

Prediction Policy Problems[†]

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Empirical policy research often focuses on causal inference. Since policy choices seem to depend on understanding the counterfactual—what happens with and without a policy—this tight link of causality and policy seems natural. While this link holds in many cases, we argue that there are also many policy applications where causal inference is not central, or even necessary.

Consider two toy examples. One policymaker facing a drought must decide whether to invest in a rain dance to increase the chance of rain. Another seeing clouds must decide whether to take an umbrella to work to avoid getting wet on the way home. Both decisions could benefit from an empirical study of rain. But each has different requirements of the estimator. One requires causality: Do rain dances cause rain? The other does not, needing only prediction: Is the chance of rain high enough to merit an umbrella? We often focus on rain dance–like policy problems. But there are also many umbrella-like policy problems. Not only are these prediction problems neglected, machine learning can help us solve them more effectively.

In this paper, we (i) provide a simple framework that clarifies the distinction between

causation and prediction; (ii) explain how machine learning adds value over traditional regression approaches in solving prediction problems; (iii) provide an empirical example from health policy to illustrate how improved predictions can generate large social impact; (iv) illustrate how “umbrella” problems are common and important in many important policy domains; and (v) argue that solving these problems produces not just policy impact but also theoretical and economic insights.¹

I. Prediction and Causation

Let Y be an outcome variable (such as rain) which depends in an unknown way on a set of variables X_0 and X . A policymaker must decide on X_0 (e.g., an umbrella or rain dance) in order to maximize a (known) payoff function $\pi(X_0, Y)$. Our decision of X_0 depends on the derivative

$$\frac{d\pi(X_0, Y)}{dX_0} = \frac{\partial \pi}{\partial X_0} \underbrace{(Y)}_{\text{prediction}} + \frac{\partial \pi}{\partial Y} \underbrace{\frac{\partial Y}{\partial X_0}}_{\text{causation}}.$$

Empirical work can help estimate the two unknowns in this equation: $\frac{\partial Y}{\partial X_0}$ and $\frac{\partial \pi}{\partial X_0}$. Estimating $\frac{\partial Y}{\partial X_0}$ requires causal inference: answering how much does X_0 affect Y ?

The other term, $\frac{\partial \pi}{\partial X_0}$, is unknown for a different reason. We know the payoff function, but since its value must be evaluated at Y , knowing the exact value of $\frac{\partial \pi}{\partial X_0}$ requires a prediction Y . We know how much utility umbrellas provide only once we know the level of rain.

Choosing X_0 therefore requires solving both causation and prediction problems. Assume

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¹A longer version of this paper (Kleinberg, Ludwig, Mullainathan, and Obermeyer 2015) fleshes out each of these points, providing greater detail on the model, the empirical work and a more thorough summary of machine learning.

away one of these terms—place an exclusion restriction—and only one problem remains. Rain dances are a pure causal inference problem because rain dances have no direct effect on pay-offs $\frac{\partial \pi}{\partial X_0} = 0$. Umbrellas are a pure prediction problem because umbrellas have no direct effect on rain $\frac{\partial Y}{\partial X_0} = 0$.

This derivative also illustrates two key features of prediction problems. First, the need for prediction arises exactly because $\frac{\partial \pi}{\partial X_0}$ depends on Y . Prediction is necessary only because the benefit of an umbrella depends on rain. As we illustrate in the final section, this kind of dependency is common for many important policy problems. Second, because only \hat{Y} enters the decision, prediction problems only require low error in \hat{Y} ; they do not require the coefficients to be unbiased or causal.

II. Machine Learning

Standard empirical techniques are not optimized for prediction problems because they focus on unbiasedness. Ordinary least squares (OLS), for example, is only the best linear *unbiased* estimator. To see how it can lead to poor predictions, consider a two variable example where OLS estimation produced $\hat{\beta}_1 = 1 \pm 0.001$ and $\hat{\beta}_2 = 4 \pm 10$, suggesting a predictor of $x_1 + 4x_2$. But given the noise in $\hat{\beta}_2$, for prediction purposes one would be tempted to place a smaller (possibly 0) coefficient on x_2 . Introducing this bias could improve prediction by removing noise.

This intuition holds more generally. Suppose we are given a dataset D of n points $(y_i, x_i) \sim G$. We must use this data to pick a function $\hat{f} \in \mathcal{F}$ so as to predict the y value of a new data point $(y, x) \sim G$. The goal is to minimize a loss function, which for simplicity we take to be $(y - \hat{f}(x))^2$.

OLS minimizes in-sample error, choosing from \mathcal{F}_{lin} , the set of linear estimators:

$$\hat{f}_{OLS} = \arg \min_{\hat{f} \in \mathcal{F}_{lin}} \sum_{i=1}^n (y_i - \hat{f}(x_i))^2,$$

but for prediction we are not interested in doing well *in sample*: we would like to do well *out of sample*. Ensuring zero bias in-sample creates

problems out of sample. To see this, consider the mean squared error at the new point x , $MSE(x) = E_D[(\hat{f}(x) - y)^2]$. This can be decomposed as

$$E_D[\underbrace{(\hat{f}(x) - E_D[\hat{y}_0])^2}_{\text{Variance}}] + \underbrace{(E_D[\hat{y}_0] - y)^2}_{\text{Bias}^2}.$$

Because the f varies from sample to sample, it produces variance (the first term). This must be traded off against bias (the second term). By ensuring zero bias, OLS allows no trade-off.

Machine learning techniques were developed specifically to maximize prediction performance by providing an empirical way to make this bias-variance trade-off (Hastie, Tibshirani, and Friedman 2009 provide a useful overview). Instead of minimizing *only* in-sample error, ML techniques minimize:

$$\hat{f}_{ML} = \arg \min_{\hat{f} \in \mathcal{F}} \sum_{i=1}^n (y_i - \hat{f}(x_i))^2 + \lambda R(f).$$

Here $R(f)$ is a *regularizer* that penalizes functions that create variance. It is constructed such that the set of functions $\mathcal{F}_c = \{f | R(f) \leq c\}$ create more variable predictions as c increases. For linear models, larger coefficients allow more variable predictions, so a natural regularizer is $R(f_\beta) = \|\beta\|^d$, which is the lasso and ridge estimators for $d = 1$ and 2 respectively. In effect, this minimization now explicitly includes a bias (in-sample error) and variance term ($R(f)$), where λ can be thought of as the price at which we trade off variance to bias. OLS is a special case where we put an infinite (relative) price on bias ($\frac{1}{\lambda} = \infty$).

A key insight of machine learning is that this price λ can be chosen *using the data itself*. Imagine we split the data into f subsets (often called “folds”). For a set of λ , we estimate the algorithm on $f - 1$ of the folds and then see which value of λ produces the best prediction in the f th fold. This cross-validation procedure effectively simulates the bias-variance trade-off by creating a way to see which λ does best “out of sample.”

These two insights—regularization and empirical choice of the regularization penalty—together also change the kinds of predictors we can consider. First, they allow for “wide” data, to predict even when we have more variables than data points. For example, researchers using language data often have ten or a hundred times as

many variables as data. Second, this allows for far more flexible functional forms. One can include many higher order interaction terms or use techniques such as decision trees which by construction allow for a high degree of interactivity.

Machine learning techniques are in one sense not new: they are a natural offshoot of non-parametric statistics. But they provide a disciplined way to predict \hat{y} which (i) uses the data itself to decide how to make the bias-variance trade-off and (ii) allows for search over a very rich set of variables and functional forms. But everything comes at a cost: one must always keep in mind that because they are tuned for \hat{y} they do not (without many other assumptions) give very useful guarantees for $\hat{\beta}$.

III. Illustrative Application

Osteoarthritis (joint pain and stiffness) is a common and painful chronic condition among the elderly. Replacement of the affected joints, most commonly hips and knees, provide relief each year to around 500,000 Medicare beneficiaries in the United States. The medical benefits B are well understood: surgery improves quality of life over the patient's remaining life expectancy Y . The costs C are both monetary (roughly \$15,000 calculated using 2010 claims data) and nonmonetary: surgeries are painful and recovery takes time, with significant disability persisting months afterwards. The benefits accrue over time, so surgery only makes sense if someone lives long enough to enjoy them; joint replacement for someone who dies soon afterward is futile—a waste of money and an unnecessary painful imposition on the last few months of life.

The payoff to surgery depends on (eventual) mortality, creating a pure prediction problem. Put differently, the policy challenge is: can we predict which surgeries will be futile using only data available at the time of the surgery? This would allow us save both dollars and disutility for patients.

To study this example we drew a 20 percent sample of 7.4 million Medicare beneficiaries, 98,090 (1.3 percent) of which had a claim for hip or knee replacement surgery in 2010.² Of

these, 1.4 percent die in the month after surgery, potentially from complications of the surgery itself, and 4.2 percent die in the 1–12 months after surgery. This low rate—roughly the average annual mortality rate for all Medicare recipients—seems to suggest on average surgeries are not futile. But the average is misleading because the policy decision is really about whether surgeries on the *predictably riskiest patients* were futile.

To answer this, we predicted mortality in the 1–12 months after hip or knee replacement using lasso (see Kleinberg, Ludwig, Mullainathan, and Obermeyer 2015 for full details).³ We used 65,395 observations to fit the models and measured performance on the remaining 32,695 observations. 3,305 independent variables were constructed using Medicare claims dated prior to joint replacement, including patient demographics (age, sex, geography); co-morbidities, symptoms, injuries, acute conditions, and their evolution over time; and health-care utilization.

These predictions give us a way to isolate predictably futile surgeries. In Table 1, we sort beneficiaries by predicted mortality risk, showing risk for the riskiest 1 percent, 2 percent, and so on, *which is highly and predictably concentrated*: for example, the 1 percent riskiest have a 56 percent mortality rate, and account for fully 10 percent of all futile surgeries.⁴

Imagine the dollars from these futile surgeries could instead have been spent on other beneficiaries who would benefit more. To understand the potential savings, we simulated the effect of substituting these riskiest recipients with other

³This interval reflects two choices. (i) We excluded deaths in the first month after surgery to focus on prediction of Y rather than the short-term causal effect of X_0 on Y (i.e., operative risk, post-surgical complications). (ii) We chose a threshold of 12 months based on studies showing substantial remaining disability six months after surgery, but improved clinical outcomes at the 12-month mark (Hamel et al. 2008). Alternatively, a “break-even” threshold could be derived empirically.

⁴One might wonder whether these riskier patients may also be the ones who also stood to benefit the most from the procedure, potentially justifying surgery. However, variables that should correlate with surgery benefit (number of physician visits for hip or knee pain, physical therapy, and therapeutic joint injections) do not vary significantly by predicted mortality risk. In practice, this exercise is approximate, since some replacements may not have been elective, e.g., for fracture or other acute events. We present alternative specifications in our more detailed paper (footnote 3).

²We restricted to fee-for-service beneficiaries with full claims data living in the continental United States, and exclude any with joint replacement in 2009.

TABLE 1—RISKIEST JOINT REPLACEMENTS

Predicted mortality percentile	Observed mortality rate	Futile procedures averted	Futile spending (\$ mill.)
1	0.435 (0.028)	1,984	30
2	0.422 (0.028)	3,844	58
5	0.358 (0.027)	8,061	121
10	0.242 (0.024)	10,512	158
20	0.152 (0.020)	12,317	185
30	0.136 (0.019)	16,151	242

Notes: We predict 1–12 month mortality using an L_1 regularized logistic regression trained on 65,395 Medicare beneficiaries undergoing joint replacement in 2010, using 3,305 claims-based variables and 51 state indicators. λ was tuned using ten-fold cross-validation in the training set. In columns 1 and 2 we sort a hold-out set of 32,695 by predicted risk into percentiles (column 1) and calculate actual 1–12 month mortality (column 2). Columns 3 and 4 show results of a simulation exercise: we identify a population of eligibles (using published Medicare guidelines: those who had multiple visits to physicians for osteoarthritis and multiple claims for physical therapy or therapeutic joint injections) who did not receive replacement and assign them a predicted risk. We then substitute the high risk surgeries in each row with patients from this eligible distribution for replacement, starting at *median* predicted risk. Column 3 counts the futile procedures averted (i.e., replaced with non-futile procedures) and column 4 quantifies the dollars saved in millions by this substitution.

beneficiaries who might have benefited from joint replacement procedures under Medicare eligibility guidelines, but did not receive them. To be conservative, rather than comparing to the lowest-risk eligibles, we draw from the median predicted risk distribution of these eligibles, and simulate effects of this replacement in columns 3 and 4. Replacing the riskiest 10 percent with lower-risk eligibles would avert 10,512 futile surgeries and reallocate the 158 million per year (if applied to the entire Medicare population) to people who benefit from the surgery, at the cost of postponing joint replacement for 38,533 of the riskiest beneficiaries who would not have died.⁵

⁵The existence of a large pool of low-risk beneficiaries potentially eligible for replacement argues against moral

IV. Prediction Problems are Common and Important

Our empirical application above highlights how improved prediction using machine learning techniques can have large policy impacts (much like solving causal inference problems has had). There are many other examples as well. In the criminal justice system, for instance, judges have to decide whether to detain or release arrestees as they await adjudication of their case—a decision that depends on a prediction about the arrestee’s probability of committing a crime. Kleinberg, Lakkaraju, Leskovec, Ludwig, and Mullainathan (2015) show that machine learning techniques can dramatically improve upon judges’ predictions and substantially reduce the amount of crime.

Other illustrative examples include: (i) in education, predicting which teacher will have the greatest value added (Rockoff et al. 2011); (ii) in labor market policy, predicting unemployment spell length to help workers decide on savings rates and job search strategies; (iii) in regulation, targeting health inspections (Kang et al. 2013); (iv) in social policy, predicting highest risk youth for targeting interventions (Chandler, Levitt, and List 2011); and (v) in the finance sector, lenders identifying the underlying credit-worthiness of potential borrowers.

Even this small set of examples are biased by what we *imagine* to be predictable. Some things that seem unpredictable may actually be more predictable than we think using the right empirical tools. As we expand our notion of what is predictable, new applications will arise.

Prediction problems can also generate theoretical insights, for example by changing our understanding of an area. Our empirical application above shows that low-value care is not due just to the standard moral-hazard explanation of health economics but also to mis-prediction. The pattern of discrepancies between human and algorithmic decisions can serve as a behavioral diagnostic about decision-making (Kleinberg, Lakkaraju, Leskovec, Ludwig, and Mullainathan 2015). And prediction can shed light on other theoretical issues. For example, understanding

hazard as an explanation for these findings, since physicians who predicted well acting consistent with moral hazard would first exhaust the low-risk pool of patients before operating on higher-risk patients.

how people change their behavior as regulators or police change the algorithms they use to target monitoring effort can shed light on the game theory of enforcement.

Prediction policy problems are, in sum, important, common, and interesting, and deserve much more attention from economists than they have received. New advances in machine learning can be adapted by economists to work on these problems, but will require a substantial amount of both theoretical and practical reorientation to yield benefits for those currently engaged in policy studies.

REFERENCES

- Chandler, Dana, Steven D. Levitt, and John A. List.** 2011. "Predicting and Preventing Shootings among At-Risk Youth." *American Economic Review* 101 (3): 288–92.
- Hamel, Mary Beth, Maria Toth, Anna Legedza, and Max Rose.** 2008. "Joint Replacement Surgery in Elderly Patients With Severe Osteoarthritis of the Hip or Knee." *Archives of Internal Medicine* 168 (13): 1430–40.
- Hastie, Trevor, Robert Tibshirani, and Jerome Friedman.** 2009. *The Elements of Statistical Learning: Data Mining, Inference, and Prediction*. New York: Springer.
- Kang, Jun Seok, Polina Kuznetsova, Michael Luca, and Yejin Choi.** 2013. "Where *Not* to Eat? Improving Public Policy by Predicting Hygiene Inspections Using Online Reviews." In *Proceedings of the 2013 Conference on Empirical Methods in Natural Language Processing*, 1443–48. Stroudsburg, PA: Association for Computational Linguistics.
- Kleinberg, Jon, Himabindu Lakkaraju, Jure Leskovec, Jens Ludwig, and Sendhil Mullainathan.** 2015. "Human decisions and machine predictions." Unpublished.
- Kleinberg, Jon, Jens Ludwig, Sendhil Mullainathan, and Ziad Obermeyer.** 2015. "Policy prediction problems." Unpublished.
- Rockoff, Jonah E., Brian A. Jacob, Thomas J. Kane, and Douglas O. Staiger.** 2011. "Can you recognize an effective teacher when you recruit one?" *Education Finance and Policy* 6 (1): 43–74.

This article has been cited by:

1. Maria Isabel Toulson Davisson Correia. 2023. Ethics in research. *Clinical Nutrition Open Science* **47**, 121-130. [[Crossref](#)]
2. Long Liu, Hongkang Xu, Mai Dao, Hua Sun. 2023. Pilot CEOs and tax avoidance: evidence from machine learning methods. *Asia-Pacific Journal of Accounting & Economics* **30**:1, 14-29. [[Crossref](#)]
3. Helen Margetts, Cosmina Dorobantu. Computational Social Science for Public Policy 3-18. [[Crossref](#)]
4. Dayeoun Jang, Byoungkwan Lee. 2022. When Machine Learning Meets Social Science: A Comparative Study of Ordinary Least Square, Stochastic Gradient Descent, and Support Vector Regression for Exploring the Determinants of Behavioral Intentions to Tuberculosis Screening. *Asian Communication Research* **19**:3, 101-118. [[Crossref](#)]
5. Hannes Mueller, Christopher Rauh. 2022. The Hard Problem of Prediction for Conflict Prevention. *Journal of the European Economic Association* **20**:6, 2440-2467. [[Crossref](#)]
6. Hutashan V. Bhagat, Manminder Singh. Machine-Learning and Deep-Learning Techniques in Social Sciences 409-428. [[Crossref](#)]
7. Hazal Colak Oz, Çiçek Güven, Gonzalo Nápoles. 2022. School dropout prediction and feature importance exploration in Malawi using household panel data: machine learning approach. *Journal of Computational Social Science* **33**. . [[Crossref](#)]
8. Pedro Henrique Melo Albuquerque, Yaohao Peng, João Pedro Fontoura da Silva. 2022. Making the whole greater than the sum of its parts: A literature review of ensemble methods for financial time series forecasting. *Journal of Forecasting* **41**:8, 1701-1724. [[Crossref](#)]
9. Francesco Decarolis, Cristina Giorgantonio. 2022. Corruption red flags in public procurement: new evidence from Italian calls for tenders. *EPJ Data Science* **11**:1. . [[Crossref](#)]
10. Ran Yan, Shining Wu, Yong Jin, Jiannong Cao, Shuaian Wang. 2022. Efficient and explainable ship selection planning in port state control. *Transportation Research Part C: Emerging Technologies* **145**, 103924. [[Crossref](#)]
11. Prothit Sen, Phanish Puranam. 2022. Do Alliance portfolios encourage or impede new business practice adoption? Theory and evidence from the private equity industry. *Strategic Management Journal* **43**:11, 2279-2312. [[Crossref](#)]
12. Zhaowei She, Turgay Ayer, Daniel Montanera. 2022. Can Big Data Cure Risk Selection in Healthcare Capitation Program? A Game Theoretical Analysis. *Manufacturing & Service Operations Management* **24**:6, 3117-3134. [[Crossref](#)]
13. Guido de Blasio, Alessio D'Ignazio, Marco Letta. 2022. Gotham city. Predicting 'corrupted' municipalities with machine learning. *Technological Forecasting and Social Change* **184**, 122016. [[Crossref](#)]
14. Christian Leuz. 2022. Towards a design-based approach to accounting research. *Journal of Accounting and Economics* **74**:2-3, 101550. [[Crossref](#)]
15. Ian Lundberg, Jennie E. Brand, Nanum Jeon. 2022. Researcher reasoning meets computational capacity: Machine learning for social science. *Social Science Research* **108**, 102807. [[Crossref](#)]
16. Cai Xu, Ishwaria M. Subbiah, Sheng-Chieh Lu, André Pfob, Chris Sidey-Gibbons. 2022. Machine learning models for 180-day mortality prediction of patients with advanced cancer using patient-reported symptom data. *Quality of Life Research* **34**. . [[Crossref](#)]
17. Emmanouil Tranos, André Carrascal-Incera, George Willis. 2022. Using the Web to Predict Regional Trade Flows: Data Extraction, Modeling, and Validation. *Annals of the American Association of Geographers* **13**, 1-23. [[Crossref](#)]

18. Alessandra Garbero, Marco Letta. 2022. Predicting household resilience with machine learning: preliminary cross-country tests. *Empirical Economics* **63**:4, 2057-2070. [[Crossref](#)]
19. Benjamin Tur, Jennifer Harstad, John Antonakis. 2022. Effect of charismatic signaling in social media settings: Evidence from TED and Twitter. *The Leadership Quarterly* **33**:5, 101476. [[Crossref](#)]
20. Allan Lee, Ilke Inceoglu, Oliver Hauser, Michael Greene. 2022. Determining causal relationships in leadership research using Machine Learning: The powerful synergy of experiments and data science. *The Leadership Quarterly* **33**:5, 101426. [[Crossref](#)]
21. Giuliano Resce, Cristina Vaquero-Piñeiro. 2022. Predicting agri-food quality across space: A Machine Learning model for the acknowledgment of Geographical Indications. *Food Policy* **112**, 102345. [[Crossref](#)]
22. Hannes Wallimann, David Imhof, Martin Huber. 2022. A Machine Learning Approach for Flagging Incomplete Bid-Rigging Cartels. *Computational Economics* **24**. . [[Crossref](#)]
23. Il Hwan Chung, Daniel W. Williams, Myung Rok Do. 2022. For Better or Worse? Revenue Forecasting with Machine Learning Approaches. *Public Performance & Management Review* **45**:5, 1133-1154. [[Crossref](#)]
24. Hans van der Heijden. 2022. Predicting industry sectors from financial statements: An illustration of machine learning in accounting research. *The British Accounting Review* **54**:5, 101096. [[Crossref](#)]
25. Luca Panzone, Guy Garrod, Felice Adinolfi, Jorgelina Di Pasquale. 2022. Molecular marketing, personalised information and willingness-to-pay for functional foods: Vitamin D enriched eggs. *Journal of Agricultural Economics* **73**:3, 666-689. [[Crossref](#)]
26. Stephan Dietrich, Aline Meysonnat, Francisco Rosales, Victor Cebotari, Franziska Gassmann. 2022. Economic development, weather shocks and child marriage in South Asia: A machine learning approach. *PLOS ONE* **17**:9, e0271373. [[Crossref](#)]
27. Zhiqiang Xu, Mahdi Aghaabbasi, Mujahid Ali, Elżbieta Macioszek. 2022. Targeting Sustainable Transportation Development: The Support Vector Machine and the Bayesian Optimization Algorithm for Classifying Household Vehicle Ownership. *Sustainability* **14**:17, 11094. [[Crossref](#)]
28. Tsun Se Cheong, Guanghua Wan, David Kam Hung Chui. 2022. Unveiling the Relationship between Economic Growth and Equality for Developing Countries. *China & World Economy* **30**:5, 1-28. [[Crossref](#)]
29. Giuliano Resce. 2022. The impact of political and non-political officials on the financial management of local governments. *Journal of Policy Modeling* **44**:5, 943-962. [[Crossref](#)]
30. Alberto Tron, Maurizio Dallochio, Salvatore Ferri, Federico Colantoni. 2022. Corporate governance and financial distress: lessons learned from an unconventional approach. *Journal of Management and Governance* **18**. . [[Crossref](#)]
31. Lida Kuang, Samruda Pobbathi, Yuri Mansury, Matthew A. Shapiro, Vijay K. Gurbani. 2022. Predicting age and gender from network telemetry: Implications for privacy and impact on policy. *PLOS ONE* **17**:7, e0271714. [[Crossref](#)]
32. Ari Hyytinen, Jarno Tuimala, Markus Hammar. 2022. Enhancing the adoption of digital public services: Evidence from a large-scale field experiment. *Government Information Quarterly* **39**:3, 101687. [[Crossref](#)]
33. Ben Green. 2022. The flaws of policies requiring human oversight of government algorithms. *Computer Law & Security Review* **45**, 105681. [[Crossref](#)]
34. O. V. Buklemishev. 2022. Artificial intelligence in the public sector. *Voprosy Ekonomiki* :6, 91-109. [[Crossref](#)]
35. Florian M. Artinger, Gerd Gigerenzer, Perke Jacobs. 2022. Satisficing: Integrating Two Traditions. *Journal of Economic Literature* **60**:2, 598-635. [[Abstract](#)] [[View PDF article](#)] [[PDF with links](#)]

36. Basil Schmid, Felix Becker, Joseph Molloy, Kay W. Axhausen, Jochen Lüdering, Julian Hagen, Annette Blome. 2022. Modeling train route decisions during track works. *Journal of Rail Transport Planning & Management* **22**, 100320. [[Crossref](#)]
37. Arne Steinkraus. 2022. Asking Why? – Das Spannungsfeld zwischen Ökonometrie und Data Science. *Wirtschaftsinformatik & Management* **14**:3, 186–191. [[Crossref](#)]
38. Boubacar Diallo. 2022. Machine learning approaches to testing institutional hypotheses: the case of Acemoglu, Johnson, and Robinson (2001). *Empirical Economics* **62**:5, 2587–2600. [[Crossref](#)]
39. Yingjie Lao, Peng Yang, Weijie Zhao, Ping Li. Identification for Deep Neural Network: Simply Adjusting Few Weights! 1328–1341. [[Crossref](#)]
40. Hyundong Nam, Songeun Kim, Taewoo Nam. 2022. Identifying the Directions of Technology-Driven Government Innovation. *Information* **13**:5, 208. [[Crossref](#)]
41. Sendhil Mullainathan, Ziad Obermeyer. 2022. Diagnosing Physician Error: A Machine Learning Approach to Low-Value Health Care. *The Quarterly Journal of Economics* **137**:2, 679–727. [[Crossref](#)]
42. Shan Huang, Michael Allan Ribers, Hannes Ullrich. 2022. Assessing the value of data for prediction policies: The case of antibiotic prescribing. *Economics Letters* **213**, 110360. [[Crossref](#)]
43. David Valle-Cruz, Vanessa Fernandez-Cortez, J. Ramon Gil-Garcia. 2022. From E-budgeting to smart budgeting: Exploring the potential of artificial intelligence in government decision-making for resource allocation. *Government Information Quarterly* **39**:2, 101644. [[Crossref](#)]
44. Teresa M. Harrison, Luis Felipe Luna-Reyes. 2022. Cultivating Trustworthy Artificial Intelligence in Digital Government. *Social Science Computer Review* **40**:2, 494–511. [[Crossref](#)]
45. Chao-Ming Hung, Hon-Yi Shi, Po-Huang Lee, Chao-Sung Chang, Kun-Ming Rau, Hui-Ming Lee, Cheng-Hao Tseng, Sung-Nan Pei, Kuen-Jang Tsai, Chong-Chi Chiu. 2022. Potential and role of artificial intelligence in current medical healthcare. *WArtificial Intelligence in Cancer* **3**:1, 1–10. [[Crossref](#)]
46. Morgan Henderson, Fei Han, Chad Perman, Howard Haft, Ian Stockwell. 2022. Predicting avoidable hospital events in Maryland. *Health Services Research* **57**:1, 192–199. [[Crossref](#)]
47. Dweepobotee Brahma, Debasri Mukherjee. 2022. Early warning signs: targeting neonatal and infant mortality using machine learning. *Applied Economics* **54**:1, 57–74. [[Crossref](#)]
48. Thomas Lefèvre, Cyrille Delpierre. Artificial Intelligence in Epidemiology 1341–1352. [[Crossref](#)]
49. Yang Bao, Gilles Hilary, Bin Ke. Artificial Intelligence and Fraud Detection 223–247. [[Crossref](#)]
50. Fatih Demir. Artificial Intelligence 137–176. [[Crossref](#)]
51. Zahid Mumtaz. Machine Learning-Based Approach for Exploring the Household Survey Data 141–200. [[Crossref](#)]
52. Li-Chin Chen, Ji-Tian Sheu, Yuh-Jue Chuang, Yu Tsao. 2022. Predicting the Travel Distance of Patients to Access Healthcare Using Deep Neural Networks. *IEEE Journal of Translational Engineering in Health and Medicine* **10**, 1–11. [[Crossref](#)]
53. Simone Plak, Ilja Cornelisz, Martijn Meeter, Chris Klaveren. 2022. Early warning systems for more effective student counselling in higher education: Evidence from a Dutch field experiment. *Higher Education Quarterly* **76**:1, 131–152. [[Crossref](#)]
54. Benjamin Bluhm, Jannic Alexander Cutura. 2022. Econometrics at Scale: Spark up Big Data in Economics. *Journal of Data Science* **49**, 413–436. [[Crossref](#)]
55. Douglas Silveira, Silvinha Vasconcelos, Marcelo Resende, Daniel O. Cajueiro. 2022. Won't Get Fooled Again: A supervised machine learning approach for screening gasoline cartels. *Energy Economics* **105**, 105711. [[Crossref](#)]

56. Augusto Cerqua, Marco Letta. 2022. Local inequalities of the COVID-19 crisis. *Regional Science and Urban Economics* **92**, 103752. [[Crossref](#)]
57. Ellicott C Matthay, Laura M Gottlieb, David Rehkopf, May Lynn Tan, David Vlahov, M Maria Glymour. 2021. What to Do When Everything Happens at Once: Analytic Approaches to Estimate the Health Effects of Co-Occurring Social Policies. *Epidemiologic Reviews* **43**:1, 33-47. [[Crossref](#)]
58. Katrina L Kezios. 2021. Is the Way Forward to Step Back? Documenting the Frequency With Which Study Goals Are Misaligned With Study Methods and Interpretations in the Epidemiologic Literature. *Epidemiologic Reviews* **43**:1, 4-18. [[Crossref](#)]
59. Ellicott C Matthay, Erin Hagan, Spruha Joshi, May Lynn Tan, David Vlahov, Nancy Adler, M Maria Glymour. 2021. The Revolution Will Be Hard to Evaluate: How Co-Occurring Policy Changes Affect Research on the Health Effects of Social Policies. *Epidemiologic Reviews* **43**:1, 19-32. [[Crossref](#)]
60. Teresa Scantamburlo. 2021. Non-empirical problems in fair machine learning. *Ethics and Information Technology* **23**:4, 703-712. [[Crossref](#)]
61. Y. Kiguchi, M. Weeks, R. Arakawa. 2021. Predicting winners and losers under time-of-use tariffs using smart meter data. *Energy* **236**, 121438. [[Crossref](#)]
62. Zhou Lu, Zhuyao Zhuo. 2021. Modelling of Chinese corporate bond default – A machine learning approach. *Accounting & Finance* **61**:5, 6147-6191. [[Crossref](#)]
63. Yunsong Chen, Xiaogang Wu, Anning Hu, Guangye He, Guodong Ju. 2021. Social prediction: a new research paradigm based on machine learning. *The Journal of Chinese Sociology* **8**:1. . [[Crossref](#)]
64. Deon Filmer, Vatsal Nahata, Shwetlena Sabarwal. Preparation, Practice, and Beliefs: A Machine Learning Approach to Understanding Teacher Effectiveness **1**, . [[Crossref](#)]
65. Silvia S. Martins, Emilie Bruzelius, Jeanette A. Stingone, Katherine Wheeler-Martin, Hanane Akbarnejad, Christine M. Mauro, Megan E. Marziali, Hillary Samples, Stephen Crystal, Corey S. Davis, Kara E. Rudolph, Katherine M. Keyes, Deborah S. Hasin, Magdalena Cerdá. 2021. Prescription Opioid Laws and Opioid Dispensing in US Counties. *Epidemiology* **32**:6, 868-876. [[Crossref](#)]
66. Zhe Hong, In Kwon Park. 2021. Comparative Analysis of Energy Poverty Prediction Models Using Machine Learning Algorithms. *Journal of Korea Planning Association* **56**:5, 239-255. [[Crossref](#)]
67. Karen Levy, Kyla E. Chasalow, Sarah Riley. 2021. Algorithms and Decision-Making in the Public Sector. *Annual Review of Law and Social Science* **17**:1, 309-334. [[Crossref](#)]
68. Han Liu, Vivian Lai, Chenhao Tan. 2021. Understanding the Effect of Out-of-distribution Examples and Interactive Explanations on Human-AI Decision Making. *Proceedings of the ACM on Human-Computer Interaction* **5**:CSCW2, 1-45. [[Crossref](#)]
69. Ben Green, Yiling Chen. 2021. Algorithmic Risk Assessments Can Alter Human Decision-Making Processes in High-Stakes Government Contexts. *Proceedings of the ACM on Human-Computer Interaction* **5**:CSCW2, 1-33. [[Crossref](#)]
70. Bryan Kelly, Asaf Manela, Alan Moreira. 2021. Text Selection. *Journal of Business & Economic Statistics* **39**:4, 859-879. [[Crossref](#)]
71. Augusto Cerqua, Roberta Di Stefano, Marco Letta, Sara Miccoli. 2021. Local mortality estimates during the COVID-19 pandemic in Italy. *Journal of Population Economics* **34**:4, 1189-1217. [[Crossref](#)]
72. Alessandra Garbero, Giuliano Resce, Bia Carneiro. 2021. Spatial dynamics across food systems transformation in IFAD investments: a machine learning approach. *Food Security* **13**:5, 1125-1143. [[Crossref](#)]
73. Akash Malhotra. 2021. A hybrid econometric-machine learning approach for relative importance analysis: prioritizing food policy. *Eurasian Economic Review* **11**:3, 549-581. [[Crossref](#)]

74. Karima Makhoulf, Sami Zhioua, Catuscia Palamidessi. 2021. Machine learning fairness notions: Bridging the gap with real-world applications. *Information Processing & Management* **58**:5, 102642. [[Crossref](#)]
75. Rafael Quintana. 2021. Who Belongs in School? Using Statistical Learning Techniques to Identify Linear, Nonlinear and Interactive Effects. *The Quantitative Methods for Psychology* **17**:3, 312-328. [[Crossref](#)]
76. Sung-Cheol Kim, Adith S. Arun, Mehmet Eren Ahsen, Robert Vogel, Gustavo Stolovitzky. 2021. The Fermi–Dirac distribution provides a calibrated probabilistic output for binary classifiers. *Proceedings of the National Academy of Sciences* **118**:34. . [[Crossref](#)]
77. Tiffany Jiang. 2021. Using Machine Learning to Analyze Merger Activity. *Frontiers in Applied Mathematics and Statistics* **7**. . [[Crossref](#)]
78. Jake M. Hofman, Duncan J. Watts, Susan Athey, Filiz Garip, Thomas L. Griffiths, Jon Kleinberg, Helen Margetts, Sendhil Mullainathan, Matthew J. Salganik, Simine Vazire, Alessandro Vespignani, Tal Yarkoni. 2021. Integrating explanation and prediction in computational social science. *Nature* **595**:7866, 181-188. [[Crossref](#)]
79. Mark Musumba, Naureen Fatema, Shahriar Kibriya. 2021. Prevention Is Better Than Cure: Machine Learning Approach to Conflict Prediction in Sub-Saharan Africa. *Sustainability* **13**:13, 7366. [[Crossref](#)]
80. Richard G. Newell, Brian C. Prest, Steven E. Sexton. 2021. The GDP-Temperature relationship: Implications for climate change damages. *Journal of Environmental Economics and Management* **108**, 102445. [[Crossref](#)]
81. Giovanni Di Franco, Michele Santurro. 2021. Machine learning, artificial neural networks and social research. *Quality & Quantity* **55**:3, 1007-1025. [[Crossref](#)]
82. Lu Hong, PJ Lamberson, Scott E Page. 2021. Hybrid Predictive Ensembles: Synergies Between Human and Computational Forecasts. *Journal of Social Computing* **2**:2, 89-102. [[Crossref](#)]
83. Chiara Binelli. 2021. Estimating Causal Effects When the Treatment Affects All Subjects Simultaneously: An Application. *Big Data and Cognitive Computing* **5**:2, 22. [[Crossref](#)]
84. Sendhil Mullainathan, Ziad Obermeyer. 2021. On the Inequity of Predicting A While Hoping for B. *AEA Papers and Proceedings* **111**, 37-42. [[Abstract](#)] [[View PDF article](#)] [[PDF with links](#)]
85. Yash Raj Shrestha, Vivianna Fang He, Phanish Puranam, Georg von Krogh. 2021. Algorithm Supported Induction for Building Theory: How Can We Use Prediction Models to Theorize?. *Organization Science* **32**:3, 856-880. [[Crossref](#)]
86. Prasanna Tantri. 2021. Fintech for the Poor: Financial Intermediation Without Discrimination*. *Review of Finance* **25**:2, 561-593. [[Crossref](#)]
87. Joshua Gallin, Raven Molloy, Eric Nielsen, Paul Smith, Kamila Sommer. 2021. Measuring aggregate housing wealth: New insights from machine learning #. *Journal of Housing Economics* **51**, 101734. [[Crossref](#)]
88. Oliver Lock, Michael Bain, Christopher Pettit. 2021. Towards the collaborative development of machine learning techniques in planning support systems – a Sydney example. *Environment and Planning B: Urban Analytics and City Science* **48**:3, 484-502. [[Crossref](#)]
89. Runshan Fu, Yan Huang, Param Vir Singh. 2021. Crowds, Lending, Machine, and Bias. *Information Systems Research* **32**:1, 72-92. [[Crossref](#)]
90. Zahid Mumtaz, Peter Whiteford. 2021. Machine Learning Based Approach for Sustainable Social Protection Policies in Developing Societies. *Mobile Networks and Applications* **26**:1, 159-173. [[Crossref](#)]
91. Stephan Müller, Holger A. Rau. 2021. Economic preferences and compliance in the social stress test of the COVID-19 crisis. *Journal of Public Economics* **194**, 104322. [[Crossref](#)]

92. Thomas Lefèvre, Cyrille Delpierre. Artificial Intelligence in Epidemiology 1-12. [[Crossref](#)]
93. Amanda Guilan. Characterization of Scientific Prediction from Language: An Analysis of Nicholas Rescher's Proposal 247-266. [[Crossref](#)]
94. Falco J. Bargagli-Stoffi, Jan Niederreiter, Massimo Riccaboni. Supervised Learning for the Prediction of Firm Dynamics 19-41. [[Crossref](#)]
95. Jorge Gallego, Gonzalo Rivero, Juan Martínez. 2021. Preventing rather than punishing: An early warning model of malfeasance in public procurement. *International Journal of Forecasting* **37**:1, 360-377. [[Crossref](#)]
96. Aziz Z. Huq. 2021. Artificial Intelligence and the Rule of Law. *SSRN Electronic Journal* . [[Crossref](#)]
97. Amitabh Chandra, Evan Flack, Ziad Obermeyer. 2021. The Health Costs of Cost-Sharing. *SSRN Electronic Journal* **21**. . [[Crossref](#)]
98. Deni Mazrekaj, Vítězslav Titl, Fritz Schiltz. 2021. Identifying Politically Connected Firms: A Machine Learning Approach. *SSRN Electronic Journal* **322**. . [[Crossref](#)]
99. Madhura Dasgupta, Samarth Gupta. 2021. Determinants of Self-Help Groups lending to Enterprises in India: A Predictive Assessment using Supervised Machine Learning Algorithms. *SSRN Electronic Journal* **23**. . [[Crossref](#)]
100. . Navigating Tough Terrain: Sound Principles, Good Maps, and Adaptive Learning 159-178. [[Crossref](#)]
101. Eun-Sung Kim. 2020. Deep learning and principal-agent problems of algorithmic governance: The new materialism perspective. *Technology in Society* **63**, 101378. [[Crossref](#)]
102. Amirhosein Jafari, Behzad Rouhanizadeh, Sharareh Kermanshachi, Munahil Murrieum. 2020. Predictive Analytics Approach to Evaluate Wage Inequality in Engineering Organizations. *Journal of Management in Engineering* **36**:6. . [[Crossref](#)]
103. Ignacio Rodríguez-Rodríguez, José-Víctor Rodríguez, Domingo-Javier Pardo-Quiles, Purificación Heras-González, Ioannis Chatzigiannakis. 2020. Modeling and Forecasting Gender-Based Violence through Machine Learning Techniques. *Applied Sciences* **10**:22, 8244. [[Crossref](#)]
104. Omar Isaac Asensio, Ximin Mi, Sameer Dharur. 2020. Using Machine Learning Techniques to Aid Environmental Policy Analysis. *Case Studies in the Environment* **4**:1. . [[Crossref](#)]
105. Justine Zhang, Sendhil Mullainathan, Cristian Danescu-Niculescu-Mizil. 2020. Quantifying the Causal Effects of Conversational Tendencies. *Proceedings of the ACM on Human-Computer Interaction* **4**:CSCW2, 1-24. [[Crossref](#)]
106. Jens Frankenreiter, Michael A. Livermore. 2020. Computational Methods in Legal Analysis. *Annual Review of Law and Social Science* **16**:1, 39-57. [[Crossref](#)]
107. Ralph Schroeder. 2020. Big data and cumulation in the social sciences. *Information, Communication & Society* **23**:11, 1593-1607. [[Crossref](#)]
108. Sangchul Park, Haksoo Ko. 2020. Machine Learning and Law and Economics: A Preliminary Overview. *Asian Journal of Law and Economics* **11**:2. . [[Crossref](#)]
109. Sangchul Park, Haksoo Ko. 2020. Machine Learning and Law and Economics: A Preliminary Overview. *Asian Journal of Law and Economics*, ahead of print. [[Crossref](#)]
110. Eric Potash, Rayid Ghani, Joe Walsh, Emile Jorgensen, Cortland Lohff, Nik Prachand, Raed Mansour. 2020. Validation of a Machine Learning Model to Predict Childhood Lead Poisoning. *JAMA Network Open* **3**:9, e2012734. [[Crossref](#)]
111. James Evans. 2020. Social Computing Unhinged. *Journal of Social Computing* **1**:1, 1-13. [[Crossref](#)]

112. Sima Sabahi, Mahour Mellat Parast. 2020. The impact of entrepreneurship orientation on project performance: A machine learning approach. *International Journal of Production Economics* **226**, 107621. [[Crossref](#)]
113. Mahdi Aghaabbasi, Zohreh Asadi Shekari, Muhammad Zaly Shah, Oloruntobi Olakunle, Danial Jahed Armaghani, Mehdi Moeinaddini. 2020. Predicting the use frequency of ride-sourcing by off-campus university students through random forest and Bayesian network techniques. *Transportation Research Part A: Policy and Practice* **136**, 262-281. [[Crossref](#)]
114. Jongbin Jung, Connor Concannon, Ravi Shroff, Sharad Goel, Daniel G. Goldstein. 2020. Simple rules to guide expert classifications. *Journal of the Royal Statistical Society: Series A (Statistics in Society)* **183**:3, 771-800. [[Crossref](#)]
115. Matthew J. Salganik, Ian Lundberg, Alexander T. Kindel, Caitlin E. Ahearn, Khaled Al-Ghoneim, Abdullah Almaatouq, Drew M. Altschul, Jennie E. Brand, Nicole Bohme Carnegie, Ryan James Compton, Debanjan Datta, Thomas Davidson, Anna Filippova, Connor Gilroy, Brian J. Goode, Eaman Jahani, Ridhi Kashyap, Antje Kirchner, Stephen McKay, Allison C. Morgan, Alex Pentland, Kivan Polimis, Louis Raes, Daniel E. Rigobon, Claudia V. Roberts, Diana M. Stanescu, Yoshihiko Suhara, Adaner Usmani, Erik H. Wang, Muna Adem, Abdulla Alhajri, Bedoor AlShebli, Redwane Amin, Ryan B. Amos, Lisa P. Argyle, Livia Baer-Bositis, Moritz Büchi, Bo-Ryehn Chung, William Eggert, Gregory Faletto, Zhilin Fan, Jeremy Freese, Tejomay Gadgil, Josh Gagné, Yue Gao, Andrew Halpern-Manners, Sonia P. Hashim, Sonia Hausen, Guanhua He, Kimberly Higuera, Bernie Hogan, Ilana M. Horwitz, Lisa M. Hummel, Naman Jain, Kun Jin, David Jurgens, Patrick Kaminski, Areg Karapetyan, E. H. Kim, Ben Leizman, Naijia Liu, Malte Möser, Andrew E. Mack, Mayank Mahajan, Noah Mandell, Helge Marahrens, Diana Mercado-Garcia, Viola Mocz, Katariina Mueller-Gastell, Ahmed Musse, Qiankun Niu, William Nowak, Hamidreza Omidvar, Andrew Or, Karen Ouyang, Katy M. Pinto, Ethan Porter, Kristin E. Porter, Crystal Qian, Tamkinat Rauf, Anahit Sargsyan, Thomas Schaffner, Landon Schnabel, Bryan Schonfeld, Ben Sender, Jonathan D. Tang, Emma Tsurkov, Austin van Loon, Onur Varol, Xiafei Wang, Zhi Wang, Julia Wang, Flora Wang, Samantha Weissman, Kirstie Whitaker, Maria K. Wolters, Wei Lee Woon, James Wu, Catherine Wu, Kengran Yang, Jingwen Yin, Bingyu Zhao, Chenyun Zhu, Jeanne Brooks-Gunn, Barbara E. Engelhardt, Moritz Hardt, Dean Knox, Karen Levy, Arvind Narayanan, Brandon M. Stewart, Duncan J. Watts, Sara McLanahan. 2020. Measuring the predictability of life outcomes with a scientific mass collaboration. *Proceedings of the National Academy of Sciences* **117**:15, 8398-8403. [[Crossref](#)]
116. Filiz Garip. 2020. What failure to predict life outcomes can teach us. *Proceedings of the National Academy of Sciences* **117**:15, 8234-8235. [[Crossref](#)]
117. . The Production of Knowledge **20**, . [[Crossref](#)]
118. Jeffrey S. Berger, Lloyd Haskell, Windsor Ting, Fedor Lurie, Shun-Chiao Chang, Luke A. Mueller, Kenneth Elder, Kelly Rich, Concetta Crivera, Jeffrey R. Schein, Veronica Alas. 2020. Evaluation of machine learning methodology for the prediction of healthcare resource utilization and healthcare costs in patients with critical limb ischemia—is preventive and personalized approach on the horizon?. *EPMA Journal* **11**:1, 53-64. [[Crossref](#)]
119. Thorsten Sellhorn. 2020. Machine Learning und empirische Rechnungslegungsforschung: Einige Erkenntnisse und offene Fragen. *Schmalenbachs Zeitschrift für betriebswirtschaftliche Forschung* **72**:1, 49-69. [[Crossref](#)]
120. YANG BAO, BIN KE, BIN LI, Y. JULIA YU, JIE ZHANG. 2020. Detecting Accounting Fraud in Publicly Traded U.S. Firms Using a Machine Learning Approach. *Journal of Accounting Research* **58**:1, 199-235. [[Crossref](#)]
121. Clement Bellet, Paul Frijters. Big Data and Wellbeing: An Economic Perspective 175-206. [[Crossref](#)]

122. Marcus H. Böhme, André Gröger, Tobias Stöhr. 2020. Searching for a better life: Predicting international migration with online search keywords. *Journal of Development Economics* **142**, 102347. [[Crossref](#)]
123. Pedro Carneiro, Sokbae Lee, Daniel Wilhelm. 2020. Optimal data collection for randomized control trials. *The Econometrics Journal* **23**:1, 1-31. [[Crossref](#)]
124. Anja Lambrecht, Catherine E. Tucker. 2020. Apparent Algorithmic Bias and Algorithmic Learning. *SSRN Electronic Journal* **66**. . [[Crossref](#)]
125. Stephan Müller, Holger Andreas Rau. 2020. Economic Preferences and Compliance in the Social Stress Test of the Corona Crisis. *SSRN Electronic Journal* . [[Crossref](#)]
126. Falco Bargagli Stoffi, Massimo Riccaboni, Armando Rungi. 2020. Machine Learning for Zombie Hunting. Firms' Failures and Financial Constraints. *SSRN Electronic Journal* . [[Crossref](#)]
127. Elliott Ash, Sergio Galletta, Tommaso Giommoni. 2020. A Machine Learning Approach to Analyzing Corruption in Local Public Finances. *SSRN Electronic Journal* . [[Crossref](#)]
128. Lu Hong, Scott Page. 2020. The Contributions of Diversity, Accuracy, and Group Size on Collective Accuracy. *SSRN Electronic Journal* **111**. . [[Crossref](#)]
129. Chenyu Hou. 2020. Learning and Subjective Expectation Formation: A Recurrent Neural Network Approach. *SSRN Electronic Journal* **2**. . [[Crossref](#)]
130. María Teresa Ballestar, Luis Miguel Doncel, Jorge Sainz, Arturo Ortigosa-Blanch. 2019. A novel machine learning approach for evaluation of public policies: An application in relation to the performance of university researchers. *Technological Forecasting and Social Change* **149**, 119756. [[Crossref](#)]
131. Jorge Mejia, Shawn Mankad, Anandasivam Gopal. 2019. A for Effort? Using the Crowd to Identify Moral Hazard in New York City Restaurant Hygiene Inspections. *Information Systems Research* **30**:4, 1363-1386. [[Crossref](#)]
132. Marlena S Bannick, Madeline McGaughey, Abraham D Flaxman. 2019. Ensemble modelling in descriptive epidemiology: burden of disease estimation. *International Journal of Epidemiology* **390**. . [[Crossref](#)]
133. David McKenzie, Dario Sansone. 2019. Predicting entrepreneurial success is hard: Evidence from a business plan competition in Nigeria. *Journal of Development Economics* **141**, 102369. [[Crossref](#)]
134. Francesco Aiello, Giuseppe Albanese, Paolo Piselli. 2019. Good value for public money? The case of R&D policy. *Journal of Policy Modeling* **41**:6, 1057-1076. [[Crossref](#)]
135. Ziad Obermeyer, Brian Powers, Christine Vogeli, Sendhil Mullainathan. 2019. Dissecting racial bias in an algorithm used to manage the health of populations. *Science* **366**:6464, 447-453. [[Crossref](#)]
136. Md Saiful Islam, Md Sarowar Morshed, Gary J. Young, Md. Noor-E-Alam. 2019. Robust policy evaluation from large-scale observational studies. *PLOS ONE* **14**:10, e0223360. [[Crossref](#)]
137. Mario Molina, Filiz Garip. 2019. Machine Learning for Sociology. *Annual Review of Sociology* **45**:1, 27-45. [[Crossref](#)]
138. Michael J. Weir, Thomas W. Sproul. 2019. Identifying Drivers of Genetically Modified Seafood Demand: Evidence from a Choice Experiment. *Sustainability* **11**:14, 3934. [[Crossref](#)]
139. Hamid R. Karimian, Behzad Rouhanizadeh, Amirhosein Jafari, Sharareh Kermanshachi. Big Data and Machine Learning 26-34. [[Crossref](#)]
140. Turgut Ozkan. 2019. Criminology in the age of data explosion: New directions. *The Social Science Journal* **56**:2, 208-219. [[Crossref](#)]
141. Henry E. Brady. 2019. The Challenge of Big Data and Data Science. *Annual Review of Political Science* **22**:1, 297-323. [[Crossref](#)]

142. Mark A Chen, Qinxi Wu, Baozhong Yang. 2019. How Valuable Is FinTech Innovation?. *The Review of Financial Studies* 32:5, 2062-2106. [[Crossref](#)]
143. Manhal Ali, Reza Salehnejad, Mohaimen Mansur. 2019. Hospital productivity: The role of efficiency drivers. *The International Journal of Health Planning and Management* 34:2, 806-823. [[Crossref](#)]
144. Aggeliki Androutsopoulou, Nikos Karacapilidis, Euripidis Loukis, Yannis Charalabidis. 2019. Transforming the communication between citizens and government through AI-guided chatbots. *Government Information Quarterly* 36:2, 358-367. [[Crossref](#)]
145. Dario Sansone. 2019. Beyond Early Warning Indicators: High School Dropout and Machine Learning. *Oxford Bulletin of Economics and Statistics* 81:2, 456-485. [[Crossref](#)]
146. Jonas Krämer, Jonas Schreyögg, Reinhard Busse. 2019. Classification of hospital admissions into emergency and elective care: a machine learning approach. *Health Care Management Science* 22:1, 85-105. [[Crossref](#)]
147. Mark Western. 2019. How to Increase the Relevance and Use of Social and Behavioral Science: Lessons for Policy-makers, Researchers and Others. *Justice Evaluation Journal* 2:1, 18-34. [[Crossref](#)]
148. Katy Börner, Staša Milojević. Science Forecasts: Modeling and Communicating Developments in Science, Technology, and Innovation 145-157. [[Crossref](#)]
149. Bruno Peyrou, Jean-Jacques Vignaux, Arthur André. Artificial Intelligence and Health Care 29-40. [[Crossref](#)]
150. K. John McConnell, Stephan Lindner. 2019. Estimating treatment effects with machine learning. *Health Services Research* 54:6, 1273. [[Crossref](#)]
151. Vivian Lai, Chenhao Tan. On Human Predictions with Explanations and Predictions of Machine Learning Models 29-38. [[Crossref](#)]
152. Nikola Banovic, Antti Oulasvirta, Per Ola Kristensson. Computational Modeling in Human-Computer Interaction 1-7. [[Crossref](#)]
153. Alejandro Noriega-Campero, Michiel A. Bakker, Bernardo Garcia-Bulle, Alex 'Sandy' Pentland. Active Fairness in Algorithmic Decision Making 77-83. [[Crossref](#)]
154. Ian Lundberg, Arvind Narayanan, Karen Levy, Matthew J. Salganik. 2019. Privacy, Ethics, and Data Access: A Case Study of the Fragile Families Challenge. *Socius: Sociological Research for a Dynamic World* 5, 237802311881302. [[Crossref](#)]
155. Matthew J. Salganik, Ian Lundberg, Alexander T. Kindel, Sara McLanahan. 2019. Introduction to the Special Collection on the Fragile Families Challenge. *Socius: Sociological Research for a Dynamic World* 5, 237802311987158. [[Crossref](#)]
156. Nicolaj Mühlbach. 2019. Tree-Based Methods: Consequences of Moving the US Embassy. *SSRN Electronic Journal* . [[Crossref](#)]
157. Emanuele Colonnelli, Jorge A. Gallego, Mounu Prem. 2019. What Predicts Corruption?. *SSRN Electronic Journal* . [[Crossref](#)]
158. Costanza Naguib. 2019. Estimating the Heterogeneous Impact of the Free Movement of Persons on Relative Wage Mobility. *SSRN Electronic Journal* . [[Crossref](#)]
159. Andreas Joseph. 2019. Shapley Regressions: A Framework for Statistical Inference on Machine Learning Models. *SSRN Electronic Journal* . [[Crossref](#)]
160. Pauline Affeldt. 2019. EU Merger Policy Predictability Using Random Forests. *SSRN Electronic Journal* . [[Crossref](#)]
161. Jonathan Samuel Hersh, Bree J. Lang, Matthew Lang. 2019. Car Accidents and 3G Coverage: New Evidence Using Cell Phone Tower Construction. *SSRN Electronic Journal* . [[Crossref](#)]

162. Sumit Agarwal, Shashwat Alok, Pulak Ghosh, Sudip Gupta. 2019. Fintech and Credit Scoring for the Millennials: Evidence using Mobile and Social Footprints. *SSRN Electronic Journal* . [[Crossref](#)]
163. Prasanna L. Tantri. 2019. Does Skillful Use of Hard Information by Machines Outperform a Combination of Hard and Soft Information of Loan Officers in Lending Decisions?. *SSRN Electronic Journal* . [[Crossref](#)]
164. Jon Kleinberg, Jens Ludwig, Sendhil Mullainathan, Cass R Sunstein. 2018. Discrimination in the Age of Algorithms. *Journal of Legal Analysis* **10**, 113-174. [[Crossref](#)]
165. Reuben Binns. 2018. Algorithmic Accountability and Public Reason. *Philosophy & Technology* **31**:4, 543-556. [[Crossref](#)]
166. Monica Andini, Emanuele Ciani, Guido de Blasio, Alessio D'Ignazio, Viola Salvestrini. 2018. Targeting with machine learning: An application to a tax rebate program in Italy. *Journal of Economic Behavior & Organization* **156**, 86-102. [[Crossref](#)]
167. Abraham D. Flaxman, Theo Vos. 2018. Machine learning in population health: Opportunities and threats. *PLOS Medicine* **15**:11, e1002702. [[Crossref](#)]
168. M. Hino, E. Benami, N. Brooks. 2018. Machine learning for environmental monitoring. *Nature Sustainability* **1**:10, 583-588. [[Crossref](#)]
169. Garret Christensen, Edward Miguel. 2018. Transparency, Reproducibility, and the Credibility of Economics Research. *Journal of Economic Literature* **56**:3, 920-980. [[Abstract](#)] [[View PDF article](#)] [[PDF with links](#)]
170. Stefan Wager, Susan Athey. 2018. Estimation and Inference of Heterogeneous Treatment Effects using Random Forests. *Journal of the American Statistical Association* **113**:523, 1228-1242. [[Crossref](#)]
171. Eric Potash. 2018. Randomization bias in field trials to evaluate targeting methods. *Economics Letters* **167**, 131-135. [[Crossref](#)]
172. Jon Kleinberg, Jens Ludwig, Sendhil Mullainathan, Ashesh Rambachan. 2018. Algorithmic Fairness. *AEA Papers and Proceedings* **108**, 22-27. [[Abstract](#)] [[View PDF article](#)] [[PDF with links](#)]
173. Dinesh Visva Gunasekeran. 2018. Regulations for the development of deep technology applications in healthcare urgently needed to prevent abuse of vulnerable patients. *BMJ Innovations* **4**:2, 111-112. [[Crossref](#)]
174. Betsy Anne Williams, Catherine F. Brooks, Yotam Shmargad. 2018. How Algorithms Discriminate Based on Data They Lack: Challenges, Solutions, and Policy Implications. *Journal of Information Policy* **8**:1, 78-115. [[Crossref](#)]
175. Betsy Anne Williams, Catherine F. Brooks, Yotam Shmargad. 2018. How Algorithms Discriminate Based on Data They Lack: Challenges, Solutions, and Policy Implications. *Journal of Information Policy* **8**, 78-115. [[Crossref](#)]
176. Edgar Dobriban, Stefan Wager. 2018. High-dimensional asymptotics of prediction: Ridge regression and classification. *The Annals of Statistics* **46**:1, 247-279. [[Crossref](#)]
177. Nikos Askitas. 3 On the Interplay Between Forgetting and Remembering 135-147. [[Crossref](#)]
178. Lena Ulbricht, Sebastian Haunss, Jeanette Hofmann, Ulrike Klinger, Jan-Hendrik Passoth, Christian Pentzold, Ingrid Schneider, Holger Straßheim, Jan-Peter Voß. Dimensionen von Big Data: Eine politikwissenschaftliche Systematisierung 151-231. [[Crossref](#)]
179. . References for Part I 169-177. [[Crossref](#)]
180. Edward L. Glaeser, Scott Duke Kominers, Michael Luca, Nikhil Naik. 2018. BIG DATA AND BIG CITIES: THE PROMISES AND LIMITATIONS OF IMPROVED MEASURES OF URBAN LIFE. *Economic Inquiry* **56**:1, 114-137. [[Crossref](#)]

181. Phanish Puranam, Yash Raj Shrestha, Vivian Fang He, Georg von Krogh. 2018. Algorithmic Induction Through Machine Learning: Opportunities for Management and Organization Research. *SSRN Electronic Journal* . [[Crossref](#)]
182. Anthony Niblett. 2018. Regulatory Reform in Ontario: Machine Learning and Regulation. *SSRN Electronic Journal* . [[Crossref](#)]
183. Alexei Alexandrov, Russell Pittman, Olga Ukhaneva. 2018. Pricing of Complements in the U.S. Freight Railroads: Cournot Versus Coase. *SSRN Electronic Journal* . [[Crossref](#)]
184. Sebastian M. Palacio. 2018. Machine Learning Forecasts of Public Transport Demand: A Comparative Analysis of Supervised Algorithms Using Smart Card Data. *SSRN Electronic Journal* . [[Crossref](#)]
185. Akos Lada, Diego Aparicio, Michael Bailey. 2018. Predicting Heterogeneous Treatment Effects in Ranking Systems. *SSRN Electronic Journal* . [[Crossref](#)]
186. Benjamin Bluhm. 2018. Time Series Econometrics at Scale: A Practical Guide to Parallel Computing in (Py)Spark. *SSRN Electronic Journal* . [[Crossref](#)]
187. Jack Blundell, Erling Risa. 2018. Do Rank-Rank Income Mobility Measures Fully Capture Broader Parental Influence on Child Income?. *SSRN Electronic Journal* . [[Crossref](#)]
188. Piotr Lityński. 2018. The Conceptualization of the Costs Projections of Metropolis' Space Dysfunctionality. *Journal of Economics and Management* **34**, 128-146. [[Crossref](#)]
189. Futoshi Narita, Rujun Yin. 2018. In Search of Information:. *IMF Working Papers* **18**:286, 1. [[Crossref](#)]
190. Frédéric Marty. 2017. Algorithmes de prix, intelligence artificielle et équilibres collusifs. *Revue internationale de droit économique* **t. XXXI**:2, 83-116. [[Crossref](#)]
191. George Garas, Isabella Cingolani, Pietro Panzarasa, Ara Darzi, Thanos Athanasiou. 2017. Network analysis of surgical innovation: Measuring value and the virality of diffusion in robotic surgery. *PLOS ONE* **12**:8, e0183332. [[Crossref](#)]
192. Miguel Paredes, Erik Hemberg, Una-May O'Reilly, Chris Zegras. Machine learning or discrete choice models for car ownership demand estimation and prediction? 780-785. [[Crossref](#)]
193. Sendhil Mullainathan, Ziad Obermeyer. 2017. Does Machine Learning Automate Moral Hazard and Error?. *American Economic Review* **107**:5, 476-480. [[Abstract](#)] [[View PDF article](#)] [[PDF with links](#)]
194. Susan Athey, Guido W. Imbens. 2017. The State of Applied Econometrics: Causality and Policy Evaluation. *Journal of Economic Perspectives* **31**:2, 3-32. [[Abstract](#)] [[View PDF article](#)] [[PDF with links](#)]
195. Sendhil Mullainathan, Jann Spiess. 2017. Machine Learning: An Applied Econometric Approach. *Journal of Economic Perspectives* **31**:2, 87-106. [[Abstract](#)] [[View PDF article](#)] [[PDF with links](#)]
196. Denzil G. Fiebig. 2017. Big Data: Will It Improve Patient-Centered Care?. *The Patient - Patient-Centered Outcomes Research* **10**:2, 133-139. [[Crossref](#)]
197. Susan Athey. 2017. Beyond prediction: Using big data for policy problems. *Science* **355**:6324, 483-485. [[Crossref](#)]
198. John Antonakis. 2017. On doing better science: From thrill of discovery to policy implications. *The Leadership Quarterly* **28**:1, 5-21. [[Crossref](#)]
199. Jongbin Jung, Connor Concannon, Ravi Shroff. 2017. Simple Rules for Complex Decisions. *SSRN Electronic Journal* . [[Crossref](#)]
200. Chiranjit Chakraborty, Andreas Joseph. 2017. Machine Learning at Central Banks. *SSRN Electronic Journal* . [[Crossref](#)]
201. Monica Andini, Emanuele Ciani, Guido de Blasio, Alessio D'Ignazio, Viola Salvestrini. 2017. Targeting Policy-Compliers with Machine Learning: An Application to a Tax Rebate Programme in Italy. *SSRN Electronic Journal* . [[Crossref](#)]

202. Daniel Martin Katz, Michael James Bommarito, Josh Blackman. 2017. Crowdsourcing Accurately and Robustly Predicts Supreme Court Decisions. *SSRN Electronic Journal* . [[Crossref](#)]
203. Wei Ai, Roy Chen, Yan Chen, Qiaozhu Mei, Webb Phillips. 2016. Recommending teams promotes prosocial lending in online microfinance. *Proceedings of the National Academy of Sciences* **113**:52, 14944-14948. [[Crossref](#)]
204. Nikolaos Askitas. 2016. Big Data is a big deal but how much data do we need?. *AStA Wirtschafts- und Sozialstatistisches Archiv* **10**:2-3, 113-125. [[Crossref](#)]
205. Ziad Obermeyer, Ezekiel J. Emanuel. 2016. Predicting the Future — Big Data, Machine Learning, and Clinical Medicine. *New England Journal of Medicine* **375**:13, 1216-1219. [[Crossref](#)]
206. Cyrus Samii. 2016. Causal Empiricism in Quantitative Research. *The Journal of Politics* **78**:3, 941-955. [[Crossref](#)]
207. Varun Rai, Adam Douglas Henry. 2016. Agent-based modelling of consumer energy choices. *Nature Climate Change* **6**:6, 556-562. [[Crossref](#)]
208. Aaron Chalfin, Oren Danieli, Andrew Hillis, Zubin Jelveh, Michael Luca, Jens Ludwig, Sendhil Mullainathan. 2016. Productivity and Selection of Human Capital with Machine Learning. *American Economic Review* **106**:5, 124-127. [[Abstract](#)] [[View PDF article](#)] [[PDF with links](#)]
209. Edward L. Glaeser, Scott Duke Kominers, Michael Luca, Nikhil Naik. 2015. Big Data and Big Cities: The Promises and Limitations of Improved Measures of Urban Life. *SSRN Electronic Journal* . [[Crossref](#)]
210. Edward L. Glaeser, Scott Duke Kominers, Michael Luca, Nikhil Naik. 2015. Big Data and Big Cities: The Promises and Limitations of Improved Measures for Urban Life. *SSRN Electronic Journal* . [[Crossref](#)]