Chapter 7:

Applications of Causal Economics to Real-World Decisions

7. Introduction

The chapter presents the core position of causal economics in facilitating informed and responsible decision-making in an incredibly broad field of domains in the real world. Knowledge of the reasons behind these different things and not just a correlation is required in formulating effective policies in the government, making good business choices, enhancing healthcare delivery, and in solving complicated environmental problems. The chapter introduces the role of causal inference between economic theory and action, noting its applicability in policy analysis, market policy, medical intervention, climatic reaction and moral government. In to achieve this base, it briefly provides the main empirical methodologies involved in the causal analysis such as the randomized experiments methodology, observational data techniques methodology, econometric model, and new AI-based simulations. The chapter then preludes the next chapters that dwell on the use of causal economics in policy making, business and industry, health care systems, environment and climate, ethics and causal research in the future.

7.1 Policy Design and Evaluation

This section describes how causal economics assists policymakers to establish the actual impacts of interventions as opposed to using correlations. It emphasizes the use of causal evidence in designing, evaluation, and innovation of effective public policies.

7.1.1 Welfare Programs

The measurement of the effectiveness of welfare programs is very difficult as the results are frequently affected by the selection bias, confounding socioeconomic variables and non-random participation and simple comparisons are misleading. To deal with these concerns causal economics may use more rigorous empirical designs, including Randomized Control Trials (RCTs) to compare treatment and control groups; Difference-in-Differences (DiD) to evaluate change in beneficiaries relative to non-beneficiaries; and Instrumental Variables (IV) to isolate exogenous variation in program participation [114]. Such methods have been popular in the assessment of welfare programs such as microfinance schemes and conditional cash transfer to establish whether any improved gains in income, education or health are due to the intervention itself. Causal diagrams are commonly used to explain the pathways by which welfare policies can have an effect and in determining possible confounders. At the core of this analysis is a counterfactual evaluation that causes one to pose a question on what would have happened to those beneficiaries without the program and in so doing all the policymakers can determine the real causal effects of the programs and not coincidental or spurious effects.

7.1.2 Education Reforms

Education reforms like class size reductions, curriculum reforms and teacher incentives programs are meant to increase the performance of the students, but the actual effectiveness of these reforms cannot be assessed without a serious causal analysis. To examine student performance through rich longitudinal records of schools and standardized test scores, researchers use these records to follow the performance of students across time and policy contexts. To ensure that causal effects are determined by differences between schools or students, some techniques like propensity score matching are employed to create similar treatment and control groups, whereas regression discontinuity designs use policy cutoffs or eligibility levels to determine credible causal effects [115]. These causal inference models enable the analysts to differentiate between the effects of reforms and confounding variables such as the socioeconomic background or the previous success. Based on these estimates, there is a tendency to use policy simulation to forecast how other reform designs or scaling options can affect educational outcomes and may thus be used to inform evidence-based decision-making in education policy.

7.2 Business and Industry Applications

This chapter illustrates how causal knowledge can help companies to realize the actual effect of strategic decisions of companies like pricing, marketing and product design. It demonstrates the benefits of causal analysis in enhancing decision-making by disentangling true and misleading effects.

7.2.1 Pricing Strategies

Pricing strategies are particularly important to business decision making where the causal analysis is used to identify the actual effects of price changes on consumer demand instead of just tracking correlated price-sales trends. The method of simple correlation based cannot be reliable since the prices tend to vary according to the demand conditions, competition or even the season and this creates endogeneity issues. The causal approach can avoid these traps by structural demand models, which explicitly model consumer preferences and firm behavior, and by using A/B testing in digital markets, where randomized price differentials permit firms to directly estimate causal behavioral responses of demand [116]. These methods are common in experiments of e-commerce dynamic pricing, allowing companies to experiment with alternative pricing policies, forecast changes in revenues, and optimize decision-making depending on the actual causal relationships, instead of correlative correlations.

7.2.2 Demand Forecasting with Causality

The incorporation of causality into demand forecasting increases its reliability because past correlations alone are not trusted as reliable tools used to forecast demand. With the inclusion of causal variables like the marketing campaigns, seasonality and competitor actions, the firms will be in a better position to understand how the demand is affected and how it will react to certain interventions. This is in contrast to classical time-series forecasting, which can tend to extrapolate historical trends without making a distinction between coincident relationships and true cause-and-effect relationships [117]. Causal modelling constructions Structural equation models and causal Bayesian networks allow an analyst to construct the underlying processes between business actions and demand consequences. In comparing the predicted demand with the actual demand in the causal adjustments, these models have better insight into the impact of strategic decisions on the future demand to further support the improved forecast and the improved planning by the managers.

7.3 Healthcare Economics

This part brings out the importance of causal reasoning in the assessment of medical treatments and health interventions to the population. It describes the use of causal evidence in supporting clinical effectiveness as well as cost-effective healthcare decisions.

7.3.1 Treatment Effectiveness

Causal analysis is a crucial part of healthcare economics because it is the only method of analyzing the effectiveness of a specific treatment and making sure that limited resources are utilized effectively. Treatment like pharmaceutical drugs, surgical procedures and health campaigns by the public should not be evaluated based on their apparent outcome but also on their actual causal effect on the patient health. Although the gold standard of estimating effects is that of Randomized Controlled Trial (RCTs), due to practical and ethical considerations, we may be compelled to use observational studies that require intensive correction to confounding factors. Average Treatment Effects (ATE) is estimated using methods like instrumental variables, propensity score matching, and other methods of causal inference with an explanation of the difference in outcomes due to that specific intervention [118]. The causal graphs are used to describe treatment-outcome pathways and determine the causes of bias. Based on these estimates, cost-effectiveness analysis integrates causal impact with economic expenditure to compare the alternative interventions so that the policymakers and healthcare providers can put a higher priority on treatments that offer the most health benefits at a given cost unit.

7.3.2 Cost-effectiveness Analysis

Cost-effectiveness analysis is the extension of causal assessment that explicitly connects causal health outcomes and economic costs of other interventions. Analysts compute the incremental cost-effectiveness ratio (ICER) using estimates based on causal techniques to estimate how much more it would cost to bring about one unit of incremental health benefit (a life-year saved or quality-adjusted life-year) of a treatment or policy change compared to the cost of a treatment or policy change [119]. Scenario modeling is instrumental in this process as it helps the researcher to model how a change in treatment protocols, pricing or coverage will alter their impact in the larger society under varying assumptions. Cost-effectiveness analysis can help make clear, evidence-based healthcare policy and resource allocation choices by visualizing the trade-offs between costs and effects, based on causal understanding and not mere associations.

7.4 Climate and Environmental Economics

This part uses the causal inference to evaluate the actual effect of environmental policies and climate measures. It demonstrates the role played by causal analysis in the design of sustainable policies and proper environmental control.

7.4.1 Policy Interventions

Policies and interventions of the environment and climate like taxation of carbon, clean energy subsidies, and urban planning policies are all meant to change the behavioral aspect of the economy by decreasing emissions and encouraging the economic factor to be more sustainable. Causal analysis plays a significant role in following the entire trail of policy intervention to behavioral response and ultimately to the environmental outcomes, including energy use change, transportation decisions, or pollution levels. Since these policies are not usually applied to fully controlled settings, researchers have turned to the econometric modeling of panel data to take advantage of cross-regional and time variation and synthetic control designs to estimate counterfactuals that are credible [120]. Causal inference by comparing pre and post implementation of policies with control regions appropriately selected can help decipher the actual environmental effect of climate policies as opposed to unrelated economic or technological trends.

7.4.2 Emission Control Strategies

The environmental externalities are focused on emission control techniques like industrial control, pollution permit technology and use of renewable energy technologies, but they have different levels of success depending on industries and geographical regions. Causal models allow policy-makers to measure the actual effect of each strategy, separating the component of the reduction of emissions that can be linked to particular interventions, and not to the overall economic or technological transformation. Multi-level modeling is also commonly employed to explain differences at the firm, industry and regional levels at the same time, in order to capture this complexity [121]. These methods enable the analyst to reveal non homogenous effects and distributional impacts in sectors. Emission cuts attributed to specific policies are also well-illustrated, increasing the level of interpretation, which can translate causal estimates into practical information useful in designing and improving environmental regulation.

7.5 Ethical and Social Implications

This part looks at the ethical and social issues surrounding the use of causal knowledge in policy and business decision-making. It focuses on equity, clarity, and responsibility in the process of causal analysis and their practical implications.

7.5.1 Fairness

In causal economics, fairness is an important ethical issue because biases during data collection, model specification, or interpretation may result in systematically unequal outcomes across social groups. Policy or business choices like credit scoring, hiring algorithms or welfare targeting may even strengthen existing inequities when causal models are constructed based on incomplete or biased data. The case of algorithmic decision-making can be used to demonstrate how poor causal assumptions can be used to make biased inferences even in cases where the models seem technically correct [122]. Causal analysis thus necessitates direct care towards equity through study of effects variance in groups and other effects through the test of conclusions strength. The fairness constraints, sensitivity analysis, and the clear consideration of the other causal assumptions are all the mitigation strategies that ensure the causal insights do not hinder the efficiency but also the ethicality and fairness of decision-making.

7.5.2 Transparency in Causal Decisions

Causal choices of the policy and business operations based on the analysis of various facts and data must be transparent to establish the credibility of the policy and business in the eyes of the population. Since causal conclusions are based on assumptions, selection of models, and interpretation of uncertainly, they should be discussed explicitly and not as technicalities. The explainable causal models make the stakeholders comprehend what decision is being made and the reasons why it is supported, and what could have happened under different conditions. Complex cause-effect relationships can also be made available to non-technical users without using technical tools, including visual causal diagrams, interpretable machine learning models, and causal explanation frameworks can also allow analysts to render counterfactual arguments in a transparent and comprehensible way [123]. Decisionmakers can also facilitate responsibility and active participation by publicly expressing assumptions, uncertainties and causal processes.

7.6 Future Directions

This part looks at new trends in causal economics, such as the use of AI and advanced simulation tools. It shows how new technologies are changing the way we do causal analysis and make decisions in the future.

7.6.1 AI and Causal Economics

Artificial intelligence and causal economics, which are becoming more and more integrated, are pushing the boundaries of data-driven decisions and making more advanced causal discovery and policy simulation possible. Machine learning methods can identify complicated causal models of high-dimensional data, and reinforcement learning enables the policymaker and companies to develop dynamic tactics that evolve with time in response to the observed results and feedback. As an example, AI-based systems of resource allocation may be used to jointly use causal models and real-time data to optimize the allocation of public funds, healthcare resources, or energy supply in various policy scenarios. Nevertheless, the following issues are also emerging with these advances: low interpretability of highly complex models, apprehension of instability when applied to dynamic settings, and the necessity to introduce ethical limitations to guarantee responsible and equitable decisions.

7.6.2 Automated Policy Simulation

This section summarizes an automation of the policy, with no human contribution, using the automated policy simulator software. The automated policy simulation is a significant technological milestone of causal economics since it provides the possibility to simulate policy decisions in real-time using digital twins and predictive simulation systems. With a combination of structural causal models and AI, policymakers will be able to experiment with various policies, including taxation, subsidies, or regulation before enforcing them and see how they are likely to result under different assumptions. These systems have a defined workflow whereby data inputs are processed through a causal model which produces forecasted outcomes of policy, after which they are used to inform a feedback loop where decisions are updated as new data is made available to us. This would enable the process of policy experimentation to be conducted safely, cost-effectively, and adaptively to minimize the use of trial and error in the real world without compromising the accuracy and responsiveness of economic policymaking.

Table 7.1: Applications and Implications of Causal Economics Across Sectors

Domain	Key Applications	Causal Methods & Tools	Core Insights & Outcomes
Public Policy	Welfare programs, education reforms	RCTs, DiD, IV, PSM, RDD, causal diagrams	Identifies true policy impacts using counterfactual reasoning
Social Protection	Microfinance, conditional cash transfers	RCTs, DiD, IV, causal graphs	Separates program effects from selection bias and confounders
Education Policy	Class size, curriculum, teacher incentives	PSM, regression discontinuity, simulations	Enables evidence-based reform design and scaling
Business Strategy	Pricing, marketing, product design	Causal modeling frameworks	Improves strategic decisions by avoiding spurious correlations
Pricing & Revenue	Dynamic pricing, demand response	Structural demand models, A/B testing	Accurately estimates causal price–demand relationships
Forecasting	Marketing effects, competition, seasonality	SEMs, causal Bayesian networks	Produces reliable forecasts grounded in causal mechanisms
Health Policy	Treatment evaluation, resource allocation	RCTs, IVs, PSM, causal graphs	Supports clinically effective and cost-efficient decisions
Medical Interventions	Drugs, surgery, public health campaigns	ATE estimation, causal diagrams	Distinguishes true treatment effects from confounding
Health Economics	Cost–benefit comparison of interventions	ICER, scenario modeling	Guides optimal allocation of healthcare resources
Environment	Climate policy, emission regulation	Panel data, synthetic control, causal models	Evaluates real environmental impact of policies
Climate Policy	Carbon taxes, clean energy subsidies	Econometric panel models, SCM	Traces policy → behavior → emissions pathways
Regulation	Industrial limits, permits, renewables	Multi-level causal modeling	Quantifies sector- and region-specific effects

Ethics & Governance	Fairness, accountability	Sensitivity analysis, fairness constraints	Ensures ethical use of causal insights
Equity	Algorithmic decisions, policy targeting	Bias analysis, subgroup causal effects	Prevents reinforcement of social inequalities
Public Trust	Explainable decision-making	Interpretable ML, causal diagrams	Builds trust through clear communication of assumptions
Innovation	AI integration, automation	AI-driven causal frameworks	Expands scope and scalability of causal analysis
AI & Policy	Resource allocation, adaptive strategies	ML, reinforcement learning, SCMs	Enhances dynamic, data-driven decision-making
Policy Innovation	Digital twins, real-time evaluation	Structural causal models + AI	Enables safe, scalable, and cost-effective experimentation

7.7 Final Chapter Conclusion

This chapter has shown that causal economics can be used as an umbrella concept of making informed decisions in various fields, such as as a part of policy, business strategy, healthcare, environmental management, and governance ethics. Causal analysis has been advanced to be beyond prediction by using classical statistical reasoning, econometric techniques and AI-based models to interpret how and why results vary in the presence of a particular intervention. With such a promise, however, there are still considerable research issues, especially with data quality and availability, model choice and identifiability, and the ethics of increasingly automated causal decision systems. Moving forward, the future of data science is in integrating the causal inference into the large and real-time decision-making processes and providing transparent and accountable methodologies. This vision will entail an interdisciplinary approach that includes economics, statistics, artificial intelligence, and the social sciences to make the causal insights scientifically sound and socially useful.

References:

[1] Lo, V. S., & Pachamanova, D. A. (2023). From meaningful data science to impactful decisions: The importance of being causally prescriptive. Data Science Journal, 22(1).

[2] Heckman, J. J., & Pinto, R. (2022). The econometric model for causal policy analysis. Annual review of economics, 14(1), 893-923.

[3] Lamsaf, A., Carrilho, R., Neves, J. C., & Proença, H. (2025). Causality, machine learning, and feature selection: a survey. Sensors, 25(8), 2373.

[4] Cox Jr, L. A. (2024). Objective causal predictions from observational data. Critical Reviews in Toxicology, 54(10), 895-924.

[5] Ahrens, A., Aitken, C., & Schaffer, M. E. (2020). Using machine learning methods to support causal inference in econometrics. In Behavioral predictive modeling in economics (pp. 23-52). Cham: Springer International Publishing.

[6] Horton, A. (2024). Causal Economic Machine Learning (CEML):" Human AI". AI, 5(4).

[7] Wyrembek, M., Baryannis, G., & Brintrup, A. (2025). Causal machine learning for supply chain risk prediction and intervention planning. International Journal of Production Research, 1-20.

[8] Pichler, M., & Hartig, F. (2023). Can predictive models be used for causal inference?. arXiv preprint arXiv:2306.10551.

[9] Renero, J., Ochoa, I., & Maestre, R. (2025). REX: Causal Discovery based on Machine Learning and Explainability techniques. arXiv preprint arXiv:2501.12706.

[10] Baiardi, A., & Naghi, A. A. (2024). The value added of machine learning to causal inference: Evidence from revisited studies. The Econometrics Journal, 27(2), 213-234.

[11] Ghouse, G., Rehman, A. U., & Bhatti, M. I. (2024). Understanding of causes of spurious associations: Problems and prospects. Journal of Statistical Theory and Applications, 23(1), 44-66.

[12] Dong, Z., Cai, W., & Zhao, S. (2024). Simpson's paradox beyond confounding. European Journal for Philosophy of Science, 14(3), 44.

[13] Busetti, S. (2023). Causality is good for practice: policy design and reverse engineering. Policy Sciences, 56(2), 419-438.

[14] Zawadzki, R. S., Grill, J. D., Gillen, D. L., & for the Alzheimer's Disease Neuroimaging Initiative. (2023). Frameworks for estimating causal effects in observational settings: comparing confounder adjustment and instrumental variables. BMC Medical Research Methodology, 23(1), 122.

[15] Abécassis, J., Dumas, É., Alberge, J., & Varoquaux, G. (2025). From prediction to prescription: Machine learning and Causal Inference. Annual Review of Biomedical Data Science.

[16] Zhang, J., Jennings, J., Hilmkil, A., Pawlowski, N., Zhang, C., & Ma, C. (2023). Towards causal foundation model: on duality between causal inference and attention. arXiv preprint arXiv:2310.00809.

[17] Yu, Y., & Xu, A. (2025). Bridging Structural Causal Inference and Machine Learning The S-DIDML Estimator for Heterogeneous Treatment Effects. arXiv preprint arXiv:2507.09718.

[18] Deng, Z., Tian, H., Zheng, X., & Zeng, D. D. (2025). Deep causal learning: representation, discovery and inference. ACM Computing Surveys, 58(2), 1-36.

[19] Shmueli, G., Martens, D., Yoo, J., & Greene, T. (2025). From What Ifs to Insights: Counterfactuals in Causal Inference vs. Explainable AI. arXiv preprint arXiv:2505.13324.

[20] Rawal, A., Raglin, A., Rawat, D. B., Sadler, B. M., & McCoy, J. (2025). Causality for trustworthy artificial intelligence: status, challenges and perspectives. ACM Computing Surveys, 57(6), 1-30.

[21] Heckman, J., & Pinto, R. (2024). Econometric causality: The central role of thought experiments. Journal of econometrics, 243(1-2), 105719.

[22] Wang, A. Z., Borland, D., & Gotz, D. (2024). An empirical study of counterfactual visualization to support visual causal inference. Information Visualization, 23(2), 197-214.

[23] Imbens, G. W. (2024). Causal inference in the social sciences. Annual Review of Statistics and Its Application, 11.

[24] Han, K., Wu, H., Wu, L., Shi, Y., & Liu, C. (2024). Estimating treatment effects using observational data and experimental data with non-overlapping support. Econometrics, 12(3), 26.

[25] Du, J., Shi, X., Zeng, D., & Mukherjee, B. (2024). Doubly robust causal inference through penalized bias-reduced estimation: combining non-probability samples with designed surveys. arXiv preprint arXiv:2403.18039.

[26] Cerqua, A., Letta, M., & Menchetti, F. (2024). Causal inference and policy evaluation without a control group.

[27] Sert, G., Chakrabortty, A., & Bhattacharya, A. (2025). Bayesian semiparametric causal inference: Targeted doubly robust estimation of treatment effects. arXiv preprint arXiv:2511.15904.

[28] Chen, Y., Phillips, P. C., & Shi, S. (2025). Bubble Mitigation Policies: Counterfactual Analysis and Treatment Effect Inference. Available at SSRN 5195264.

[29] Wang, E. (2024). Structural counterfactual analysis in macroeconomics: theory and inference. Available at SSRN 4956650.

[30] Babilla, T. U. K. (2023). Tax policy reform and universal basic income effectiveness in a currency union: Implications for long-term growth, inequality, and welfare. Journal of Government and Economics, 10, 100075.

[31] Peprah, E., Ocansey, E. O., & Asirifi, E. K. (2025). ECONOMIC IMPACT OF TAX REFORMS IN DEVELOPING ECONOMIES: ANALYZING GROWTH, INEQUALITIES, REVENUE, AND POLICY MODERATORS.

[32] Imbens, G., Kallus, N., Mao, X., & Wang, Y. (2025). Long-term causal inference under persistent confounding via data combination. Journal of the Royal Statistical Society Series B: Statistical Methodology, 87(2), 362-388.

[33] Wu, Y., Markham, A., Wang, L., Solus, L., & Ma, Z. (2025). Data-driven causal behaviour modelling from trajectory data: A case for fare incentives in public transport. Journal of Public Transportation, 27, 100114.

[34] Zhang, Q., Wang, W., She, J., & Ma, Z. (2025). Understanding bus network delay propagation: Integration of causal inference and complex network theory. Journal of Transport Geography, 123, 104098.

[35] Keller, B., & Branson, Z. (2024). Defining, identifying, and estimating causal effects with the potential outcomes framework: a review for education research. Asia Pacific Education Review, 25(3), 575-594.

[36] Byrnes, J. E., & Dee, L. E. (2025). Causal inference with observational data and unobserved confounding variables. Ecology Letters, 28(1), e70023.

[37] Benz, L., Levis, A. W., & Haneuse, S. (2025). Comparing causal inference methods for point exposures with missing confounders: a simulation study. BMC Medical Research Methodology, 25(1), 222.

[38] Heng, S., Zhang, J., & Feng, Y. (2025). Design-Based Causal Inference with Missing Outcomes: Missingness Mechanisms, Imputation-Assisted Randomization Tests, and Covariate Adjustment. Journal of the American Statistical Association, (just-accepted), 1-23.

[39] Lee, S. Y. T., Roys, N. A., & Seshadri, A. (2024). The causal effect of parents' education on children's earnings (No. w32223). National Bureau of Economic Research.

[40] Tennant, P. W., Arnold, K. F., Ellison, G. T., & Gilthorpe, M. S. (2022). Analyses of 'change scores' do not estimate causal effects in observational data. International journal of epidemiology, 51(5), 1604-1615.

[41] Greenland, S. (2022). The causal foundations of applied probability and statistics. In *Probabilistic and causal inference: The works of Judea Pearl* (pp. 605-624).

[42] Pearl, J. (2022). Probabilities of causation: three counterfactual interpretations and their identification. In *Probabilistic and causal inference: the works of Judea Pearl* (pp. 317-372).

[43] Mediano, P. A., Rosas, F. E., Luppi, A. I., Jensen, H. J., Seth, A. K., Barrett, A. B., ... & Bor, D. (2022). Greater than the parts: a review of the information decomposition approach to causal emergence. *Philosophical Transactions of the Royal Society A*, *380*(2227), 20210246.

[44] Hünermund, P., & Louw, B. (2025). On the nuisance of control variables in causal regression analysis. *Organizational Research Methods*, *28*(1), 138-151.

[45] Dul, J. (2024). A different causal perspective with Necessary Condition Analysis. *Journal of Business Research*, *177*, 114618.

[46] Du, Y., & Gui, W. (2022). Statistical inference of adaptive type II progressive hybrid censored data with dependent competing risks under bivariate exponential distribution. *Journal of Applied Statistics*, *49*(12), 3120-3140.

[47] Sindhu, T. N., Shafiq, A., & Huassian, Z. (2024). Generalized exponentiated unit Gompertz distribution for modeling arthritic pain relief times data: classical approach to statistical inference. *Journal of Biopharmaceutical Statistics*, *34*(3), 323-348.

[48] Arkes, J. (2023). *Regression analysis: a practical introduction*. Routledge.

[49] Tyagi, K., Rane, C., & Manry, M. (2022). Regression analysis. In *Artificial intelligence and machine learning for EDGE computing* (pp. 53-63). Academic Press.

[50] Hünermund, P., & Bareinboim, E. (2025). Causal inference and data fusion in econometrics. *The Econometrics Journal*, *28*(1), 41-82.

[51] Imbens, G. W. (2022). Causality in econometrics: Choice vs chance. *Econometrica*, *90*(6), 2541-2566.

[52] Celli, V. (2022). Causal mediation analysis in economics: Objectives, assumptions, models. *Journal of Economic Surveys*, *36*(1), 214-234.

[53] Hünermund, P., & Bareinboim, E. (2025). Causal inference and data fusion in econometrics. *The Econometrics Journal*, *28*(1), 41-82.

[54] Plagborg-Møller, M., & Wolf, C. K. (2022). Instrumental variable identification of dynamic variance decompositions. *Journal of Political Economy*, *130*(8), 2164-2202.

[55] Berry, S. T., & Compiani, G. (2023). An instrumental variable approach to dynamic models. *The Review of Economic Studies*, *90*(4), 1724-1758.

[56] Arkhangelsky, D., & Imbens, G. (2024). Causal models for longitudinal and panel data: A survey. *The Econometrics Journal*, *27*(3), C1-C61.

[57] Klosin, S. (2025). *High-Dimensional Statistics for Causal Inference and Panel Data* (Doctoral dissertation, Massachusetts Institute of Technology).

[58] Imai, K., Kim, I. S., & Wang, E. H. (2023). Matching methods for causal inference with time-series cross-sectional data. *American Journal of Political Science*, *67*(3), 587-605.

[59] Sheehan, P., Kwon, M., & Steiner, P. M. (2024, September). *Quasi-experimental designs for causal inference: Addressing threats to validity from a graphical models perspective*.

[60] Kuś, A. (2024). Using quasi-experimental designs for causal effects. *Zeszyty Naukowe. Organizacja i Zarządzanie/Politechnika Śląska*, (194), 217-232.

[61] Orsi, R., Mouchart, M., & Wunsch, G. (2022). Causality in Econometric Modeling: FromTheory to Structural Causal Modeling. *Journal of Econometrics and Statistics*, *2*(1), 61-90.

[62] Heckman, J. J., & Pinto, R. (2022). The econometric model for causal policy analysis. *Annual review of economics*, *14*(1), 893-923.

[63] Garg, P., & Fetzer, T. (2025). Causal claims in economics. *arXiv preprint arXiv:2501.06873*.

[64] Liu, H., Wong, W. K., Cong, P. T., Nassani, A. A., Haffar, M., & Abu-Rumman, A. (2023). Linkage among Urbanization, energy Consumption, economic growth and carbon Emissions. Panel data analysis for China using ARDL model. *Fuel*, *332*, 126122.

[65] Arif, S., & MacNeil, M. A. (2023). Applying the structural causal model framework for observational causal inference in ecology. *Ecological Monographs*, *93*(1), e1554.

[66] Zhou, X., & Yamamoto, T. (2023). Tracing causal paths from experimental and observational data. *The Journal of Politics*, *85*(1), 250-265.

[67] Baetu, T. M. (2022). The virtues and limitations of randomized experiments. *Acta Analytica*, *37*(4), 453-470.

[68] Chalfin, A., Hansen, B., Lerner, J., & Parker, L. (2022). Reducing crime through environmental design: Evidence from a randomized experiment of street lighting in New York City. *Journal of Quantitative Criminology*, *38*(1), 127-157.

[69] Hernán, M. A., Wang, W., & Leaf, D. E. (2022). Target trial emulation: a framework for causal inference from observational data. *Jama*, *328*(24), 2446-2447.

[70] Liu, F., & Panagiotakos, D. (2022). Real-world data: a brief review of the methods, applications, challenges and opportunities. *BMC Medical Research Methodology*, *22*(1), 287.

[71] Feng, Y. (2024). Introduction to causal graphs for education researchers. *Asia Pacific Education Review*, *25*(3), 595-609.

[72] Digitale, J. C., Martin, J. N., & Glymour, M. M. (2022). Tutorial on directed acyclic graphs. *Journal of Clinical Epidemiology*, *142*, 264-267.

[73] Younas, A., & Inayat, S. (2025). Understanding and Managing Confounders, Mediators and Colliders in Research. *Journal of Evaluation in Clinical Practice*, *31*(7), e70298.

[74] Van Cauwenberg, J., De Paepe, A., & Poppe, L. (2023). Lost without a cause: time to embrace causal thinking using Directed Acyclic Graphs (DAGs). *International Journal of Behavioral Nutrition and Physical Activity*, *20*(1), 145.

[75] Qi, X., Xie, T., Li, Y., Mahloujifar, S., & Mittal, P. (2023). Revisiting the assumption of latent separability for backdoor defenses. In *The eleventh international conference on learning representations*.

[76] Bellemare, M. F., Bloem, J. R., & Wexler, N. (2024). The Paper of How: Estimating Treatment Effects Using the Front-Door Criterion. *Oxford Bulletin of Economics and Statistics*, *86*(4), 951-993.

[77] Kenig, B. Enumerating Optimal Cost-Constrained Adjustment Sets. In *The 41st Conference on Uncertainty in Artificial Intelligence*.

[78] Kurz, C. F., Krzywinski, M., & Altman, N. (2024). Propensity score matching.

[79] Kurz, C. F. (2022). Augmented inverse probability weighting and the double robustness property. *Medical Decision Making*, *42*(2), 156-167.

[80] Heng, S., & Kang, H. (2024). Generalized rosenbaum bounds sensitivity analysis for matched observational studies with treatment doses: Sufficiency, consistency, and efficiency. *arXiv preprint arXiv:2403.14152*.

[81] Borde, H. S. D. O., Kratsios, A., Law, M. T., Dong, X., & Bronstein, M. (2024). Neural Spacetimes for DAG Representation Learning. *arXiv preprint arXiv:2408.13885*.

[82] Ramkumar, N., Iribarne, A., Olmstead, E. M., Malenka, D. J., & Mackenzie, T. A. (2024). Why are we weighting? Understanding the estimates from propensity score weighting and matching methods. *Circulation: Cardiovascular Quality and Outcomes*, *17*(1), e007803.

[83] Borgonovo, E. (2023). Sensitivity analysis. *Tutorials in operations research: Advancing the frontiers of OR/MS: From methodologies to applications*, 52-81.

[84] Doutreligne, M., & Varoquaux, G. (2025). How to select predictive models for decision-making or causal inference. *GigaScience*, *14*, giaf016.

[85] Kern, C., Fischer-Abaigar, U., Schweisthal, J., Frauen, D., Ghani, R., Feuerriegel, S., ... & Kreuter, F. (2025). Algorithms for reliable decision-making need causal reasoning. *Nature Computational Science*, *5*(5), 356-360.

[86] Lin, L., Sperrin, M., Jenkins, D. A., Martin, G. P., & Peek, N. (2021). A scoping review of causal methods enabling predictions under hypothetical interventions. *Diagnostic and prognostic research*, *5*(1), 3.

[87] Athey, S., & Wager, S. (2021). Policy learning with observational data. *Econometrica*, *89*(1), 133-161.

[88] Zahid, A., Kamiran, F., Abbas, S., Qureshi, B., & Karim, A. (2025). Data-Driven Uplift Modeling. *IEEE Access*.

[89] Hünermund, P., & Bareinboim, E. (2025). Causal inference and data fusion in econometrics. *The Econometrics Journal*, *28*(1), 41-82.

[90] Jaroszewicz, S. (2024). Class flipping for uplift modeling and Heterogeneous Treatment Effect estimation on imbalanced RCT data. *arXiv preprint arXiv:2412.10009*.

[91] Xu, D., Yao, D., Lachapelle, S., Taslakian, P., Von Kügelgen, J., Locatello, F., & Magliacane, S. (2024). A sparsity principle for partially observable causal representation learning. *arXiv preprint arXiv:2403.08335*.

[92] Gnecco, N., Terefe, E. M., & Engelke, S. (2024). Extremal random forests. *Journal of the American Statistical Association*, *119*(548), 3059-3072.

[93] Nie, X., & Wager, S. (2021). Quasi-oracle estimation of heterogeneous treatment effects. *Biometrika*, *108*(2), 299-319.

[94] Li, L., Wei, K., Han, J., & Zhu, Y. (2025). Digital empowerment and the development resilience in rural households: causal inference based on double machine learning. *Empirical Economics*, 1-41.

[95] Athey, S., & Wager, S. (2021). Policy learning with observational data. *Econometrica*, *89*(1), 133-161.

[96] Harrison, C. (2024). Personalized Treatment Recommendations for Diabetes Patients.

[97] Dubé, J. P., & Misra, S. (2023). Personalized pricing and consumer welfare. *Journal of Political Economy*, *131*(1), 131-189.

[98] Kallus, N. (2022). What's the harm? sharp bounds on the fraction negatively affected by treatment. *Advances in Neural Information Processing Systems*, *35*, 15996-16009.

[99] Bottmer, L., Imbens, G. W., Spiess, J., & Warnick, M. (2024). A design-based perspective on synthetic control methods. *Journal of Business & Economic Statistics*, *42*(2), 762-773.

[100] Rudner, T. G., Pong, V., McAllister, R., Gal, Y., & Levine, S. (2021). Outcome-driven reinforcement learning via variational inference. *Advances in Neural Information Processing Systems*, *34*, 13045-13058.

[101] Orlova, E. V. (2023). Inference of factors for labor productivity growth used randomized experiment and statistical causality. *Mathematics*, *11*(4), 863.

[102] Lawes, M., West, S. G., & Eid, M. (2025). A guide to causal inference in life-event studies. *Advances in Methods and Practices in Psychological Science*, *8*(1), 25152459241302015.

[103] Shojaie, A., & Fox, E. B. (2022). Granger causality: A review and recent advances. Annual Review of Statistics and Its Application, 9(1), 289-319.

[104] Dufour, J. M., & Wang, E. (2025). Causal mechanism and mediation analysis for macroeconomics dynamics: a bridge of Granger and Sims causality. arXiv preprint arXiv:2509.05284.

[105] Nazlioglu, S., & Karul, C. (2024). Testing for Granger causality in heterogeneous panels with cross-sectional dependence. Empirical Economics, 67(4), 1541-1579.

[106] Arkhangelsky, D., & Imbens, G. (2024). Causal models for longitudinal and panel data: A survey. The Econometrics Journal, 27(3), C1-C61.

[107] Dávila-Fernández, M. J., & Oreiro, J. L. (2023). Competitiveness and dynamic cumulative causation in an export-led growing economy. Industrial and Corporate Change, 32(2), 522-550.

[108] Cyrek, M. (2024). Structural change and economic growth: Causality relationships in the case of Poland. Equilibrium. Quarterly Journal of Economics and Economic Policy, 19(3), 841-869.

[109] Alola, A. A., Adebayo, T. S., & Onifade, S. T. (2022). Examining the dynamics of ecological footprint in China with spectral Granger causality and quantile-on-quantile approaches. International Journal of Sustainable Development & World Ecology, 29(3), 263-276.

[110] Xu, X., & Zhang, Y. (2023). House price information flows among some major Chinese cities: linear and nonlinear causality in time and frequency domains. International Journal of Housing Markets and Analysis, 16(6), 1168-1192.

[111] Shahbaz, M., Balcilar, M., Mahalik, M. K., & Akadiri, S. S. (2023). Is causality between globalization and energy consumption bidirectional or unidirectional in top and bottom globalized economies?. International Journal of Finance & Economics, 28(2), 1939-1964.

[112] Xu, X., & Zhang, Y. (2023). Contemporaneous causality among residential housing prices of ten major Chinese cities. International Journal of Housing Markets and Analysis, 16(4), 792-811.

[113] Elsayed, A. H., Gozgor, G., & Lau, C. K. M. (2022). Causality and dynamic spillovers among cryptocurrencies and currency markets. International Journal of Finance & Economics, 27(2), 2026-2040.

[114] Oladele, O. K. (2024). Causal Inference in Machine Learning: From Counterfactuals to Real-World Decision Systems.

[115] Muralidharan, K., Niehaus, P., & Sukhtankar, S. (2025). Identity verification standards in welfare programs: Experimental evidence from India. *Review of Economics and Statistics*, *107*(2), 372-392.

[116] Yu, H., & Guo, Y. (2023, June). Generative artificial intelligence empowers educational reform: current status, issues, and prospects. In *Frontiers in Education* (Vol. 8, p. 1183162). Frontiers Media SA.

[117] Cakranegara, P. A., Kurniadi, W., Sampe, F., Pangemanan, J., & Yusuf, M. (2022). The impact of goods product pricing strategies on consumer purchasing power: a review of the literature. *Jurnal Ekonomi*, *11*(03), 1115-1120.

[118] Wang, Y., Ding, G., Zeng, Z., & Yang, S. (2025). Causal-Aware Multimodal Transformer for Supply Chain Demand Forecasting: Integrating Text, Time Series, and Satellite Imagery. *IEEE Access*.

[119] Pauley, D., Cuijpers, P., Papola, D., Miguel, C., & Karyotaki, E. (2023). Two decades of digital interventions for anxiety disorders: a systematic review and meta-analysis of treatment effectiveness. *Psychological Medicine*, *53*(2), 567-579.

[120] Brent, R. J. (2023). Cost-benefit analysis versus cost-effectiveness analysis from a societal perspective in healthcare. *International Journal of Environmental Research and Public Health*, *20*(5), 4637.

[121] De La Iglesia Martinez, A., & Labib, S. M. (2023). Demystifying normalized difference vegetation index (NDVI) for greenness exposure assessments and policy interventions in urban greening. *Environmental research*, *220*, 115155.

[122] Awewomom, J., Dzeble, F., Takyi, Y. D., Ashie, W. B., Ettey, E. N. Y. O., Afua, P. E., ... & Akoto, O. (2024). Addressing global environmental pollution using environmental control techniques: a focus on environmental policy and preventive environmental management. *Discover Environment*, *2*(1), 8.

[123] Plecko, D., & Bareinboim, E. (2023). Causal fairness for outcome control. *Advances in Neural Information Processing Systems*, *36*, 47575-47597.