Structural models for policy-making

Coping with parametric uncertainty

Philipp Eisenhauer, Janoś Gabler, and Lena Janys

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Open Source Economics

Structural models

Highly parameterized computational economic models that represent deep structural relationship of theoretical economic models that are invariant to policy changes and are estimated to data (Hood & Koopmans, 1953).

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Famous examples

- Optimal replacement of GMC bus engines
- The career decisions of young men
- The technology of skill formation

Motivation

- Facilitate academic rigor
- Study mechanisms
- Predict public policies

Structural models

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Uncertainty

- Model specification
- Numerical approximation

Structural models

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Uncertainty

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- Numerical approximation
- Parameter estimation

Coping with uncertainty

A proper accounting of uncertainty is a prerequisite for using computational models in policy-making (National Research Council, 2012; SAPEA, 2019).

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- Climate science
- Engineering

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Toolkits

- Textbooks
- High-performance computing

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- Engineering

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- Statistical decision theory

As-if analysis

In economics, however, we use the point estimates as a plug-in for the true parameter and the model is analyzed as-if the true parameters are known (Manski, 2021).

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Consequences

- Fragile findings as facts
- Dueling certitudes stifle constructive debate
- Knowledge gaps are not identified

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- Policy advice not framed as a decision problem under uncertainty

Examples of as-if analysis

Contributions

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Contributions

- We develop an approach that deals with parametric uncertainty and frames model-informed policy-making as a decision problem under uncertainty.
- We use the seminal human capital investment model by Keane and Wolpin (1997) as 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.

Roadmap

1. **Modeling framework**
2. **Empirical setup**
3. **Results**
4. **Conclusion**

Modeling framework

Structural econometric model

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

Setup

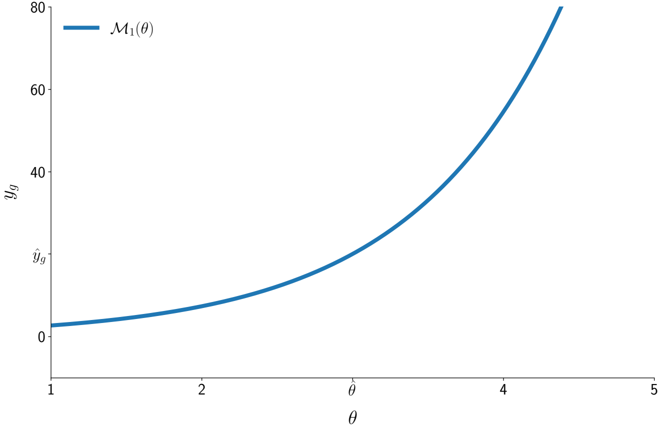
Structural econometric model

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

Notation

$\mathscr{M}$	mapping under status-quo	y_g	counterfactual
$\mathscr{M}_g$	mapping under policy g	$\hat{\boldsymbol{\theta}}$	estimated parameter
$\boldsymbol{\theta}_0$	true parameter	$\boldsymbol{\Theta}(\alpha)$	confidence set with coverage $1-\alpha$

Comparing models



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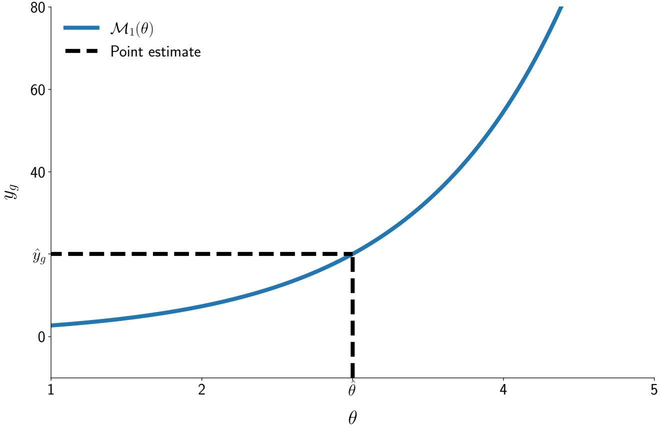

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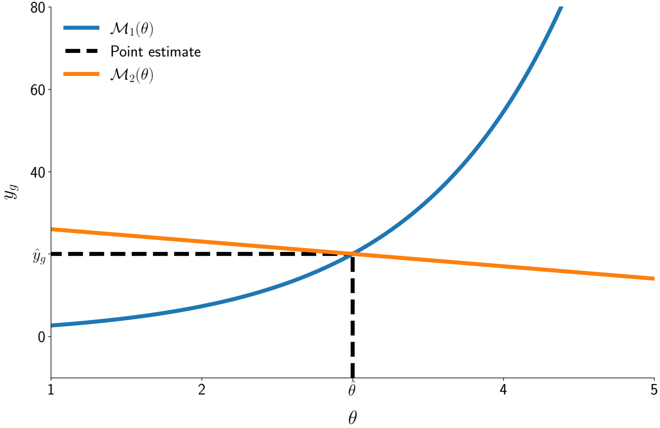

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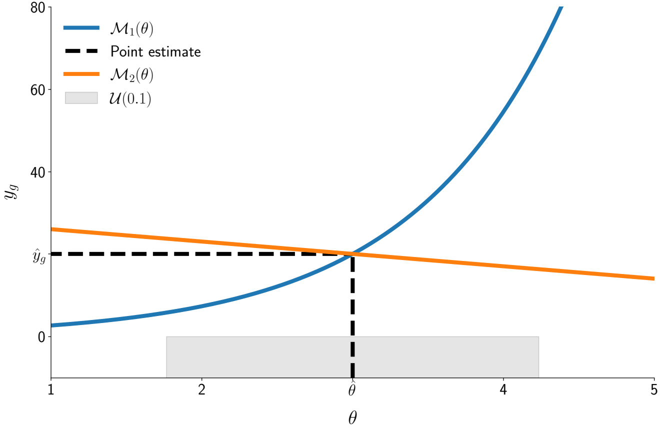

Decision-theoretic framework

As-if decisions with point estimates

- As-if optimization

As-if decisions with point estimates

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

Decision-theoretic framework

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As-if decisions with set estimates (Manski, 2021)

- Maximin criterion
- Minimax regret rule
- Subjective Bayes

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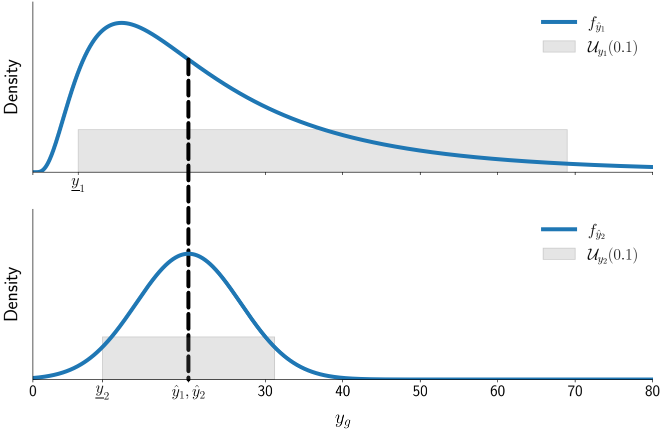
- Subjective Bayes $g^* = \arg\max_{g \in \mathcal{G}} \int_{\mathcal{U}(\alpha)} M_g(\boldsymbol{\theta}) \, \mathrm{d}f(\boldsymbol{\theta})$

Comparing policies



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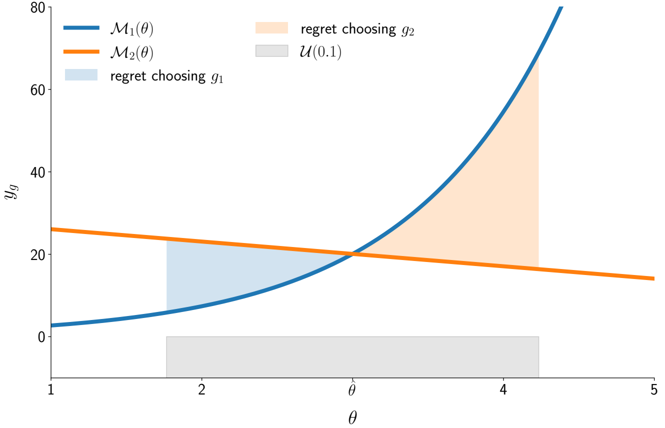

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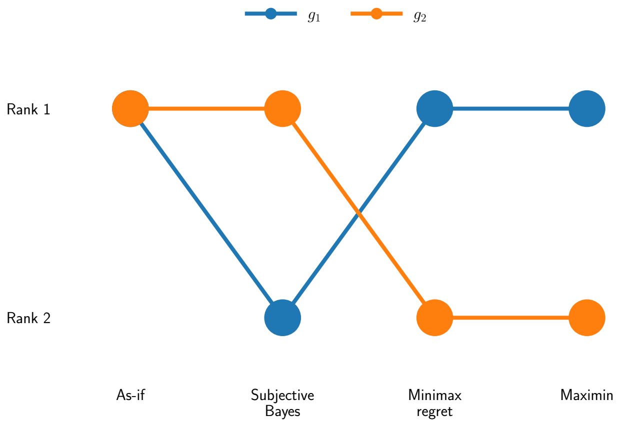

Empirical setup

Understanding individual decisions

- Human capital investment
- Consumption–savings decision

Eckstein–Keane–Wolpin models

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Predicting effects of policies

- Educational policy
- Welfare programs

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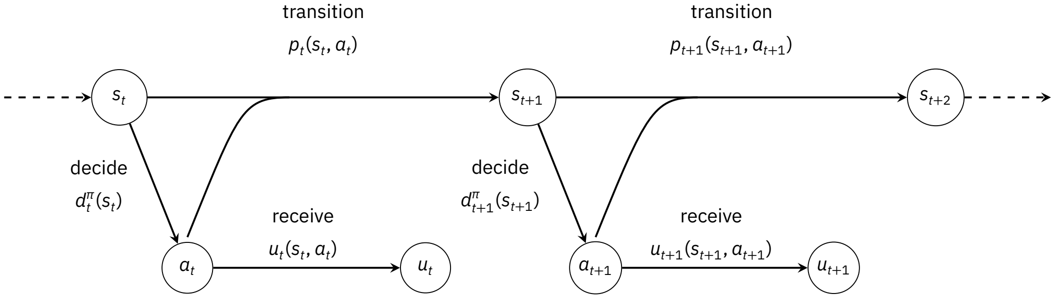
Mathematical framework and implementation

- Finite-horizon discrete Markov decision problem
- Backward induction algorithm

Timing of events



Individual's objective

$$\max_{\pi \in \Pi} \mathrm{E}_{s_1}^{\pi}\left[\sum_{t=1}^{T} \delta^{t-1} u_t(s_t, a_t^{\pi}(s_t))\right]$$

Core economics

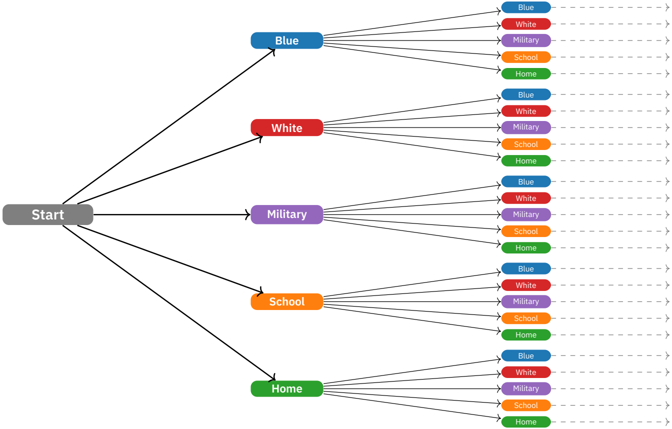
- Rational expectations
- Exponential discounting
- Time-separability

Seminal paper

Keane, M. P., & Wolpin, K. I. (1997). The career decisions of young men. *Journal of Political Economy*, *105*(3), 473–522.

- The study follows individuals over their working life from young adulthood at age 16 to retirement at age 65 where the decision period $t = 16, \dots, 65$ is a school year.
- Individuals decide $a \in \mathscr{A}$ whether to work in a blue-collar or white-collar occupation ($a = 1, 2$), to serve in the military ($a = 3$), to attend school ($a = 4$), or to stay at home ($a = 5$).
- Authors use the model to predict and understand the effects of numerous human capital policies.

Decision tree



Immediate utility

$$u_t(s_t) = \begin{cases} \zeta_a(s_t) + w_a(s_t) & \text{if } a \in \{1, 2, 3\} \\ \zeta_a(s_t) & \text{if } a \in \{4, 5\} \end{cases}$$

Informed by reduced-form evidence

- Mincer equation
- Diploma effects
- Skill depreciation
- Mobility and search costs
- Monetary and psychic cost of schooling

Transitions

- Work experience $\boldsymbol{k}_t$ and years of completed schooling h_t evolve deterministically.

$$
\begin{aligned}
k_{a,t+1} &= k_{a,t} + \mathbf{I}[a_t = a] \qquad \text{if } a \in \{1, 2, 3\} \\
h_{t+1} &= h_t \;\; + \mathbf{I}[a_t = 4]
\end{aligned}
$$

- Productivity shocks $\boldsymbol{\varepsilon}_t$ are uncorrelated across time and follow a multivariate normal distribution with mean $\mathbf{0}$ and covariance matrix $\boldsymbol{\Sigma}$.

- Given the structure of the utility functions and the distribution of the shocks, the state at time t is $s_t = \{\boldsymbol{k}_t, h_t, t, a_{t-1}, \boldsymbol{e}, \boldsymbol{\varepsilon}_t\}$.

Utility of schooling

$$\zeta_4(s_t) = \underbrace{e_{j,4}}_{\text{type}} + \underbrace{\beta_{tc_1} \cdot \mathbf{I}[h_t \geq 12] + \beta_{tc_2} \cdot \mathbf{I}[h_t \geq 16]}_{\text{tuition costs}} + \underbrace{\gamma_{4,4} \cdot t + \gamma_{4,5} \cdot \mathbf{I}[t < 18]}_{\text{time trend}}$$

$$+ \underbrace{\beta_{rc_1} \cdot \mathbf{I}[a_{t-1} \neq 4, h_t < 12] + \beta_{rc_2} \cdot \mathbf{I}[a_{t-1} \neq 4, h_t \geq 12]}_{\text{re-enrollment cost}} + \ldots + \varepsilon_{4,t}$$

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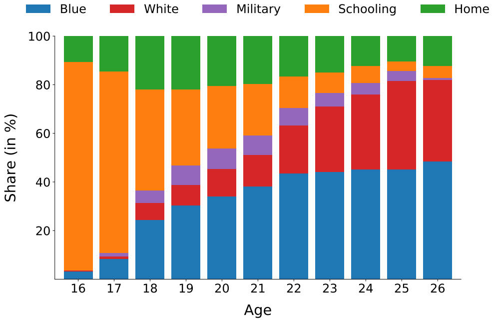
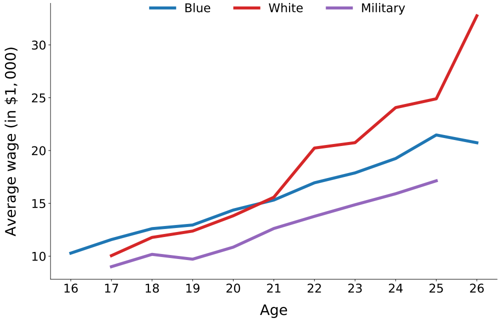
National Longitudinal Survey of Youth 1979

- 1,373 individuals starting at age 16
- Life cycle histories
  - School attendance
  - Occupation-specific work status
  - Wage
- Likelihood-based estimation

Data descriptives



(a) Choices



(b) Wages

Determining the confidence set

We implement the Confidence Set bootstrap (Rao, 1973; Woutersen & Ham, 2019).

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1. We draw a large sample of $\hat{\boldsymbol{\theta}}_m$ from the asymptotic distribution of our estimates.
2. We keep draws that are elements of the estimated confidence set $\hat{\boldsymbol{\Theta}}(\alpha)$.
3. We compute $\hat{y}_{g,m}$ for all remaining draws.
4. We calculate the uncertainty set $\mathcal{U}_{y_g}(\alpha)$ based on the lowest and highest value of $\hat{y}_{g,m}$.

Algorithmic description

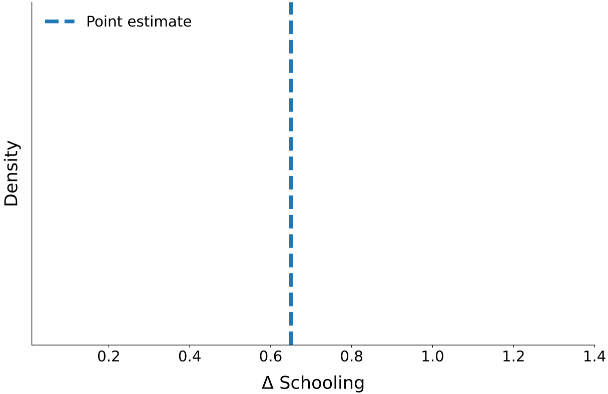
Results

Policy setting

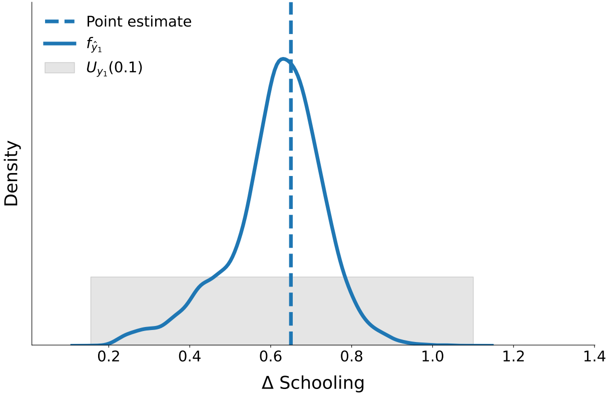
We study the policy of introducing a $2,000 tuition subsidy with the goal to increase average final schooling.

- General subsidy
- Targeted subsidy based on initial endowment

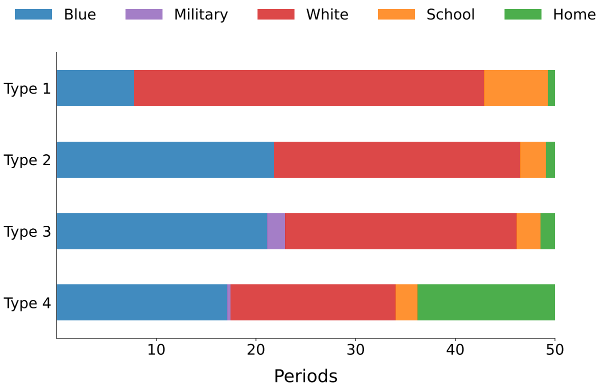
Prediction of impact



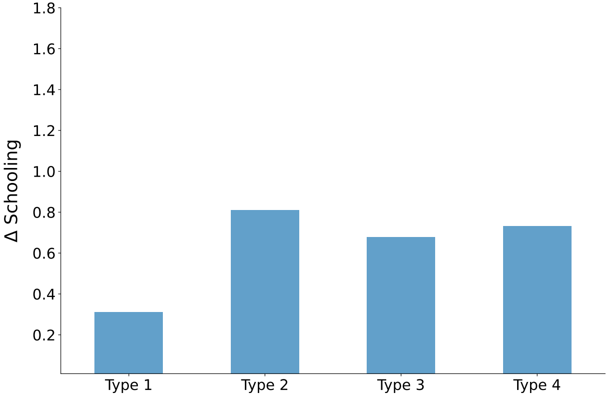
Prediction of impact and its uncertainty



Type heterogeneity



As-if ranking of policy alternatives



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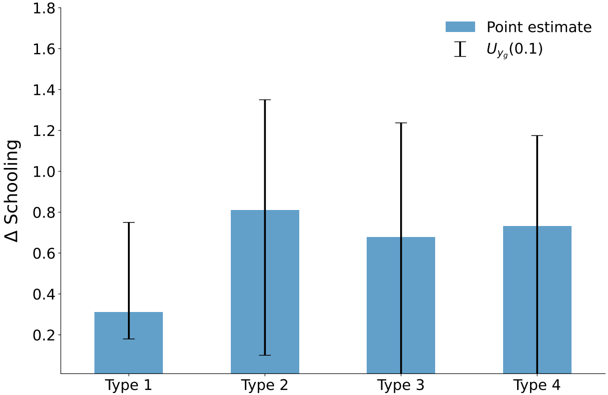
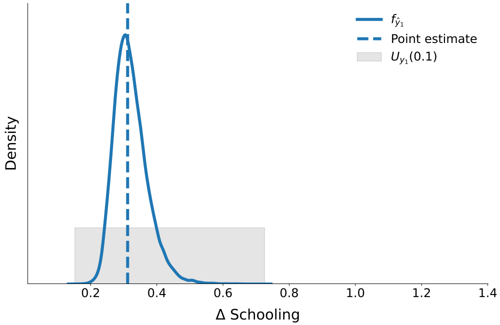
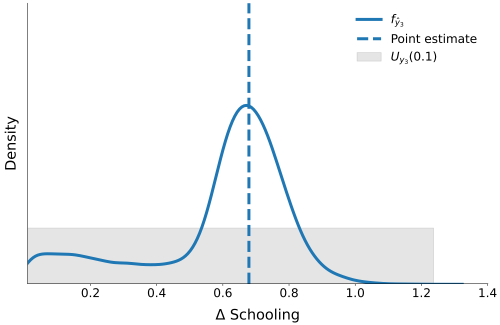


Heterogeneity in uncertainty

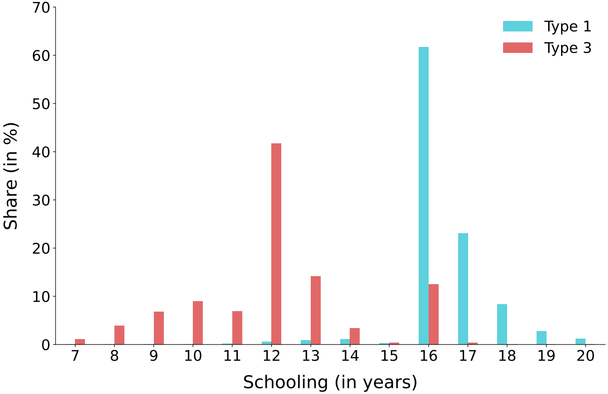


(a) Type 1

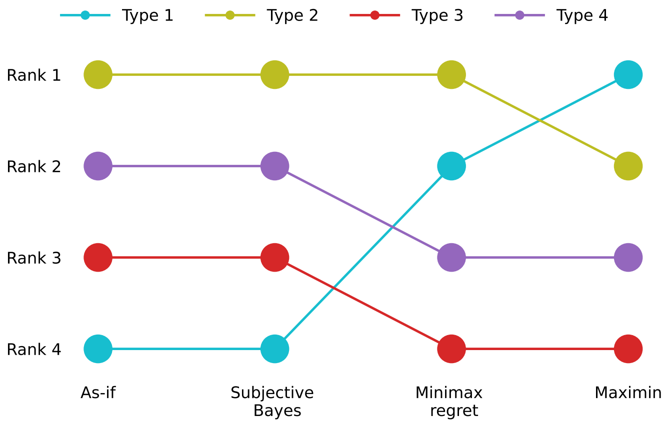


(b) Type 3

Economics behind uncertainty

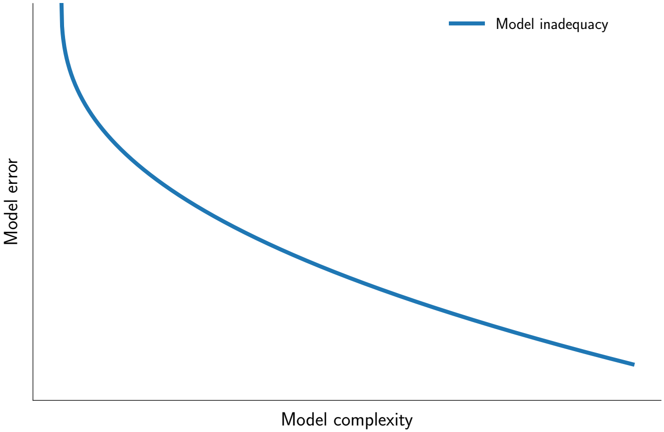


Decision-theoretic ranking of policies



Conclusion

Price of complexity



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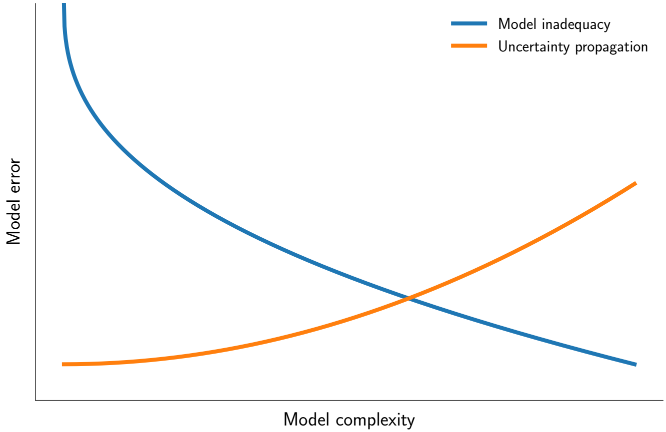

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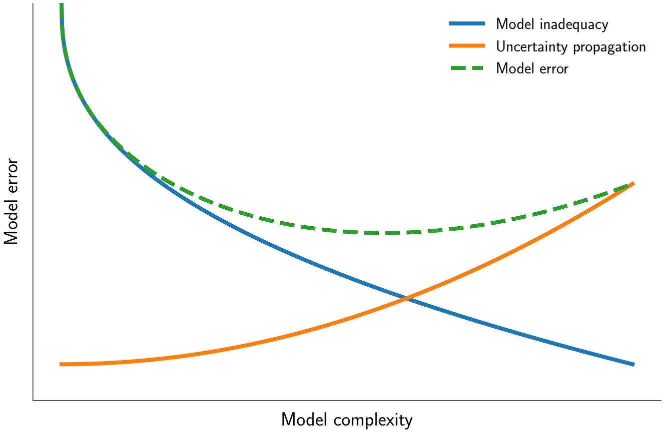

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Conclusion (1/3)

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Conclusion (2/3)

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Conclusion (3/3)

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Appendix

Data and estimation

Dataset

$$\mathscr{D} = \{a_{it}, \bar{s}_{it}, \bar{u}_{it} : i = 1, \ldots, N; t = 1, \ldots, T_i\}$$

State variables

- $s_t = (\bar{s}_t, \varepsilon_t)$
  - $\bar{s}_t$ observed
  - ε_t unobserved

Data and estimation

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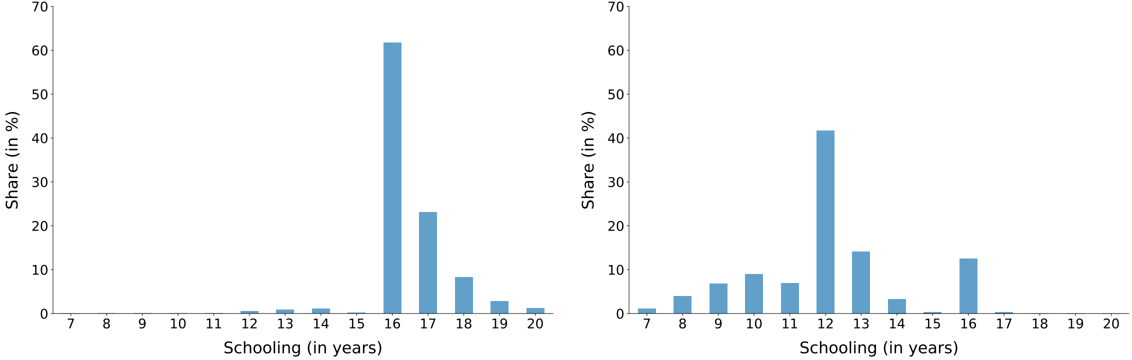
Likelihood-based estimation

$$\hat{\boldsymbol{\theta}} = \arg\max_{\boldsymbol{\theta} \in \boldsymbol{\Theta}} \prod_{i=1}^{N} \prod_{t=1}^{T_i} p_{it}(a_{it}, \bar{u}_{it} \mid \bar{s}_{it}, \boldsymbol{\theta})$$

Explore model fit

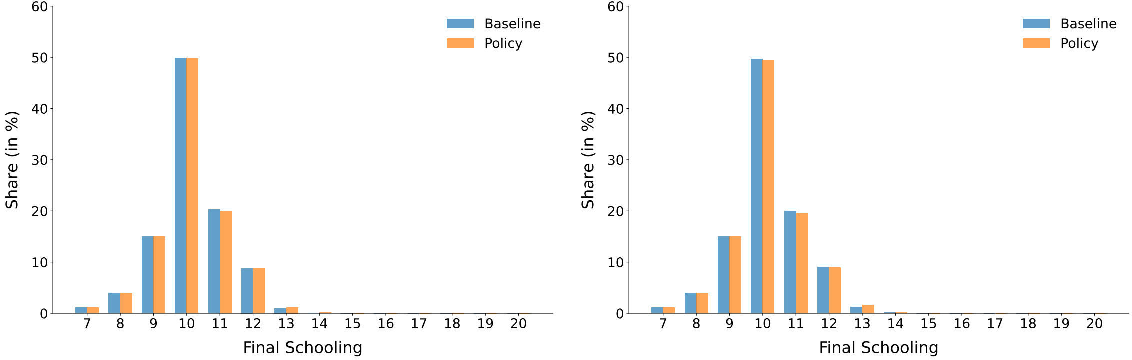


(a) Type 1

(b) Type 3

Figure 1. Final distribution of schooling

Heterogeneity in uncertainty

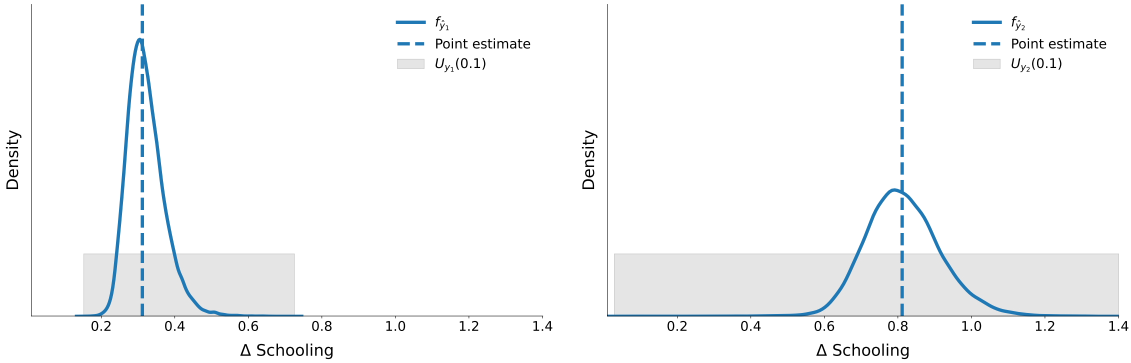


(a) Low δ

(b) High δ

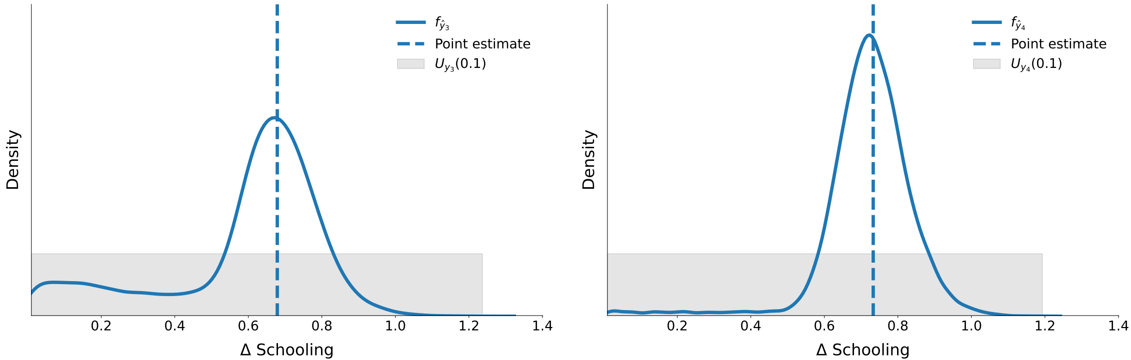
Figure 2. Policy impact and time preference

Tracing out the impact of time preference



(a) Type 1 **(b)** Type 2

Figure 3. Prediction and uncertainty



(a) Type 3

(b) Type 4

Figure 4. Prediction and uncertainty

Examples of as-if analysis

Economic mechanisms

- Eisenhauer, P., Heckman, J. J., & Mosso, S. (2015). Estimation of dynamic discrete choice models by maximum likelihood and the simulated method of moments. *International Economic Review*, *56*(2), 331–357
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Examples of as-if analysis

Optimal policy design

- Cunha, F., Heckman, J. J., & Schennach, S. (2010). Estimating the technology of cognitive and noncognitive skill formation. *Econometrica*, *78*(3), 883–931
- Todd, P. E., & Wolpin, K. I. (2006). Assessing the impact of a school subsidy program in Mexico: Using a social experiment to validate a dynamic behavioral model of child schooling and fertility. *American Economic Review*, *96*(5), 1384–1417
- Blundell, R., & Shephard, A. (2012). Employment, hours of work and the optimal taxation of low-income families. *The Review of Economic Studies*, *79*(2), 481–510

State of literature

It is worth noting that no DCDP [discrete choice dynamic programming] work that we are aware of has ever reported a distribution of policy simulations that accounts for parameter uncertainty; and, it is also rarely done in nonstructural work.

– Keane, Todd, and Wolpin (2011)

Confidence Set bootstrap algorithm

for $m = 1, \dots, \bar{M}$ **do**

  Draw $\boldsymbol{\theta}_m \sim \mathcal{N}(\hat{\boldsymbol{\theta}}, \hat{\boldsymbol{\Sigma}})$

  Compute $c = (\boldsymbol{\theta}_m - \bar{\boldsymbol{\theta}})' \hat{\boldsymbol{\Sigma}}^{-1} (\boldsymbol{\theta}_m - \bar{\boldsymbol{\theta}})$

  if $(\hat{\boldsymbol{\theta}}_m - \hat{\boldsymbol{\theta}})' \hat{\boldsymbol{\Sigma}}^{-1} (\hat{\boldsymbol{\theta}}_m - \hat{\boldsymbol{\theta}}) \leq \chi^2_l (1 - \alpha)$ **then**

    Compute $\hat{y}_{g,m} = \mathcal{M}_g(\hat{\boldsymbol{\theta}}_m)$

    Add $\hat{y}_{g,m}$ to sample $Y = \{\hat{y}_{g,1}, \dots, \hat{y}_{g,m-1}\}$

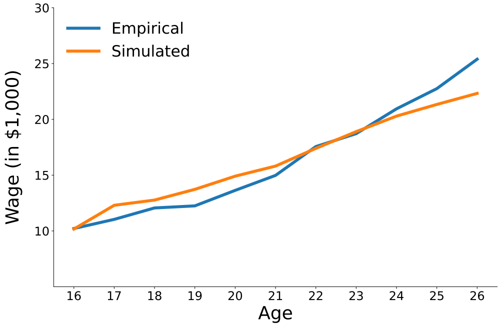
  end if

end for

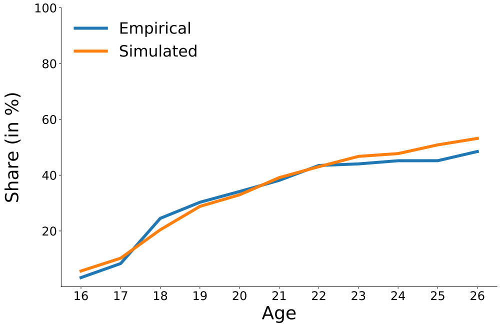
Set $\boldsymbol{\Theta}_{y_g}(\alpha) = [\min(Y), \max(Y)]$

Confidence set bootstrap

Model fit



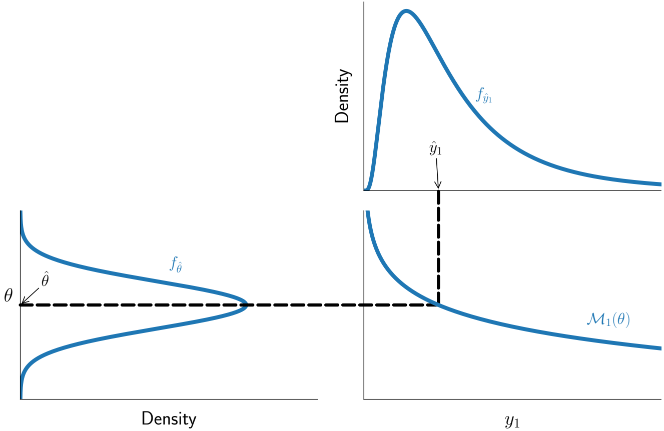
(a) Average wage



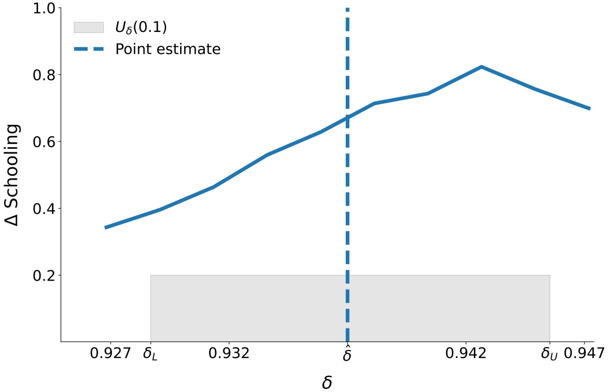
(b) Blue-collar

Data and estimation

Uncertainty propagation



Tracing out the impact of time preference



Explore the economics behind it

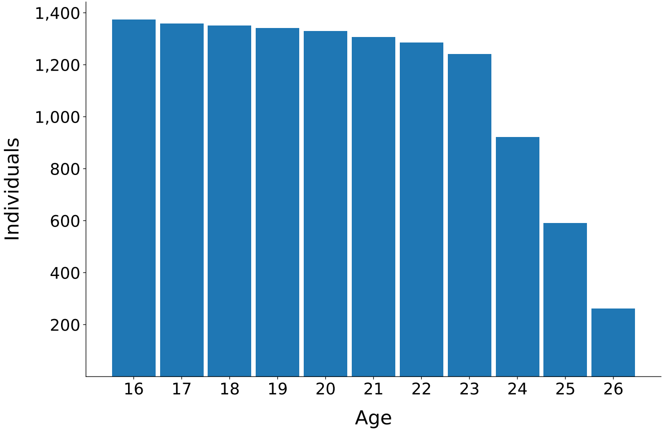
respy

A research code for the flexible specification, simulation, and estimation of Eckstein–Keane–Wolpin models.

Anaconda Cloud 2.0.0dev5 | Platforms linux-64,win-32,noarch,osx-64,linux-32,win-64 | docs passing | License MIT
Continuous Integration Workflow passing | codecov 85% | code style black

Core devs Tobias Raabe, Janoś Gabler
Docs respy.readthedocs.io

Sample size



1,400
1,200
1,000
800
600
400
200
Individuals
16
17
18
19
20
21
22
23
24
25
26
Age

Related literature

- **Local sensitivity analysis:** Andrews et al. (2017), Andrews et al. (2020), Christensen and Connault (2019), Jørgensen (2021)
- **Global sensitivity analysis:** Cai and Lontzek (2019), Harenberg et al. (2019), Miftakhova (2021)
- **Public policy and uncertainty:** Berger et al. (2021), Hansen (2021), Manski (2013)
- **Statistical decision theory:** Gilboa (2009), Manski (2021)

Next steps

- Generalize our work building on asymptotic optimality theory for statistical treatment rules
- Address the computational burden of our analysis using surrogate modeling and adaptive sampling methods
- Incorporate ideas from the literature on global sensitivity analysis to identify the parameters most responsible for the uncertainty in predictions
- Link our work with the literature on inference under (local) model misspecification to refine the construction of our uncertainty sets