The Unreasonable Effectiveness of Algorithms

Based on BFI Working Paper No. 2024-11, "The Unreasonable Effectiveness of Algorithms," by Jens Ludwig, University of Chicago; Sendhil Mullainathan, University of Chicago; and Ashesh Rambachan, Massachusetts Institute of Technology

Policies that implement the use of algorithms for making pretrial release decisions, referring medical patients for testing, and guiding workplace safety inspections would provide large benefits and pay for themselves in the long run.

Are algorithms getting too much attention within economics? Bubbles arise when valuation exceeds fundamentals, when enthusiasm for *what might be* overtakes *what actually is*. In this paper, the authors look, just as one would with a stock, at the *fundamentals*: what tangible value do algorithms create in addressing economic issues? To answer this question, the authors focus on their effectiveness in addressing public policy problems—the sort of algorithm that is migrating from the online world to real-world domains of traditional interest to economists.

Figure 1 • Welfare Gains from Re-Ranking



A growing body of research illustrates the potential policy applications of algorithms. In the context of criminal justice, for example, algorithms can use data from prior cases to predict the likelihood that recently arrested defendants will re-offend or skip court.[1] Using these algorithmic predictions to decide which defendants to detain during the time between arrest and trial could allow for up to 40% fewer pretrial detentions (with no increase in failures to appear in court or re-arrests). This research suggests a considerable social benefit from replacing or augmenting human judges with algorithms, at least in the context of pretrial release decisions.

$$\textbf{MVPF} = \frac{\text{Benefits}}{\text{Net Government Cost}}$$

Note: The Marginal Value of Public Funds, or MVPF is calculated as the ratio of two numbers: the benefits that a policy provides to its recipients divided by the policy's net cost to the government. For more information (and a helpful guide) visit policyimpacts.org

To measure these social benefits systematically, the authors borrow a framework from public finance called the **Marginal Value of Public Funds (MVPF)**.

The MVPF is the ratio of a policy's benefit—which is measured using individuals' **willingness to pay**—divided by its net cost. The authors calculate the MVPF of policies that implement algorithms to make pretrial release decisions, as well as policies that implement algorithms for deciding whether to refer patients to follow-up 'stress tests' to determine whether they are having a heart attack[2] and for predicting which work sites are likely to have another injury in the future.[3] They find the following:

- Each algorithm produces an MVPF of infinity. In other words, policies that implement the use of algorithms in each context would both produce large benefits and pay for themselves in the long run.

How is this possible? The authors offer two explanations:

The first reason is related to ranking. The usual logic of policy interventions assumes that governments have already capitalized on the highest-benefit policy interventions. A large body of research shows that misranking is common, however, and an algorithm that improves this ranking can

[1]Kleinberg, Jon, Himabindu Lakkaraju, Jure Leskovec, Jens Ludwig and Sendhil Mullainathan (2018a) "Human decisions and machine predictions." Quarterly Journal of Economics.

[2]Mullainathan, Sendhil and Ziad Obermeyer (2022) "Diagnosing physician error: A machine learning approach to low-value care." Quarterly Journal of Economics. 137(2): 679-727.

[3]Johnson, Matthew S., David I. Levine and Michael W. Toffel (2023) "Improving regulatory effectiveness through better targeting: Evidence from OSHA." American Economic Journal: Applied Economics. 15(4): 30–67.

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Marginal Value of Public Funds (MVPF): A term coined by Nathaniel Hendren and Ben Sprung-Keyser in their 2020 paper "A Unified Welfare Analysis of Government Policies," the benefit that a policy provides its recipients divided by its net cost.

Willingness to pay: an economic concept that represents the maximum amount a person is willing to spend for a good or service significantly enhance **social returns** and reduce **inefficiencies**.

The second key reason algorithms can yield such high MVPFs is because they operate at scale. While traditional policies often become less effective as they are scaled up, algorithms can be run over and over again at low **marginal cost** without loss of fidelity.

The upshot is that algorithmic policies hold immense promise. The authors clarify that they are not arguing that the government should start scaling algorithms with high MVPFs, but instead that these algorithmic policies are worth further exploration and R&D, since these are at least as promising as other policies economists work on.

So, is there *too much* attention being paid to algorithms? These calculations suggest that—at least within policy applications—algorithms are receiving *too little* attention.

Social returns: the benefits that society receives from a policy, including both the private returns that accrue to individual beneficiaries and the positive externalities that accrue to others

Inefficiencies: Instances where resources are not allocated optimally, leading to a loss of potential economic welfare

Marginal cost: The change in the total cost that results from producing one additional unit of a good or service

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ABOUT OUR SCHOLARS

Jens Ludwig

Edwin A. and Betty L. Bergman Distinguished Service Professor, Pritzker Director of UChicago's Crime Lab, Codirector of the Education Lab, Harris School of Public Policy

Sendhil Mullainathan

Roman Family University Professor of Computation and Behavioral Science, Chicago Booth

THE UNIVERSITY OF CHICAGO HARRIS SCHOOL OF PUBLIC POLICY

CHICAGO BOOTH The University of Chicago Booth School of Business