
Uncertainty quantification and robust decision-making

A transdisciplinary research program

Eisenhauer & al. (2021)

May 19, 2021

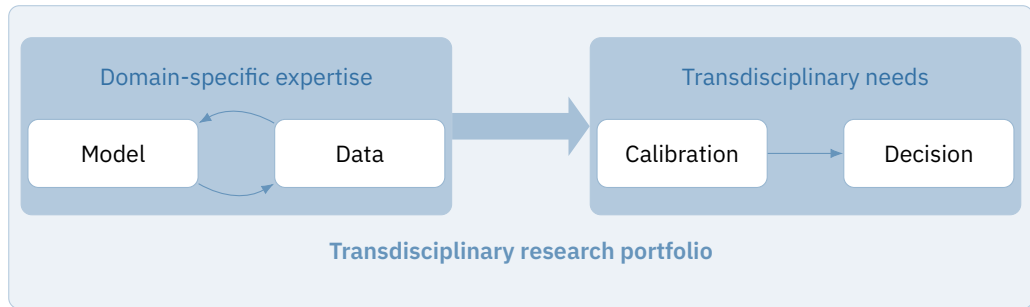


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Economics

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Transdisciplinary research approach



- **Epidemiologists** guide public mitigation efforts in the current pandemic by predicting the effect of social distancing rules on the disease's spread.
- Economists evaluate alternative welfare programs and forecast their impact on inequality in a variety of economic outcomes.
- Financial institutions manage their capital requirements by conducting stress tests about their business viability under adverse market conditions.

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Computational models

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⇒ **Uncertainty pervades**

Components of our analysis

- **Uncertainty quantification** is a systematic attempt to characterize, manage, and reduce uncertainty.
- Robust decision-making seeks to identify potential robust strategies in light of uncertainty, characterize the vulnerabilities of such strategies, and evaluate trade-offs among them.
- Statistical decision theory is concerned with the making of decisions when in the presence of data which sheds light on some of the uncertainties involved in the decision problem.

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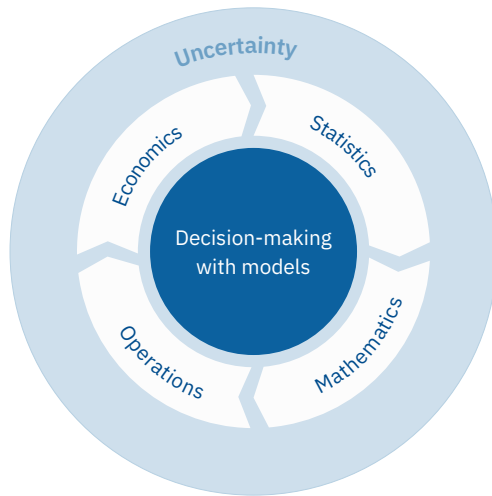
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Decision-making with models

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Setup

Computational model

$$\mathbb{R}^n \supset \boldsymbol{\theta} \ni \boldsymbol{\theta} \mapsto \mathcal{M}(\boldsymbol{\theta}) = y$$

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Notation

\mathcal{M} mapping under status-quo

\mathcal{M}_g mapping under action g

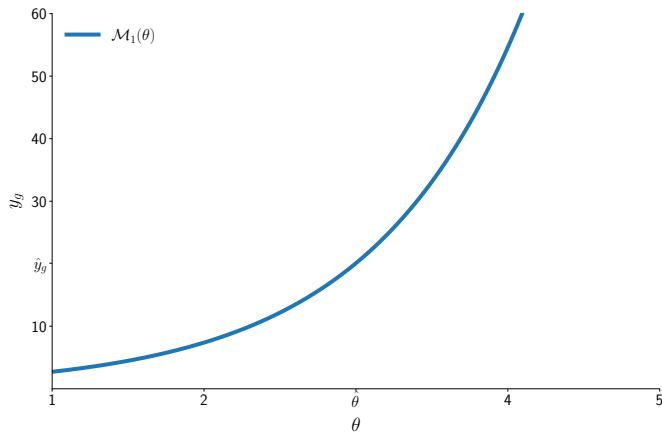
$\boldsymbol{\theta}_0$ true parameter

y quantity of interest

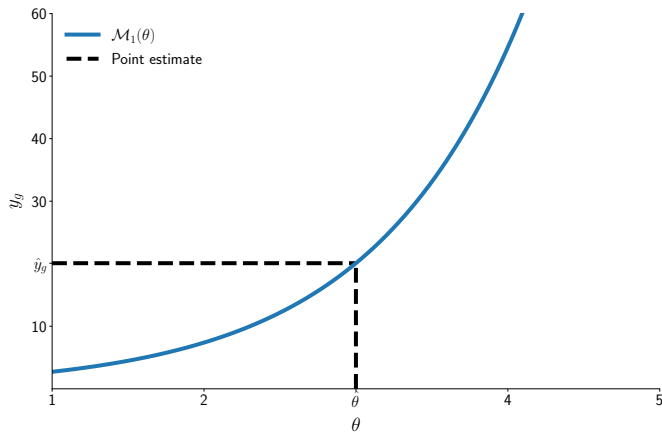
$\hat{\boldsymbol{\theta}}$ estimated parameter

$\boldsymbol{\theta}(\alpha)$ confidence set with coverage $1 - \alpha$

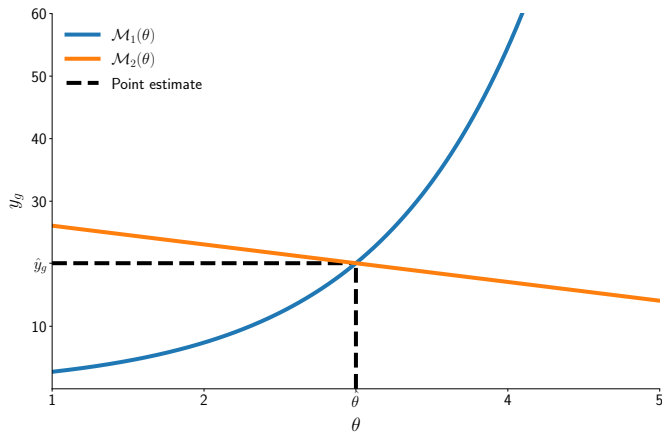
Comparing actions



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Embracing statistical decision theory

- Promote a well-reasoned and transparent decision-making process
- Clarify trade-off between actions
- Facilitate communication of uncertainty



Abraham Wald

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⇒ **Conceptually simple, computationally challenging**



Abraham Wald

Decision-theoretic framework

As-if decisions with point estimates

- As-if optimization $g^* = \arg \max_{g \in \mathcal{G}} U(M_g(\hat{\theta}))$

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Decision-theoretic framework

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As-if decisions with set estimates

- Maximin criterion
- Minimax regret rule
- Subjective Bayes

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- Subjective Bayes

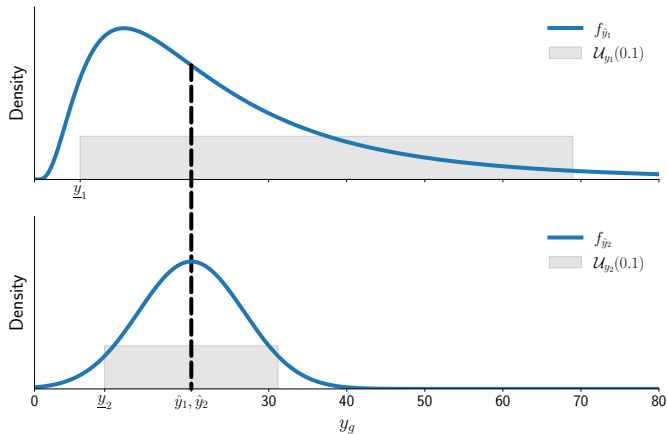
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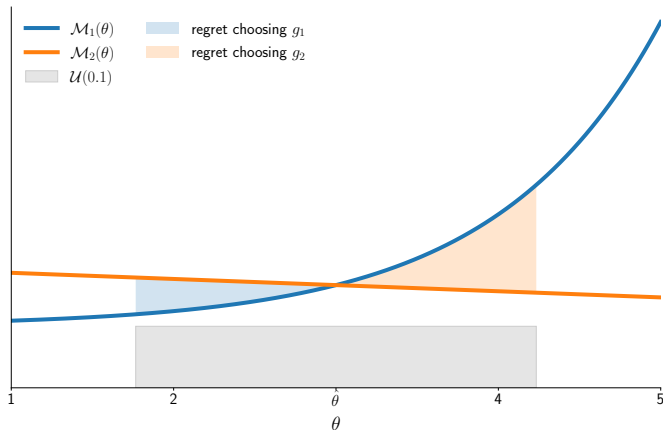
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- Subjective Bayes $g^* = \arg \max_{g \in \mathcal{G}} \int_{\mathcal{U}(\alpha)} U(M_g(\theta)) \, d\mathbf{f}(\theta)$

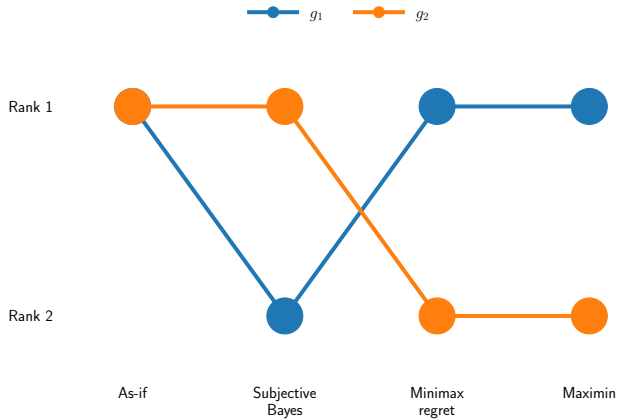
Comparing actions



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Conclusion



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- **Develop** a coupled epidemiological-economic model focusing on uncertainties
- Reach out to practitioners using models to inform decision-making
 - Private sector
 - European Central Bank
- Strengthen institutional foundation of research group
- Publish of first batch of working papers

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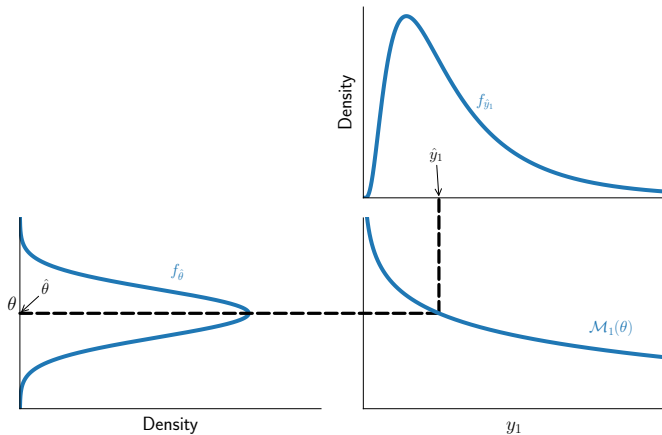
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Appendix

Propagating uncertainty



Counterfactual Policy Evaluation

- Counterfactuals to answer "what-if" questions.
- Attribute cause and effect between interventions and outcomes.
- Especially difficult in scenarios where we can't conduct randomized experiments.

Examples

- How would universal basic income on a national scale affect labor supply?
- What would the earth climate look like if more climate action was taken?
- How do compulsory schooling laws affect educational attainment of youths?

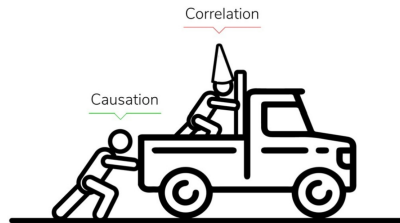
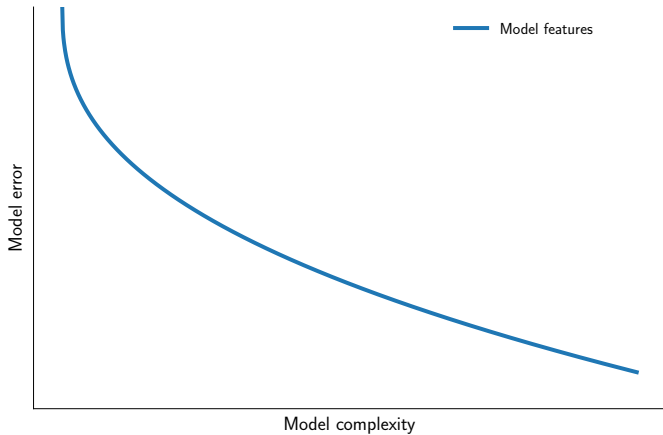
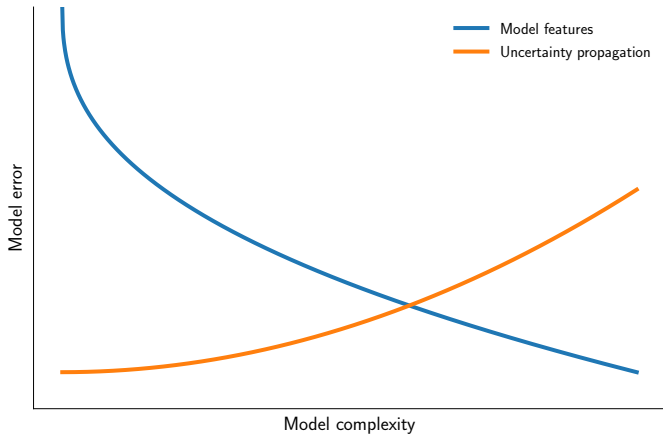


Figure 1. Source: Madhavan (2021)

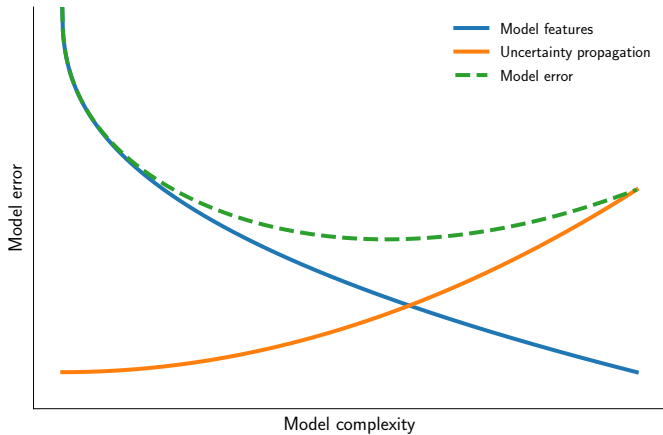
Price of complexity



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OSE data science

We teach methods of causal analysis and expose students to the Python data science ecosystem. We emphasize the use of simulation experiments and reproducible workflows.

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OSE scientific computing

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- Cloud-hosted
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- Complete environments
- Scalable workflows

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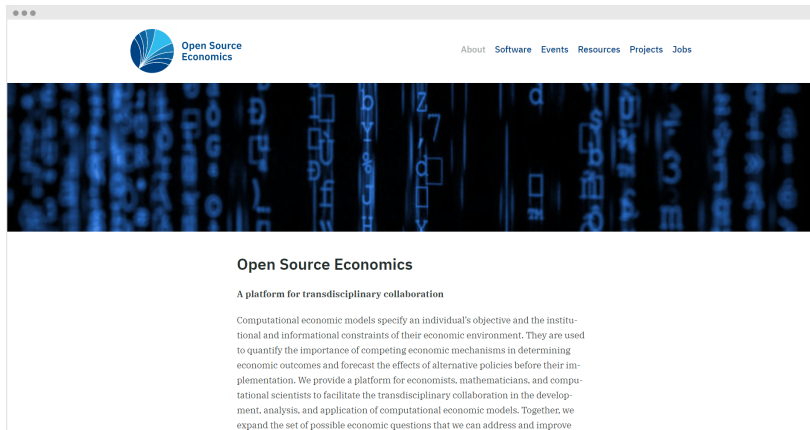
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Structural models for policy-making*

Coping with parametric uncertainty

Philipp Eisenhauer & Janos Gabler & Lena Janys

University of Bonn

April 16, 2021

arXiv:2103.01115v2 [econ.EM] 15 Apr 2021

The ex-ante evaluation of policies using structural econometric models is based on estimated parameters as a stand-in for the truth. This practice ignores uncertainty in the counterfactual policy predictions of the model. We develop a generic approach that deals with parametric uncertainty using uncertainty sets and frames model-informed policy-making as a decision problem under uncertainty. The seminal human capital investment model by *Kennedy and Wolpin (1997)* provides us with a well-known, influential, and empirically-grounded test case. We document considerable uncertainty in their policy predictions and highlight the resulting policy recommendations from using different formal rules on decision-making under uncertainty.

*Corresponding author: Philipp Eisenhauer, peisenh@uni-bonn.de. Philipp Eisenhauer and Lena Janys are both funded by the Deutsche Forschungsgemeinschaft (DFG, German Research Foundation) under Germany's Excellence Strategy - EXC 2125/1 - 390838866 and the TRA Modeling (University of Bonn) as part of the Excellence Strategy of the federal and state governments. Janos Gabler is grateful for financial support by the German Research Foundation (DFG) through CRC-TR 221 (Project C01) and funding by IZA Institute of Labor Economics. Lena Janys is funded by the Deutsche Forschungsgemeinschaft (DFG, German Research Foundation) under Germany's Excellence Strategy - EXC 2125/1 - 390838866. Philipp Eisenhauer was funded by a postdoctoral fellowship by the AXA Research Fund. We thank Tim Menzinger for his help in the early stages of the project. We thank Max Borch, Janina Freyberger, Anika Gakke, David Hamann, Kim Judd, Gergor Reisk, Jörg Storr, and Rafael Suckale for numerous helpful discussions. We thank Michael Kenane and Kenneth Wolpin for providing the dataset used in our analysis. We thank Anika Gakke for her outstanding research assistance. We are grateful to the Social Sciences Computing Service (SSCS) at the University of Chicago for the permission to use their computational resources. Eisenhauer: University of Bonn, peisenh@uni-bonn.de; Gabler: University of Bonn and IZA, janos.gabler@uni-bonn.de; Janys: University of Bonn, janys@uni-bonn.de.

Robust decision-making under risk and ambiguity*

Maximilian Bosch¹ and Philipp Eisenhauer²

¹Berlin School of Economics

²University of Bonn

April 23, 2021

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Economists often estimate a subset of their model parameters outside the model and let the decision-makers inside the model treat these point estimates as-if they are correct. This practice ignores model ambiguity and opens the door for model misspecification and post-decision disappointment. We develop a framework to explore and evaluate decision rules that explicitly account for the uncertainty in the first step estimation and assess their performance in a decision-theoretic setting. We show how to operationalize our analysis by studying a stochastic dynamic investment model where the decision-maker takes ambiguity about the model's transition dynamics directly into account.

JEL Codes D81, C44, D25

Keywords decision-making under uncertainty, robust Markov decision process

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