International Academic Institute for Science and Technology

International Academic Journal of Economics
Vol. 13, No. 3, 2026, pp. 46-53.

ISSN 2454-2474

International Academic Journal of Economics

www.iaiest.com

Economic Policy Optimization Using Data-Driven Decision Models

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Abstract

Policymaking in economics will always require an efficient way of handling data that is large in size and complexity in order to deal with the new trends in economics. There may be some challenges in applying traditional ways of making decisions on economic policies in case the economic environment becomes dynamic and interrelated. This study has looked at the possibility of using decision models based on data in optimizing economic policies in terms of incorporating data collection, data processing, predictive evaluation, policy evaluation, and decision support. A qualitative and conceptual research method has been used in the study based on the analysis of the related literature on data analytics, economic decision-making, predictive modeling, policy evaluation, and evidence-based governance. The suggested perspective considered the ways in which economic data could be used to create insights into policy alternatives, economic impact estimation, resource allocation, and economic risks. It was found that economic data models, when applied together with relevant institutional capacity and decision-making, could make economic policy decision-making processes more transparent, efficient, evidence-based, and adaptive. At the same time, data availability, quality issues, privacy, the reliability of models, institutional capacity, and algorithmic bias might have some influence on how effectively such solutions might work. Thus, the suggested perspective included an integrated approach in which economic data-driven decision models could enhance economic policy development, implementation, monitoring, and evaluation.

Keywords: Economic Policy Optimization, Data-Driven Decision-Making, Predictive Analytics, Evidence-Based Policy, Economic Modeling, Policy Simulation, Data Analytics.

DOI: 10.71086/IAJE/V13I3/IAJE1321
Received: 26 June 2026/Revised: 11 July 2026/Accepted: 21 August 2026/Published: 30 September 2026

Introduction

Emergence of Data-Driven Economic Policy Decision-Making

There have been increasing efforts in using huge amounts of economic, financial, demographic, social and administrative data in making decisions in economic policy. Governments create information on employment, inflation, production, consumption, trading, investments, government spending, taxes, and domestic circumstances. Digitalization has enabled the use of such data in the analysis of economic conditions and policymaking through the use of empirical evidence in economic decision-making (Einav & Levin, 2014). There have also been changes in how the relationships between economic variables are analyzed in the field of data-driven economics. In the past, such analysis was mainly done based on structured datasets and conventional econometric models.

The modern environment, however, has seen the development of high-frequency, unstructured, and alternative data. Big data and computing tools have made it possible to identify patterns and measure economic events through timely policy analysis (Varian, 2014). The availability of digital information has extended the scope of data that can be used in economic policy analysis. Unstructured data like texts and news have played a great role in creating knowledge on economic expectations and market sentiments. The use of such data as measurable variables has improved data-driven economic analysis (Gentzkow et al., 2019).

Role of Data Analytics in Economic Policy Formulation

Data analytics is one of the tools that can help turn economic data into policy-relevant insights. Economic data usually contain many relationships, tendencies, variations, and interactions that cannot be uncovered through the means of descriptive analysis only. Analytical and computational tools can assist in examining economic trends and tendencies, relationships, and changes, which will extend the set of analytical tools for policymakers (Athey & Imbens, 2019). Econometric and machine learning techniques can also aid in predicting, classifying, selecting variables, and recognizing patterns in particular cases of analysis of large and complicated datasets. Moreover, the use of such approaches does not substitute but complements economic reasoning since it allows policymakers to have more empirical evidence. Data analytics can also make policymaking processes more flexible because of the possibility to engage in continuous analysis and not conduct periodic analysis of the economy. Data analytics can help track the economic performance of the country or region, spot deviations from the expected situation, and provide necessary information for policy evaluation and resource allocation processes.

Predictive Analytics and Economic Decision Support

Predictive analytics has become ever more pertinent for economic policymaking due to the fact that decision-makers need to predict future situations rather than react to events that occurred in the past. Inflation, employment, growth rate, demand, and investment forecasts can provide helpful insights in assessing policy reactions. Prediction involves modeling based on historical and actual data on the patterns and potential future outcomes (Athey & Imbens, 2019). Nevertheless, an accurate prediction does not imply the right action to implement by policymakers. They should consider other policy alternatives, their consequences, limitations, and policy aims. Thus, prediction-based policymaking should include the direct link between predictions and actions (Kleinberg et al., 2015). Thus, predictive analytics can become a part of decision-support systems based on economic data, forecasts, policy goals, and scenario analysis. It will allow for comparing alternatives and adapting to economic uncertainty. Nonetheless, predictive analytics becomes one part of the wider policy decision-making process.

Research Problem, Research Gap, Objectives, and Significance

However, such decisions are usually made under conditions of uncertainty, changing market conditions, scarcity of resources, and conflicting economic interests. Decision-makers can have large amounts of economic data available to them, but the presence of the data does not necessarily guarantee the successful transformation of the data into effective decision-making. Limited availability of the data, complex analysis required, the changing nature of the economy, as well as the challenges of evaluating different policy alternatives, make it difficult for decision-making to be effective. It is thus necessary to develop an integrated approach linking data collection, data analysis, forecasting, economic modeling, policy analysis, and decision-making in a unified policy optimization process.

The gap in the research is that the existing literature lacks an integrated approach to the use of economic forecasting, machine learning, data analytics, and evaluation to enhance economic policy optimization. The current research fills this gap by linking data gathering, prediction, policy simulation, implementation, monitoring, and feedback within the decision-making process. The objectives of the current study are to propose a conceptual framework on how to use data-driven decision models in economic policy optimization. These data analytics, economic modeling, prediction, policy simulation, evidence-based decision-making, and feedback are integrated into the proposed framework.

Literature Review

Data-Driven Decision-Making in Economic Policy

Data-driven approaches in the development of economic policy have become increasingly necessary because of the impact that many interconnected aspects have on the economic environment and the rapid changes that may occur in it. Uncertainty in policies can occur due to changes in the fiscal environment, monetary policy, politics, economic environment abroad, and other causes. Policy economic uncertainty can be calculated via some systematic indicators that measure the uncertainty regarding government policy and its implications on the economy (Baker et al., 2016). Analysis of the persistence and cross-country features of economic policy uncertainty will be helpful for making better decisions regarding policies (Abakah et al., 2021). Economic policy uncertainty can have short- and long-term effects that affect economic expectations and the decision-making environment. Various economic and institutional factors can cause differences in uncertainty over time and across countries.

A data-driven policy system can include uncertainty indicators in the analytical process and allow taking into account a changing environment when analyzing different policy options. Knowledge of the variation is important for creating flexible decision models (Duca & Saving, 2018). The approach of data-driven decision-making could thus form the backbone of systematic monitoring of the economic state, as well as identification of the associated risks and evaluation of the potential measures to be adopted. Instead of using the economic data only as a historical record, decision-makers can employ a sophisticated system for continuous analysis and comparison of different courses of action.

Predictive Analytics and Economic Forecasting

Predictive analytics forms an essential component of contemporary economic decision-making, given that economic policies often depend on forecasts of future results. Machine learning algorithms may be employed in order to detect patterns and make predictions based on high-dimensional data sets. Their use in the field of economics has broadened the arsenal of methodologies for studying economic phenomena and making forecasts (Belloni et al., 2014). Alternatively, machine learning may be used alongside traditional econometric techniques to offer predictive analysis when the relationship between variables is complicated (Mullainathan & Spiess, 2017). Moreover, machine learning and econometrics may be helpful in solving issues of treatment and structural effects when regular methods fail to work in the setting of high-dimensional data. For instance, double/debiased machine learning is one of the ways of using machine learning combined with statistical inference despite certain problems of complex models and many variables (Chernozhukov et al., 2018).

A growing body of recent studies looks at the use of machine learning in economic policymaking. Machine learning can be used in policymaking to predict events, evaluate counterfactual scenarios, target policies, and compare alternatives. Its relevance not only depends on prediction accuracy but also on the link between predictions and policymaking goals. Hence, predictive analytics is an element of a larger policymaking process in which forecasts are used to inform the choice of policy alternatives (Haghighi et al., 2025).

Economic Modeling, Policy Simulation, and Scenario Analysis

Economic modeling offers a formal method to represent the interrelations between economic variables and assess possible consequences of the implementation of certain policies. Economic models, together with data-driven analysis tools, allow for testing alternative policies under various assumptions. High-dimensional analysis techniques can improve the capability to identify the structural and causal relations, which can serve as the basis for economic policy evaluation (Belloni et al., 2014). Policy simulation goes further in the direction of using predictions for assessing the impact of certain policy measures. Prediction-based policymaking allows connecting the forecasts of the future development of events with alternative policy actions and their consequences.

The problem is that policymakers, when making decisions about what should be done in certain situations, are not only interested in forecasting possible developments but also in identifying the action that can lead to better results in a particular case. Machine learning-based policy optimization can be helpful in developing the framework for choosing policy interventions (Battiston et al., 2024). The application of economic modeling, forecasting, and simulation will enable a scenario where various policies will be evaluated prior to the adoption of a policy measure. This may involve the Integration of economic goals, constraints, uncertainties, and forecasting the likely impacts. This process will help in policy optimization through evaluation of alternative policies which meet the established economic goals. Comparison of the forecasted and actual results will enhance future policymaking efforts.

Evidence-Based Policy, Data Analytics, Challenges, and Research Gap

The practice of evidence-based policy is becoming increasingly reliant upon the capability of public bodies to convert large volumes of diverse data into actionable policy knowledge. Several key themes have been discovered in research concerning the role of big data analytics in decision-making. Such developments suggest that a system of data-driven policymaking can help formulate, implement, monitor, and evaluate policies if adequate analytical and institutional capacity is present (Suominen & Hajikhani, 2021). However, several issues arise when attempting to conduct data-driven optimization of economic policy. Economic policy datasets can vary according to their quality, completeness, timeliness, structure, and accessibility. Moreover, predictive models may yield unreliable outcomes when dealing with incomplete data sets or if the correlations identified in historical data fail to hold. Finally, the economic policy environment can be affected by various types of uncertainty, structural changes, institutional constraints, or other unforeseen circumstances. Ensemble learning and other modern approaches show promise in the analysis and forecasting of economic policy uncertainty, yet their methodology and reliability pose some issues (Lolić et al., 2022).

Research Gap: While the extant literature offers rich insights into data analytics, machine learning, economic forecasts, policy uncertainty, and forecasting-based policy analysis, each of these concepts is usually considered individually and as a method or analytical component in its own right. In conceptual terms, there is a need for an integration of these concepts into a single framework encompassing the process of gathering and processing economic data, conducting predictive analytics, modeling of economics, policy simulation, policy optimization, implementation of policy decisions, and providing feedback. This research attempts to fill this void with an introduction of the conceptual model of Economic Policy Optimization Using Data-Driven Decision Models.

Methodology

Research Design, Literature Selection, and Secondary Data Sources

The study utilized a qualitative and conceptual research design aimed at analyzing the role of data-driven decision models in economic policy optimization. There were no surveys, interviews, experiments, and hypothesis testing used. It utilized a synthesis of the academic literature devoted to the issues of data-driven decision-making, economic analytics, predictive modeling, machine learning, economic forecasting, policy simulation, and evidence-based policymaking. The conceptual research design was chosen since it would allow synthesizing the concepts and integrating them into a model of economic policy optimization. The relevant academic literature was chosen and analyzed in the following themes: economic data management, analytical preparation, predictive analytics, economic modeling, policy impact assessment, policy simulation, optimization, and decision support. Special attention was paid to the literature on machine learning, economic forecasting, policy uncertainty, prediction-based policies, and big data analytics. The literature was synthesized in order to reveal the connections between data input, analysis, policymaking, evaluation, and decision-making in order to provide a conceptual framework for the transformation of economic data into policy insight.

Thematic Analysis and Development of the Data-Driven Economic Policy Framework

Thematic analysis was carried out for the purpose of finding common themes and relations among the chosen literature. The thematic analysis centered on the dimensions linked to data-driven optimization of economic policy, namely economic data collection and Integration, data processing, predictive analytics, economic forecasting, economic modeling, policy impact assessment, policy simulation, scenario evaluation, decision-making support, and policy monitoring. The dimensions were classified depending on the roles they play in the process of policymaking. The framework was formulated in accordance with the themes found during the analysis as a set of interrelated steps rather than analytical processes. It starts with the economic data collection and Integration from various sources, then data processing and preparation for analysis take place. Economic modeling and forecasting of the future economic state are carried out to estimate the future economic state. The next stage consists of policy simulation and scenario analysis, and policy optimization and decision-making follow that. It is through these stages that alternative policies are compared based on economic objectives and outcomes. Lastly, the process of monitoring and feedback of policy helps link the policy implementation process with the evaluation stage.

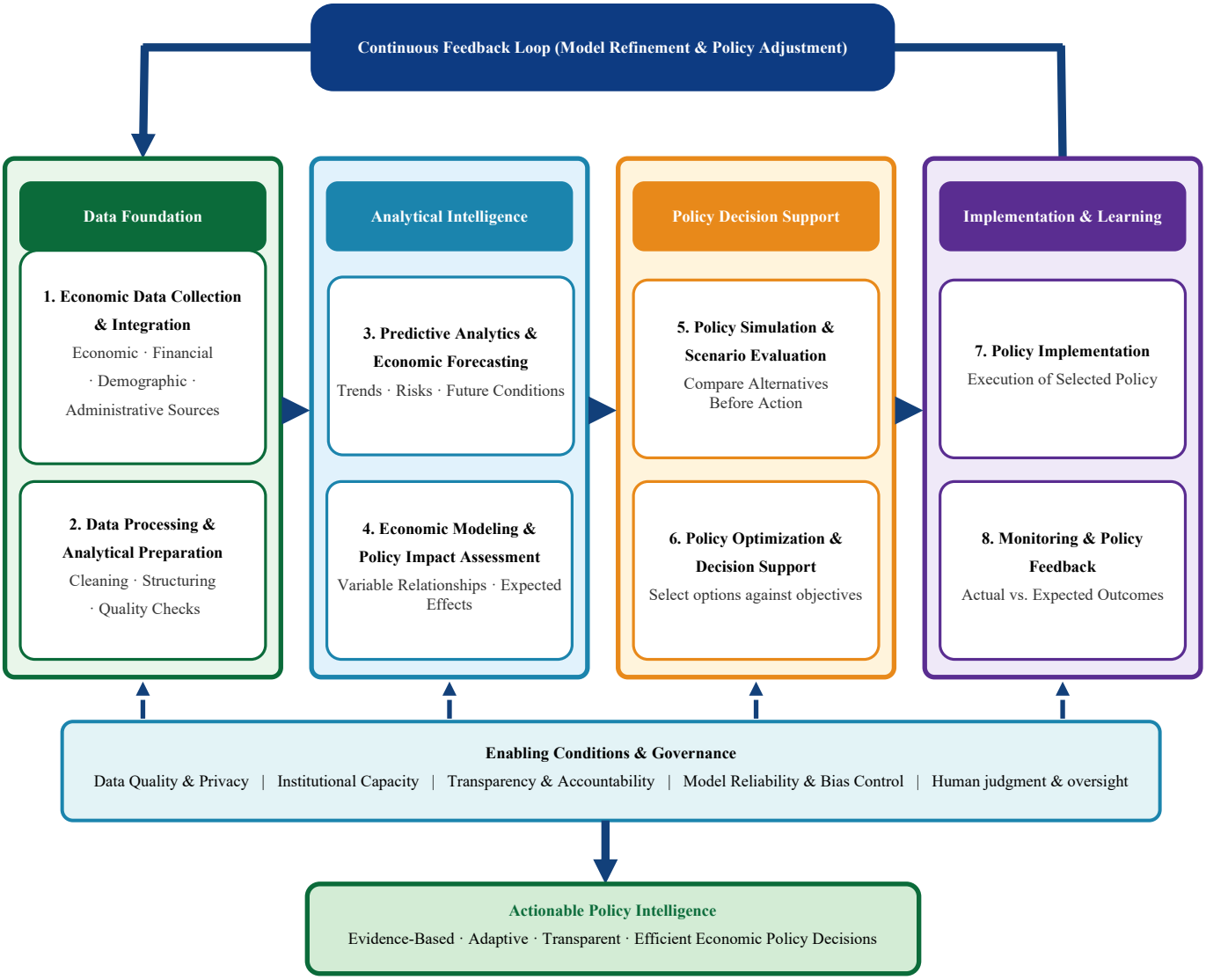


Fig. 1: Data-Driven Economic Policy Optimization Architecture

Figure 1 above shows the suggested architecture for optimizing economic policies using data. The diagram shows the process from economic data collection and preparation to predictive analysis, economic modeling, policy simulation, decision-making, implementation, and monitoring. The feedback loop stresses the iterative aspect of economic policymaking, whereby the outcome of the policy may feed into further analysis and policy improvements.

Conceptual Evaluation and Interpretation

Conceptual evaluation of the framework was conducted through an analysis of the logical interrelationships between its key elements and their contribution to economic policy optimization. In particular, the assessment took into account whether the sequence of such steps as data collection, analysis preparation, prediction, modeling, simulation, decision-making, and feedback represented a reasonable structure for converting economic information into policy intelligence. At the same time, it was considered the connection between the results of predictive analysis and decision-making since the latter cannot be viewed as optimization of policymaking solely based on analytical predictions. Furthermore, the framework was analyzed taking into account its ability to provide evidence for economic policymaking, its adaptiveness, and its informed nature. Data-based models can help decision-makers to understand economic patterns, predict developments, compare various scenarios of policymaking, and evaluate their consequences prior to policy adoption. At the same time, the framework understands the necessity of considering such factors as objectives of economic policy, capabilities, limitations, uncertainties, and judgment in the evaluation of model outputs.

Lastly, the conceptual approach underscores the need for continuous monitoring and feedback. Economic circumstances may vary even after the implementation of a certain policy, and hence, the success of such a policy cannot always be predicted from initial estimations only. Monitoring of actual results compared to anticipated results may give information to further adjust the policy and fine-tune the model. The methodology thus led to the formation of an integrated conceptual framework that links the following elements: economic data gathering, preparatory analysis, forecasting, economic modeling, policy analysis, optimization, decision-making, implementation, monitoring, and feedback.

Findings and Discussion

Data-Driven Economic Policy Optimization and Decision Support

According to the conceptual analysis, data integration, economic data, analytical processing, predictive analytics, economic modeling, and policy evaluation were the components for the optimization of economic policy decisions. The Integration of diverse data regarding the economic, financial, demographic, administrative, and market conditions could give better insights into the state of the economy, its trends, and risks. Predictive analytics would be helpful for economic forecasting and anticipation of economic events. When used along with economic modeling and policy simulations, the predictive outputs would allow assessment of the possible effects of the policies and comparison of the various intervention options. The results of the analysis also revealed that the decision support systems based on data analytics would enable effective evaluation of policy decisions using objectives, resources, risks, expectations, impacts, and other considerations. Therefore, data analytics and predictive models were useful means for enhancing human decision-making, not the full replacement of policymakers.

Table 1: Key Dimensions of Data-Driven Economic Policy Optimization

Dimension	Key Elements	Role in Policy Decision-Making	Expected Contribution
Data Collection & Integration	Economic, Financial, Demographic, Administrative, Market Data	Provides Evidence for Analysis	Better Understanding of Economic Conditions
Data Processing & Preparation	Cleaning, Structuring, Quality Checks	Improves Data Reliability	Higher-Quality Analytical Inputs
Predictive Analytics & Forecasting	Trends, Forecasting, Risk Prediction	Anticipates Future Conditions	Early Identification of Risks and Opportunities
Economic Modeling & Impact Assessment	Economic Relationships, Effects, Objectives, Constraints	Evaluates Policy Consequences	Better Understanding of Policy Impacts
Policy Simulation & Scenario Evaluation	Alternative Policies, Scenarios, Outcome Comparison	Compares Options Before Implementation	More Informed Policy Choices
Policy Optimization & Decision Support	Policy Selection, Resource Allocation, Human Judgment	Aligns Choices with Economic Objectives	Evidence-Based and Efficient Decisions
Policy Implementation	Execution, Coordination, Resource Deployment	Converts Decisions into Action	Improved Policy Implementation
Monitoring & Feedback	Outcomes, Evaluation, Model Refinement	Supports Policy Adjustment	Adaptive Policymaking
Governance & Enabling Conditions	Privacy, Transparency, Accountability, Oversight	Ensures Responsible Model Use	Greater Reliability and Trust

As can be seen in table 1, which provides a summary of the key dimensions discovered via conceptual analysis, each dimension is involved in the data-driven process of economic policy optimization in its own way. Thus, policy optimization is not based solely on forecasting capabilities, but also involves such aspects as data quality, economic modeling, policy simulation, implementation, monitoring, governance, and human involvement.

Policy Effectiveness, Challenges, Governance, and Implementation Implications

Conceptually, there is an indication that the effectiveness of policies can be increased through the use of data-driven methods throughout the policy process. Continuous monitoring allows policymakers to evaluate differences between actual and expected results, make necessary improvements, enhance analysis models, and make better decisions in the future. This helps in creating an adaptive policymaking environment that can cope with changes in economic conditions. Nevertheless, there are issues regarding data availability, quality, timeliness, consistency, uncertainty, reliability of models, economic relations, etc., that might influence the policy effects. Proper implementation of such

policies also demands sufficient technical and analytical capacities, skills, as well as collaboration among organizations. It should be understood that effective governance plays an important role in optimizing economic policy based on data analysis. Transparency, responsibility, data security, evaluation of models, human judgment, and institutions can facilitate proper implementation of the proposed framework.

Conclusion and Future Directions

Summary of Conceptual Findings, Contributions, and Implications

The research paper was devoted to the role of the application of data-driven decision models in improving economic policy optimization. The conceptual model revealed economic data integration, preparation, predictive analytics, economic modeling, policy simulation, decision support, and monitoring as the crucial elements of the integrated approach to policy optimization. The framework presented by the researchers showed the way to connect the above-mentioned elements to transform economic data into policy intelligence. Hence, the paper provided a conceptual perspective on the issue of using data-driven analysis in evidence-based economic policymaking. The results obtained in the course of the research showed that the data-driven approach can help policymakers detect economic trends and forecast future economic development. The connection between predictive intelligence, economic modeling, and policy simulation can provide the systematic foundation for comparing different interventions. However, it is important to mention that analytical outputs have to be interpreted taking into account economic goals, institutional capacity, policy constraints, and uncertainty. The theoretical contribution of the study is its incorporation of several phases of analysis into a single perspective on economic policy optimization. The proposed framework brings together the use of data analysis, forecasting, modeling, and policy simulation in one decision-making process for economic policies, which may prove helpful to policymakers and governmental organizations as well as to economists and researchers.

Limitations and Future Research Directions

Since the framework was conceptual and based on academic secondary literature, the proposed model cannot be empirically tested in the present study because there were no governmental datasets, policies, or measures used. As a result, the framework is conceptual, and it offers an explanation of the possible relations between the capabilities to analyze the data in order to optimize economic policies. Moreover, the framework may be affected by many factors, such as differences in institutions, availability of the data, economic structure, technological capability, or goals of the policy.

Further research can empirically analyze the proposed framework, using real economic datasets and policy examples. For example, quantitative research may focus on finding out whether the combination of predictive analytics, economic modeling, and policy simulations leads to the improvement of forecasting ability, efficiency of the policies, resource allocation, or economic performance. Comparative research may focus on analyzing the possibility of using the framework in different countries, economic sectors, and institutional settings. Moreover, further research may deal with artificial intelligence, economic monitoring in real time, scenario analysis automation, explanation of models, and human-AI cooperation.

References

Abakah, E. J. A., Caporale, G. M., & Gil-Alana, L. A. (2021). Economic policy uncertainty: Persistence and cross-country linkages. *Research in International Business and Finance*, *58*, 101442. https://doi.org/10.1016/j.ribaf.2021.101442

Athey, S., & Imbens, G. W. (2019). Machine learning methods that economists should know about. *Annual review of economics*, *11*(1), 685-725. https://doi.org/10.1146/annurev-economics-080217-053433

Baker, S. R., Bloom, N., & Davis, S. J. (2016). Measuring economic policy uncertainty. *The quarterly journal of economics*, *131*(4), 1593-1636. https://doi.org/10.1093/qje/qjw024

Battiston, P., Gamba, S., & Santoro, A. (2024). Machine learning and the optimization of prediction-based policies. *Technological Forecasting and Social Change*, *199*, 123080. https://doi.org/10.1016/j.techfore.2023.123080

Belloni, A., Chernozhukov, V., & Hansen, C. (2014). High-dimensional methods and inference on structural and treatment effects. *Journal of Economic Perspectives*, *28*(2), 29-50. https://doi.org/10.1257/jep.28.2.29

Chernozhukov, V., Chetverikov, D., Demirer, M., Duflo, E., Hansen, C., Newey, W., & Robins, J. (2018). Double/debiased machine learning for treatment and structural parameters. *The Econometrics Journal, 21*(1), C1–C68. https://doi.org/10.1111/ectj.12097

Duca, J. V., & Saving, J. L. (2018). What drives economic policy uncertainty in the long and short runs: European and US evidence over several decades. *Journal of Macroeconomics*, *55*, 128-145. https://doi.org/10.1016/j.jmacro.2017.09.002

Einav, L., & Levin, J. (2014). The data revolution and economic analysis. *Innovation policy and the economy*, *14*(1), 1-24. https://doi.org/10.1086/674019

Gentzkow, M., Kelly, B., & Taddy, M. (2019). Text as data. *Journal of Economic Literature*, *57*(3), 535-574. https://doi.org/10.1257/jel.20181020

Haghighi, M., Joseph, A., Kapetanios, G., Kurz, C., Lenza, M., & Marcucci, J. (2025). Machine learning for economic policy. *Journal of Econometrics*, *249*, 105970. https://doi.org/10.1016/j.jeconom.2025.105970

Kleinberg, J., Ludwig, J., Mullainathan, S., & Obermeyer, Z. (2015). Prediction policy problems. *American Economic Review*, *105*(5), 491-495. https://doi.org/10.1257/aer.p20151023

Lolić, I., Sorić, P., & Logarušić, M. (2022). Economic policy uncertainty index meets ensemble learning. *Computational Economics*, *60*(2), 401-437. https://doi.org/10.1007/s10614-021-10153-2

Mullainathan, S., & Spiess, J. (2017). Machine learning: An applied econometric approach. *Journal of economic perspectives*, *31*(2), 87-106. https://doi.org/10.1257/jep.31.2.87

Suominen, A., & Hajikhani, A. (2021). Research themes in big data analytics for policymaking: Insights from a mixed-methods systematic literature review. *Policy & Internet*, *13*(4), 464-484. https://doi.org/10.1002/poi3.258

Varian, H. R. (2014). Big data: New tricks for econometrics. *Journal of economic perspectives*, *28*(2), 3-28. https://doi.org/10.1257/jep.28.2.3