Uncertainty quantification and robust decision-making

A transdisciplinary research program

Eisenhauer & al. (2021)

April 20, 2021

Open Source Economics

Uncertainty quantification and robust decision-making

Computational models

- **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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$\Rightarrow$ **Uncertainty pervades**

Uncertainty quantification and robust decision-making

- **Uncertainty quantification** is a systematic attempt to characterize, manage, and reduce uncertainty.
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Economics

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- interesting questions
- administrative data sources
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Structural econometric model

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Setup

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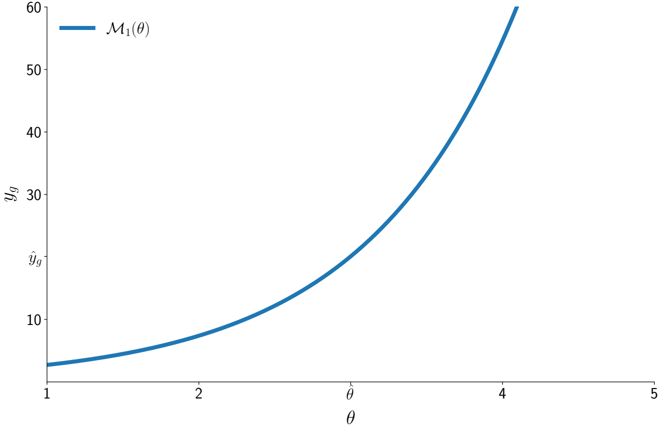
Notation

$\mathscr{M}$	mapping under status-quo	y	quantity of interest
$\mathscr{M}_g$	mapping under policy g	$\hat{\boldsymbol{\vartheta}}$	estimated parameter
$\boldsymbol{\vartheta}_0$	true parameter	$\boldsymbol{\Theta}(\alpha)$	confidence set with coverage $1-\alpha$

Comparing models



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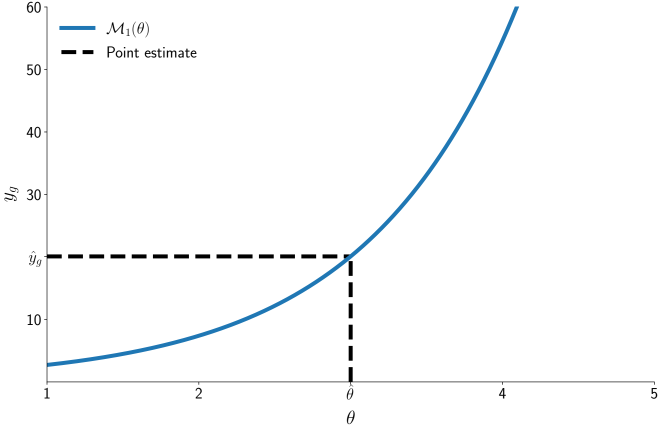

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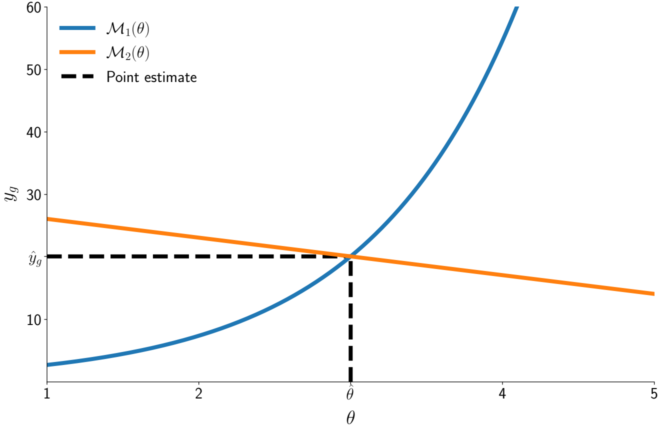

Embracing statistical decision theory

- promote a well-reasoned and transparent policy process
- clarify trade-off between alternatives
- facilitate communication of uncertainty

Decision-theoretic framework

As-if decisions with point estimates

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

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- Subjective Bayes

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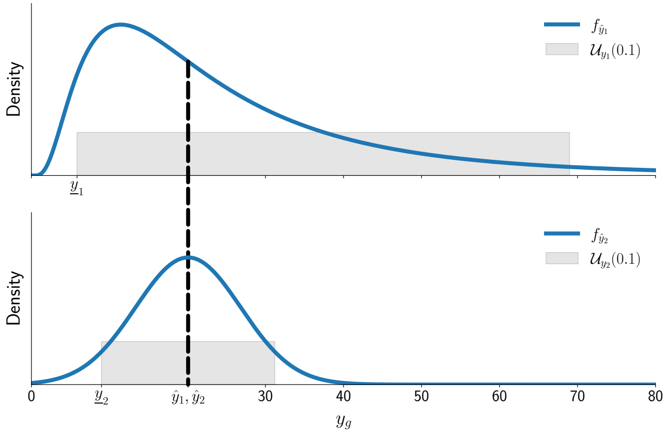
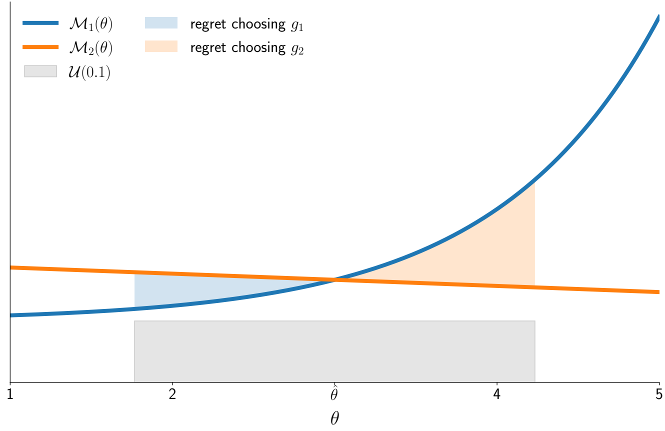
- Subjective Bayes $g^* = \arg\max_{g \in \mathcal{G}} \int_{\mathcal{U}(\alpha)} U(M_g(\boldsymbol{\vartheta})) \mathrm{d}f(\boldsymbol{\vartheta})$

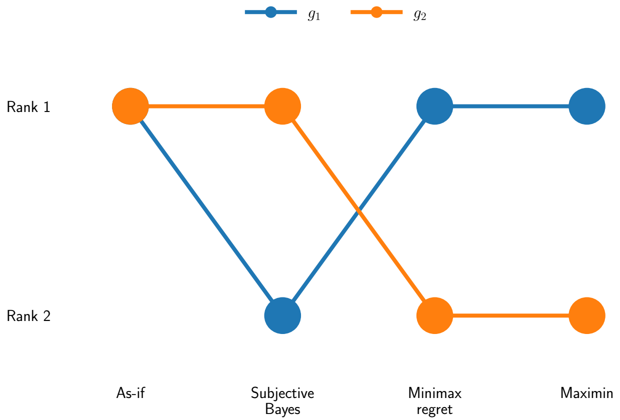
Comparing policies



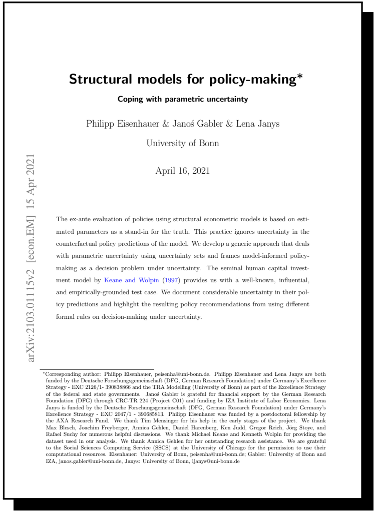
Comparing policies



Comparing policies



First steps



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Structural models for policy-making*

Coping with parametric uncertainty

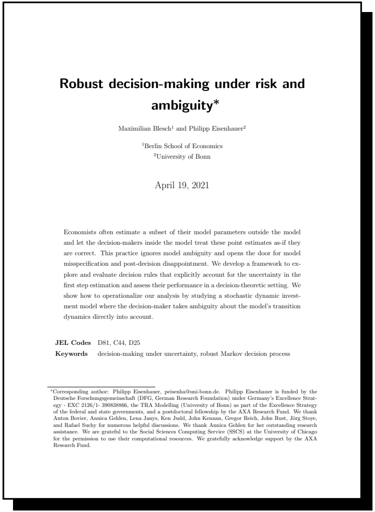
Philipp Eisenhauer & Janoś Gabler & Lena Janys

University of Bonn

April 16, 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 Keane 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, peisenha@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 2126/1- 390838866 and the TRA Modelling (University of Bonn) as part of the Excellence Strategy of the federal and state governments. Janoś Gabler is grateful for financial support by the German Research Foundation (DFG) through CRC-TR 224 (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 2047/1 - 390685813. Philipp Eisenhauer was funded by a postdoctoral fellowship by the AXA Research Fund. We thank Tim Mensinger for his help in the early stages of the project. We thank Max Blesch, Joachim Freyberger, Annica Gehlen, Daniel Harenberg, Ken Judd, Gregor Reich, Jörg Stoye, and Rafael Suchy for numerous helpful discussions. We thank Michael Keane and Kenneth Wolpin for providing the dataset used in our analysis. We thank Annica Gehlen 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, peisenha@uni-bonn.de; Gabler: University of Bonn and IZA, janos.gabler@uni-bonn.de, Janys: University of Bonn, ljanys@uni-bonn.de



Robust decision-making under risk and ambiguity*

Maximilian Blesch[1] and Philipp Eisenhauer[2]

[1]Berlin School of Economics
[2]University of Bonn

April 19, 2021

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.

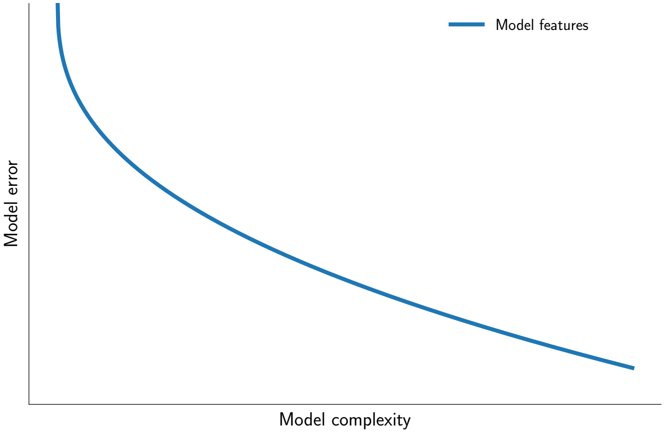
JEL Codes D81, C44, D25

Keywords decision-making under uncertainty, robust Markov decision process

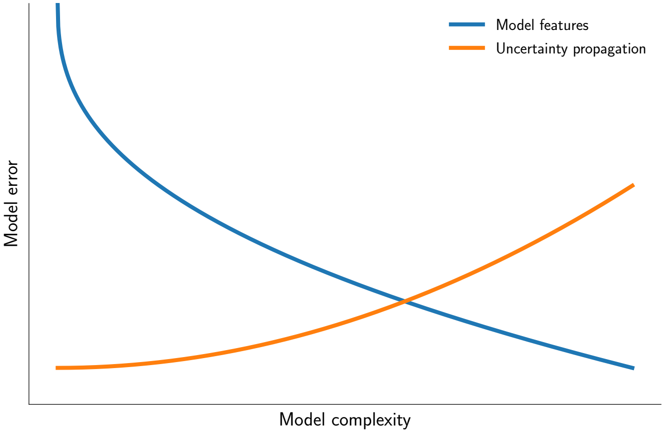
*Corresponding author: Philipp Eisenhauer, peisenha@uni-bonn.de. Philipp Eisenhauer is funded by the Deutsche Forschungsgemeinschaft (DFG, German Research Foundation) under Germany's Excellence Strategy - EXC 2126/1- 390838866, the TRA Modelling (University of Bonn) as part of the Excellence Strategy of the federal and state governments, and a postdoctoral fellowship by the AXA Research Fund. We thank Anton Bovier, Annica Gehlen, Lena Janys, Ken Judd, John Kennan, Gregor Reich, John Rust, Jörg Stoye, and Rafael Suchy for numerous helpful discussions. We thank Annica Gehlen 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. We gratefully acknowledge support by the AXA Research Fund.

Conclusion

Price of complexity



Price of complexity



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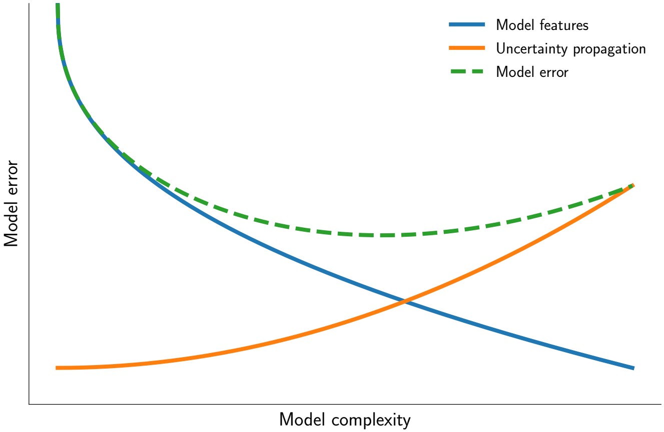

Let's stay in touch!

http://bit.ly/ose-github

http://bit.ly/ose-zulip

https://twitter.com/open_econ

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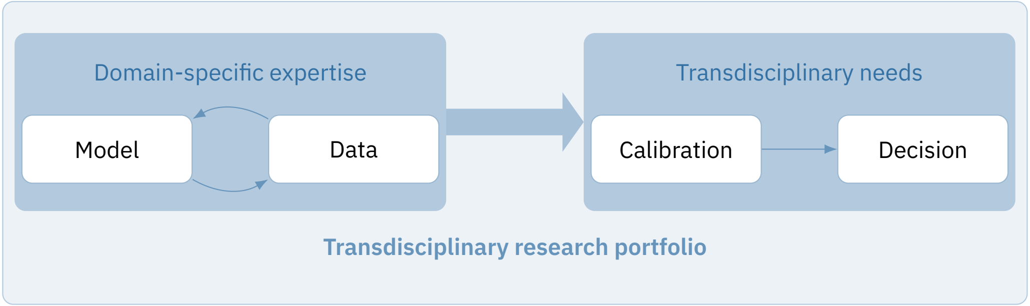
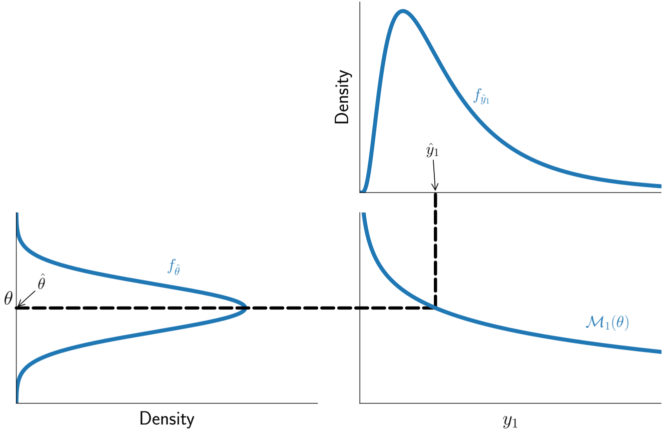
Appendix

Transdisciplinary research approach



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?

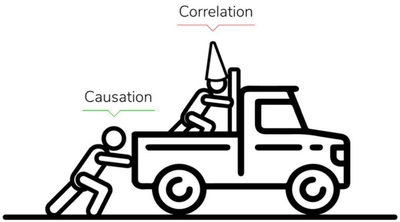


Figure 1. Source: Madhavan (2021)

References

References (1/2)

Andrews, Isaiah, Matthew Gentzkow, and Jesse M. Shapiro. 2017. “Measuring the sensitivity of parameter estimates to estimation moments.” *Quarterly Journal of Economics* 132 (4): 1553–92.

Andrews, Isaiah, Matthew Gentzkow, and Jesse M. Shapiro. 2020. “On the informativeness of descriptive statistics for structural estimates.” *Econometrica* 88 (6): 2231–58.

Armstrong, Timothy B, and Michal Kolesár. 2021. “Sensitivity analysis using approximate moment condition models.” *Quantitative Economics* 12 (1): 77–108.

Berger, Loïc, Nicolas Berger, Valentina Bosetti, Itzhak Gilboa, Lars Peter Hansen, Christopher Jarvis, Massimo Marinacci, and Richard D Smith. 2020. “Rational policymaking during a pandemic.” *Proceedings of the National Academy of Sciences* 118 (4):

Bertsimas, Dimitris, Vishal Gupta, and Nathan Kallus. 2018. “Data-driven robust optimization.” *Mathematical Programming* 167 (2): 235–92.

Blesch, Max, and Philipp Eisenhauer. 2021. “Robust investments under risk and ambiguity..” *under revision,*

Blundell, Richard. 2017. “What have we learned from structural models?” *American Economic Review* 107 (5): 287–92.

Bonhomme, Stéphane, and Martin Weidner. 2020. “Minimizing sensitivity to model misspecification.” *arXiv Working Paper,*

Bugni, Federico, and Takuya Ura. 2019. “Inference in dynamic discrete choice problems under local misspecification.” *Quantitative Economics* 10 (1): 67–103.

Christensen, Timothy, and Benjamin Connault. 2019. “Counterfactual sensitivity and robustness.” *arXiv Working Paper,*

Gilboa, Itzhak. 2009. *Theory of decision under uncertainty*. New York City, NY: Cambridge University Press.

Harenberg, Daniel, Stefano Marelli, Bruno Sudret, and Viktor Winschel. 2019. “Uncertainty quantification and global sensitivity analysis for economic models.” *Quantitative Economics* 10 (1): 1–41.

Jørgensen, Thomas H. 2021. “Sensitivity to calibrated paramters.” *Review of Economics and Statistics* forthcoming:

References (2/2)

Manski, Charles F. 2021. “Econometrics for decision making: Building foundations sketched by Haavelmo and Wald.” ArXiv Working Paper. National Bureau of Economic Research. URL: http://www.nber.org/papers/w26596.

Marinacci, Massimo. 2015. “Model uncertainty.” *Journal of the European Economic Association* 13 (6): 1022–100.

SAPEA. 2019. “Making sense of science for policy under conditions of complexity and uncertainty.” Berlin: Science Advice for Policy by European Academies.

Wolpin, Kenneth I. 2013. *The limits to inference without theory*. Cambridge, MA: MIT University Press.

Woutersen, Tiemen, and John Ham. 2019. “Confidence sets for continuous and discontinuous functions of parameters.” *SSRN Working Paper*,