Structural models for policy-making

Coping with parametric uncertainty

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Open Source Economics

Structural models

Motivation

- Facilitate academic rigor
- Study mechanisms
- Predict public policies

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Uncertainty

- Model specification
- Numerical approximation

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Uncertainty

- Model specification
- Numerical approximation
- Parameter estimation

As-if analysis

In economics, however, we often 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
- Policy advice not framed as a decision problem under uncertainty

Examples of as-if analysis

Coping with uncertainty

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

Examples

- Weather forecasting
- Climate science
- Engineering

Toolkits

- Textbooks
- High-performance computing

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- We develop an approach that deals with parametric uncertainty and frames model-informed policy-making as a decision problem under uncertainty.

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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.

Related literature

Modeling framework

Setup

Structural econometric model

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

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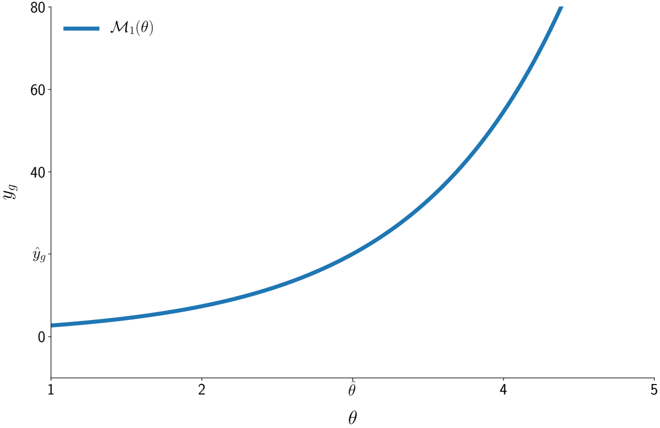
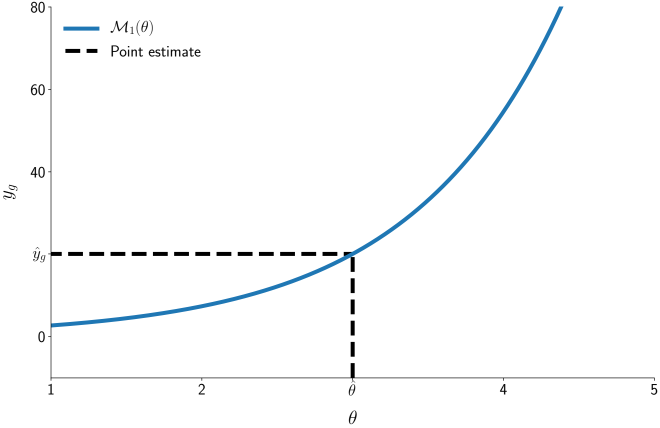
Notation

$\mathscr{M}$	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 $1-\alpha$

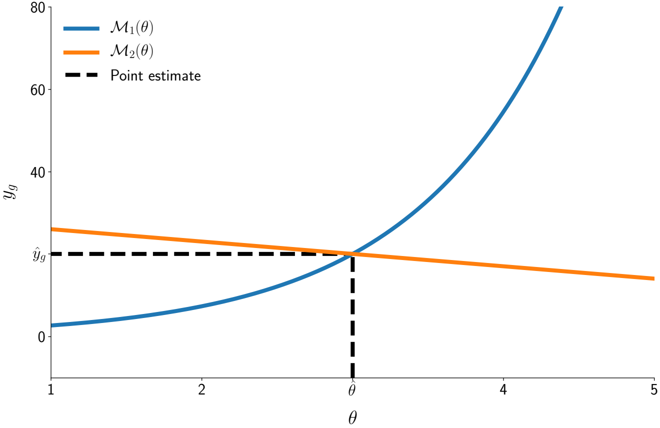
Comparing models



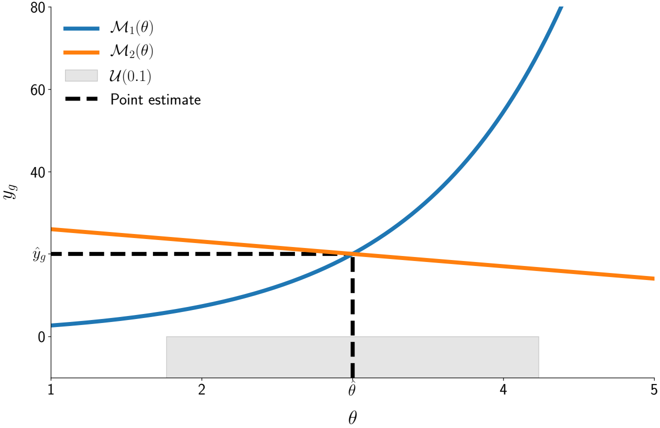
Comparing models



Comparing models



Comparing models



As-if decisions with point estimates

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

Decision-theoretic framework

As-if decisions with point estimates

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

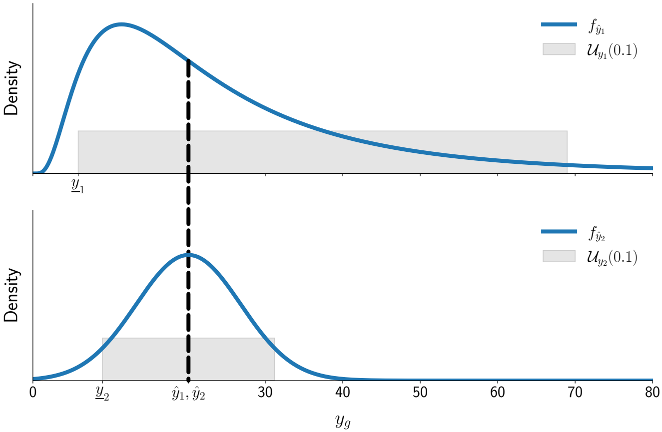
As-if decisions with set estimates (Bertsimas et al., 2018; Manski, 2021)

- Maximin criterion $g^* = \arg\max_{g \in \mathcal{G}} \min_{\boldsymbol{\theta} \in \mathcal{U}(\alpha)} U(M_g(\boldsymbol{\theta}))$

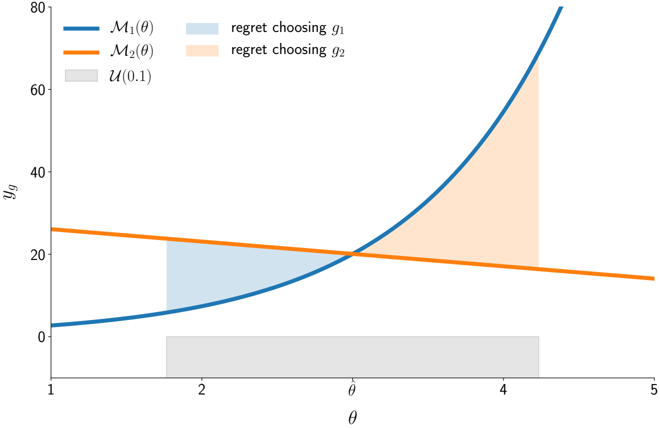
- Minimax regret rule $g^* = \arg\min_{g \in \mathcal{G}} \max_{\boldsymbol{\theta} \in \mathcal{U}(\alpha)} \left[\max_{\tilde{g} \in \mathcal{G}} U(M_{\tilde{g}}(\boldsymbol{\theta})) - U(M_g(\boldsymbol{\theta}))\right]$

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

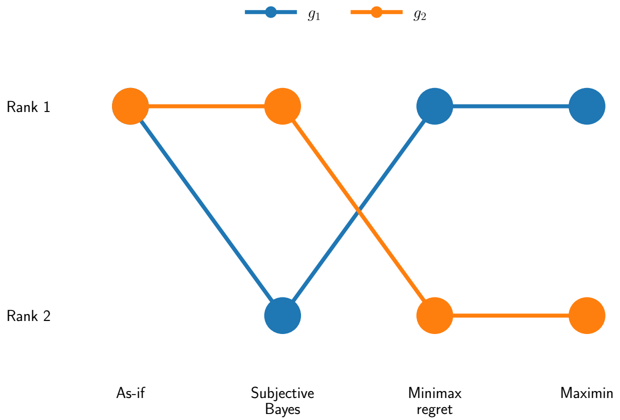
Comparing policies



Comparing policies



Comparing policies



Empirical setup

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 $t = 16, \ldots, 65$ 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.

Determining the confidence set

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

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

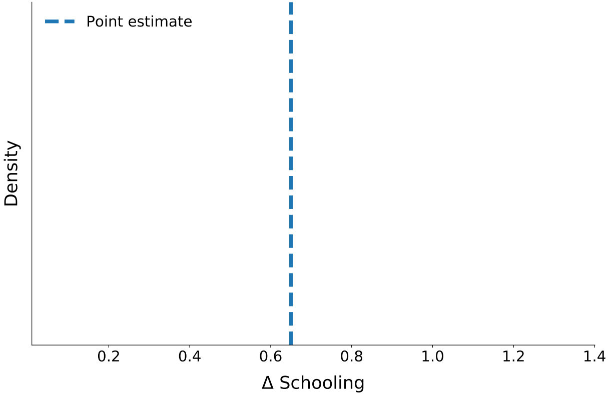
Results

Policy setting

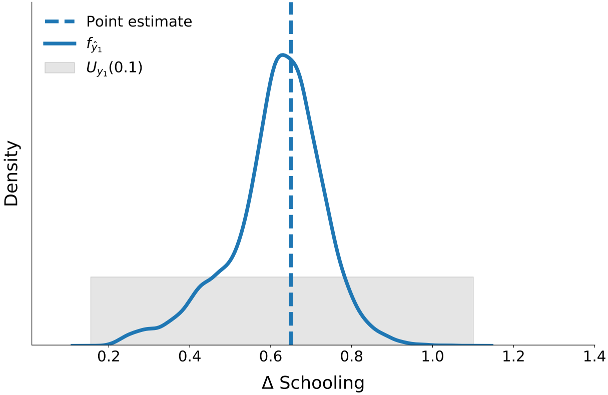
We study the policy of introducing a $\$2,000$ tuition subsidy with the goal to increase average final schooling.

- General subsidy
- Targeted subsidy based on initial endowment

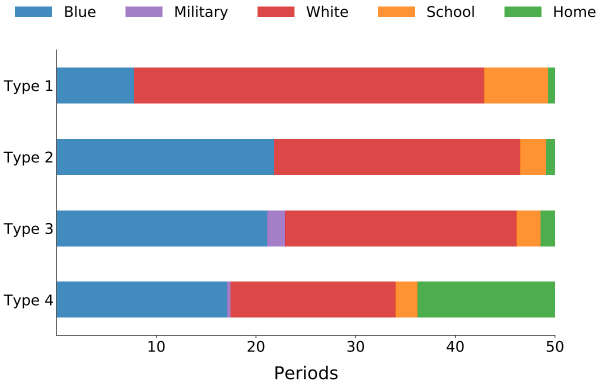
Prediction of impact



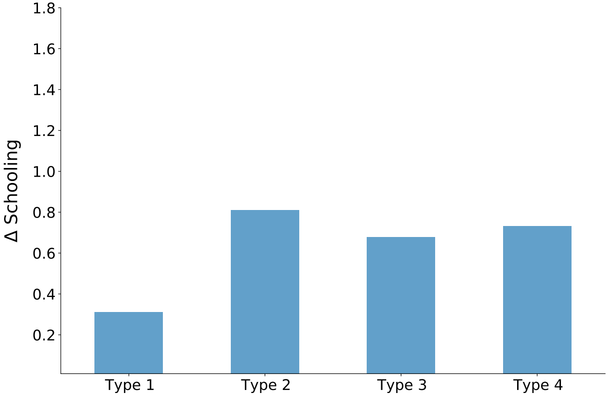
Prediction of impact and its uncertainty



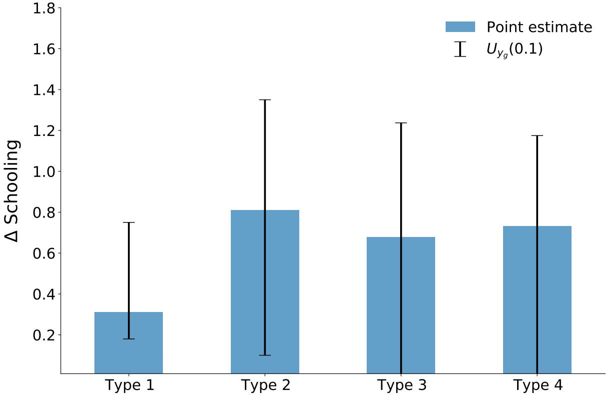
Type heterogeneity



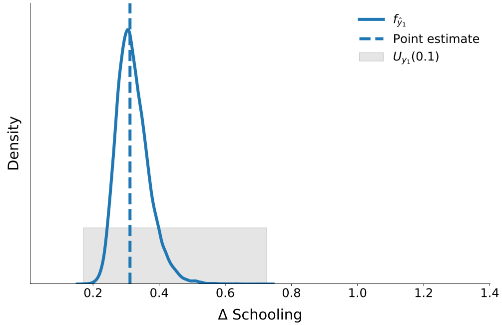
As-if ranking of policy alternatives



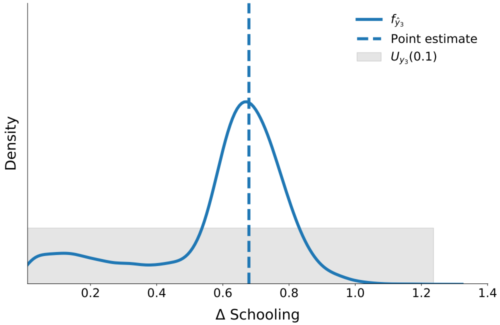
As-if ranking of policy alternatives



Heterogeneity in uncertainty

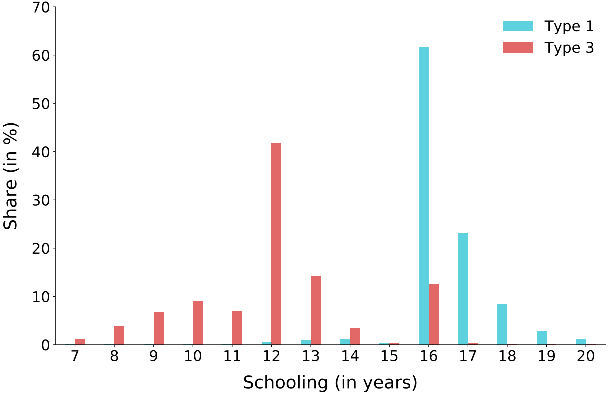


(a) Type 1

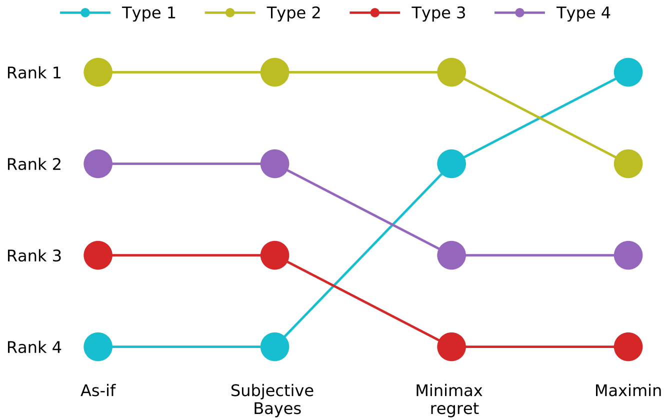


(b) Type 3

Economics behind uncertainty



Decision-theoretic ranking of policies

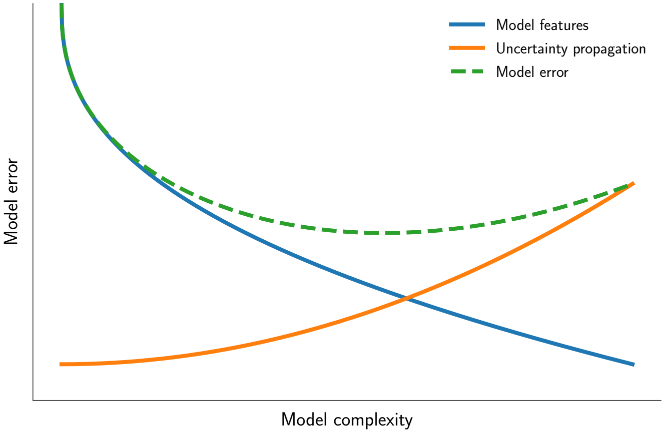


Conclusion

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

Price of complexity



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Conclusion (1/2)

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Conclusion (2/2)

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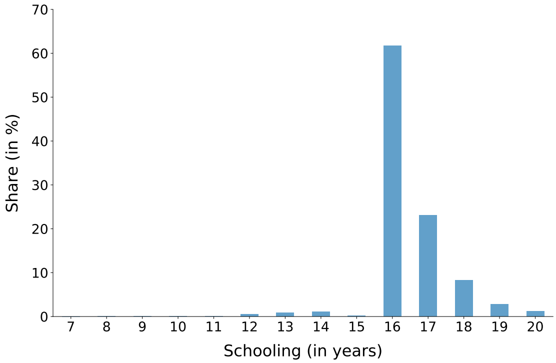
Woutersen, T., & Ham, J. (2019). Confidence sets for continuous and discontinuous functions of parameters. *SSRN Working Paper*.

Appendix

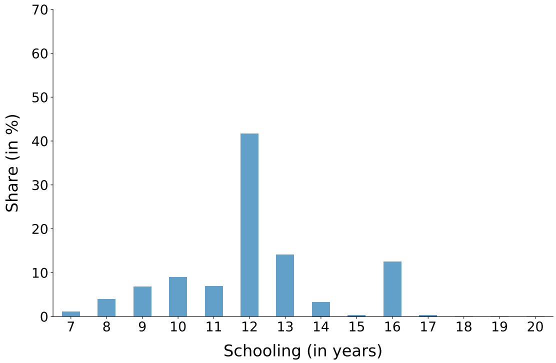
Related literature

- **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)
- **Public policy and uncertainty:** Berger et al. (2021), Hansen (2020), Manski (2013)
- **Statistical decision theory:** Gilboa (2009), Manski (2021)

Related literature



(a) Type 1



(b) Type 3

Figure 1. Final distribution of schooling

Heterogeneity in uncertainty

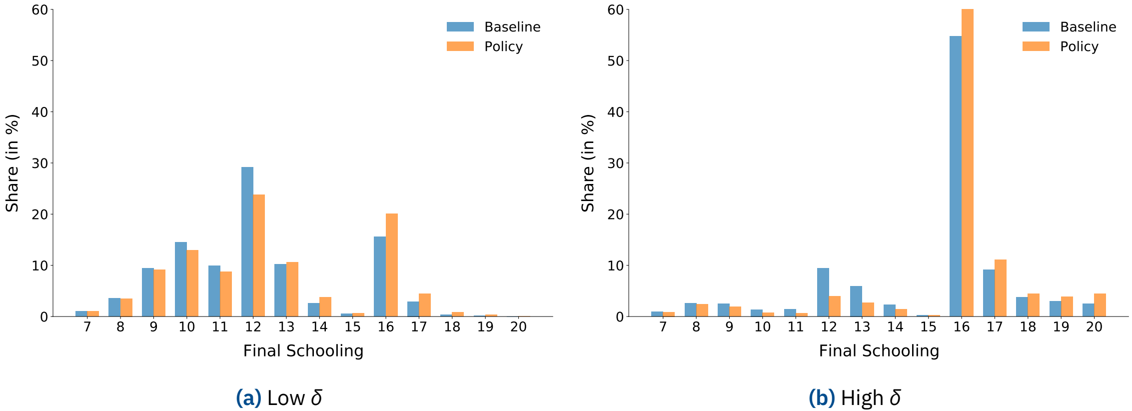
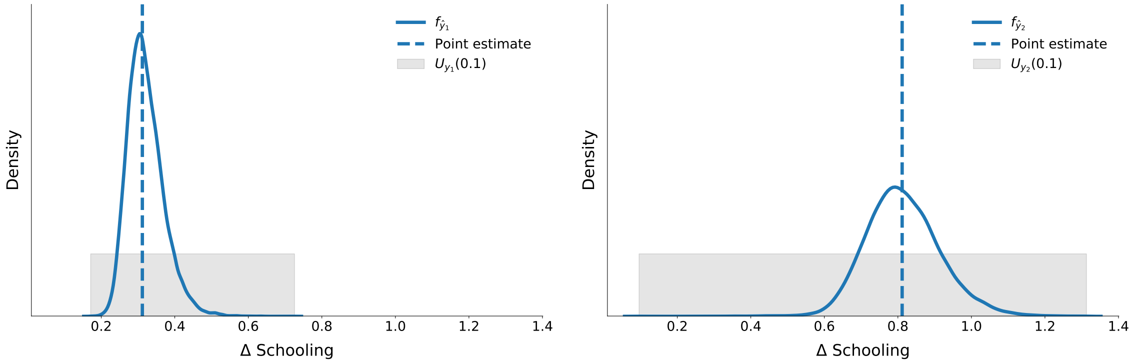


Figure 2. Policy impact and time preference

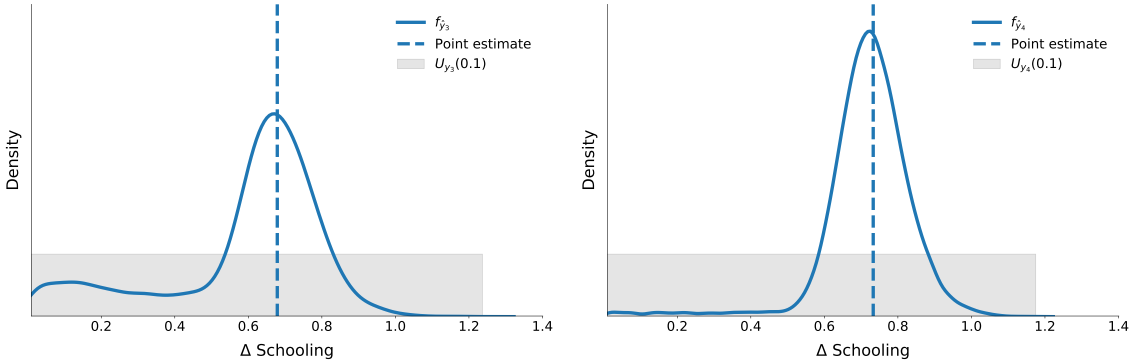
Tracing out the impact of time preference



(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
- Adda, J., Dustmann, C., & Stevens, K. (2017). The career costs of children. *Journal of Political Economy*, *125*(2), 293–337
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Examples of as-if analysis

Optimal policy design

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- 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
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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 $m = 1, \ldots, \bar{M}$ **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 $\hat{y}_{g,m} = \mathscr{M}_g(\hat{\boldsymbol{\theta}}_m)$

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

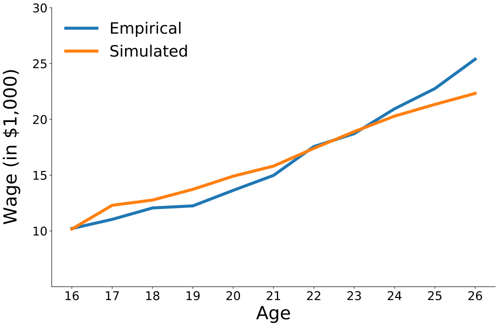
  end if

end for

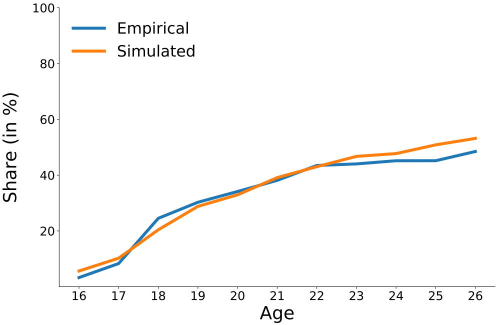
Set $\boldsymbol{\Theta}_{y_g}(\alpha) = [\min(Y), \max(Y)]$

Confidence set bootstrap

Model fit



(a) Average wage



(b) Blue-collar

Data and estimation

Uncertainty propagation