
Eckstein-Keane-Wolpin models

An invitation for transdisciplinary collaboration

The OSE team

March 30, 2021



Open Source
Economics

Computational modeling in economics

Motivation

- Facilitate academic rigor
- Study mechanisms
- Predict public policies

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- Predict public policies

Transdisciplinary in nature

- Economic model
- Mathematical framework
- Computational implementation

Eckstein–Keane–Wolpin models

Understanding individual decisions

- Human capital investment
- Consumption–savings decision

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Predicting effects of policies

- Welfare programs
- Tax schedules

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Mathematical framework and implementation

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

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⇒ Transdisciplinary research on their **economics**, data, and computation

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Partners



Institute for
Numerical Simulation



Roadmap

- Economic model
- Mathematical formulation
- Calibration

Roadmap

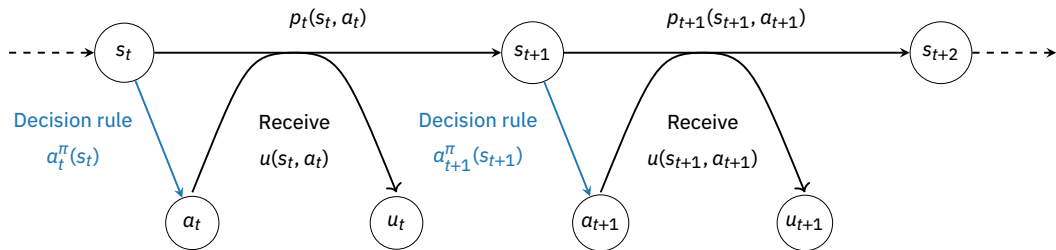
- Economic model
- Mathematical formulation
- Calibration
- Example
- Pipeline
- Projects

Economic model

Decision problem

$t = 1, \dots, T$	decision period
$s_t \in S$	state
$a_t \in A$	action
$p_t(s_t, a_t)$	conditional distribution
$a_t(s_t)$	decision rule
$\pi = (a_1^\pi(s_1), \dots, a_T^\pi(s_T))$	policy
$u_t(s_t, a_t)$	immediate utility
δ	discount factor

Timing of events



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

Core economics

- Rational expectations
- Exponential discounting
- Time-separability

Mathematical formulation

Dynamic programming

Policy evaluation

$$v_t^\pi(s_t) = \mathbb{E}_{s_t}^\pi \left[\sum_{j=0}^{T-t} \delta^j u_{t+j}(s_{t+j}, a_{t+j}^\pi(s_{t+j})) \right]$$

Optimality equations

$$v_t^{\pi^*}(s_t) = \max_{a_t \in A} \left\{ u_t(s_t, a_t) + \delta \mathbb{E}_{s_t}^{\pi^*} \left[v_{t+1}^{\pi^*}(s_{t+1}) \right] \right\}$$

Backward induction algorithm

for $t = T, \dots, 1$ **do**

if $t = T$ **then**

$$v_T^{\pi^*}(s_T) = \max_{a_T \in A} \left\{ u_T(s_T, a_T) \right\} \quad \forall s_T \in S$$

else

 Compute $v_t^{\pi^*}(s_t)$ for each $s_t \in S$ by

$$v_t^{\pi^*}(s_t) = \max_{a_t \in A} \left\{ u_t(s_t, a_t) + \delta \mathbb{E}_{s_t}^{\pi} \left[v_{t+1}^{\pi^*}(s_{t+1}) \right] \right\}$$

 and set

$$a_t^{\pi^*}(s_t) = \arg \max_{a_t \in A} \left\{ u_t(s_t, a_t) + \delta \mathbb{E}_{s_t}^{\pi} \left[v_{t+1}^{\pi^*}(s_{t+1}) \right] \right\}$$

end if

end for

Calibration procedure

Data

Dataset

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

State variables

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

Procedures

Likelihood-based

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

Simulation-based

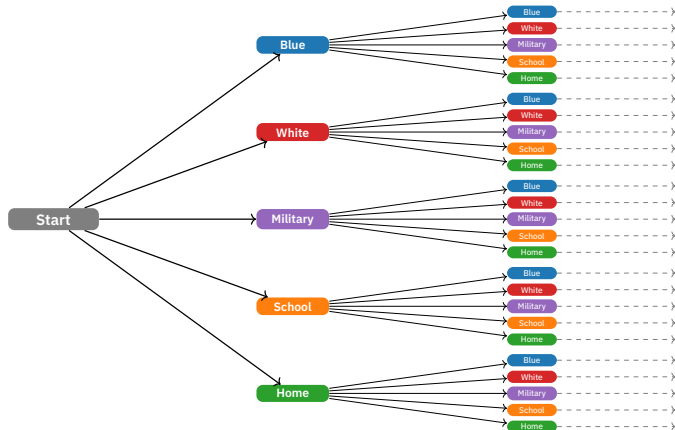
$$\hat{\vartheta} = \arg \min_{\vartheta \in \Theta} (M_D - M_S(\vartheta))' W (M_D - M_S(\vartheta))$$

Example

Michael P. Keane and Kenneth I. Wolpin. 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 $a \in \mathcal{A}$ 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 ($a = 5$).

Decision tree



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

Informed by reduced-form evidence

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

- Work experience k_t and years of completed schooling h_t evolve deterministically.

$$k_{a,t+1} = k_{a,t} + 1[a_t = a] \quad \text{if } a \in \{1, 2, 3\}$$

$$h_{t+1} = h_t + 1[a_t = 4]$$

- Productivity shocks ε_t are uncorrelated across time and follow a multivariate normal distribution with mean $\mathbf{0}$ and covariance matrix Σ .
- Given the structure of the utility functions and the distribution of the shocks, the state at time t is $s_t = \{k_t, h_t, t, a_{t-1}, \mathbf{e}, \varepsilon_t\}$.

Utility of blue-collar occupation

- Non-pecuniary

$$\begin{aligned}\zeta_1(\cdot) = & \alpha_1 + c_{1,1} \cdot \mathbf{1}[a_{t-1} \neq 1] + c_{1,2} \cdot \mathbf{1}[k_{1,t} = 0] \\ & + \vartheta_1 \cdot \mathbf{1}[h_t \geq 12] + \vartheta_2 \cdot \mathbf{1}[h_t \geq 16] + \vartheta_3 \cdot \mathbf{1}[k_{3,t} = 1]\end{aligned}$$

- Wage component

$$w_1(\cdot) = r_1 x_1(\cdot),$$

where $x_1(\cdot)$ is the occupation-specific skill level.

$$x_1(\cdot) = \exp \left(\Gamma_1(\mathbf{k}_t, h_t, t, a_{t-1}, e_{j,1}) \cdot \varepsilon_{1,t} \right)$$

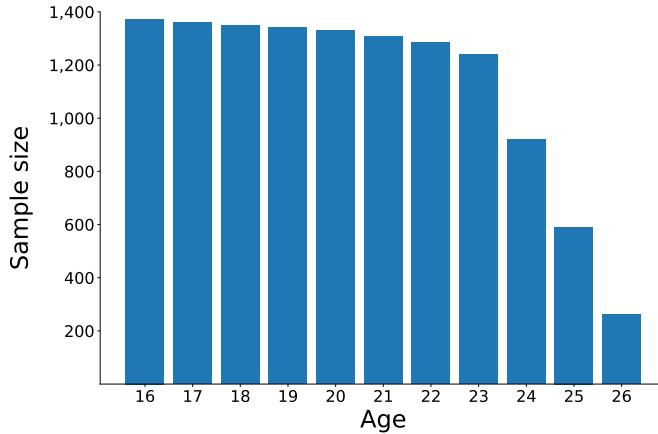
- Parameterization of the deterministic component of the skill production function:

$$\begin{aligned} \Gamma_1(\cdot) = & e_{j,1} + \beta_{1,1} \cdot h_t + \beta_{1,2} \cdot \mathbf{1}[h_t \geq 12] + \beta_{1,3} \cdot \mathbf{1}[h_t \geq 16] \\ & + \gamma_{1,1} \cdot k_{1,t} + \gamma_{1,2} \cdot (k_{1,t})^2 + \gamma_{1,3} \cdot \mathbf{1}[k_{1,t} > 0] \\ & + \gamma_{1,4} \cdot t + \gamma_{1,5} \cdot \mathbf{1}[t < 18] \\ & + \gamma_{1,6} \cdot \mathbf{1}[a_{t-1} = 1] + \gamma_{1,7} \cdot k_{2,t} + \gamma_{1,8} \cdot k_{3,t} \end{aligned}$$

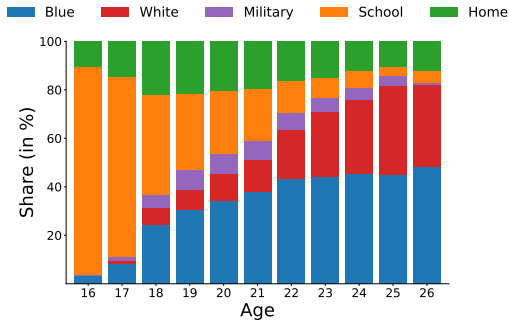
National Longitudinal Survey of Youth 1979

- 1,373 individuals starting at age 16
- Life cycle histories
 - School attendance
 - Occupation-specific work status
 - Wages

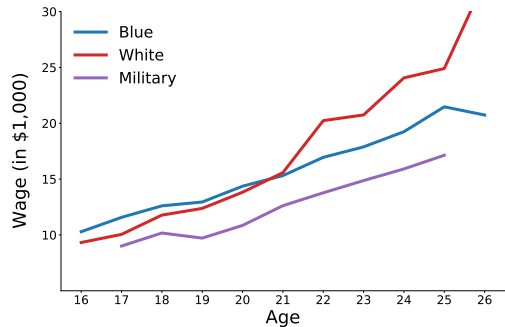
Sample size



Data descriptives

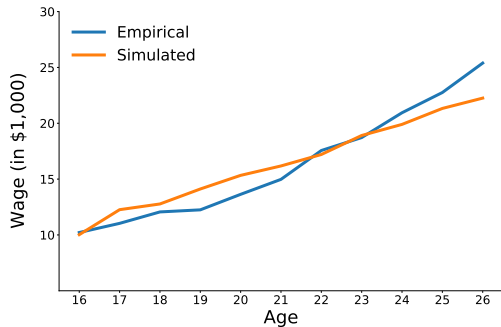


(a) Choices

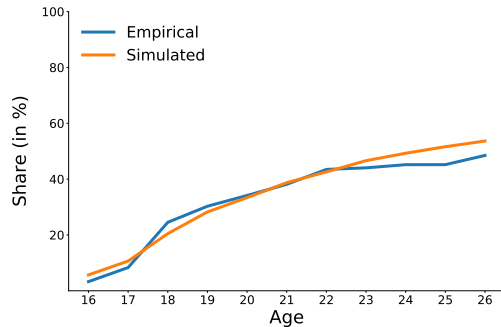


(b) Wages

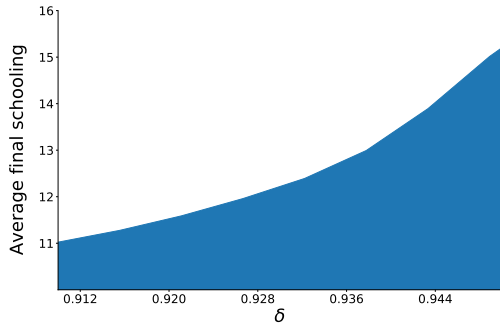
Calibration results



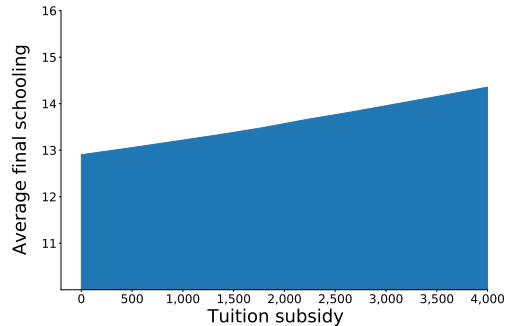
(a) Average wage



(b) Blue-collar



(a) Time preference



(b) Tuition subsidy

Pipeline

Tooling

respy

GitHub [OpenSourceEconomics/respy](https://github.com/OpenSourceEconomics/respy)

Docs respy.readthedocs.io

estimagic

GitHub [OpenSourceEconomics/estimagic](https://github.com/OpenSourceEconomics/estimagic)

Docs estimagic.readthedocs.io

Workflow

```
import respy as rp
from estimagic import maximize

# obtain model input
params, options, df = rp.get_example_model("kw_97_extended_respy")

# process model specification
log_like = rp.get_log_like_func(params, options, df)
simulate = rp.get_simulate_func(params, options)

# perform calibration
results, params_rslt = maximize(log_like, params, "nlopt_bobyqa")

# conduct analysis
df_rslt = simulate(params_rslt)
```

Model parameterization

		value	name
category	name		
delta	delta	9.370735e-01	delta_delta
wage_white-collar	constant	8.741888e+00	wage_white-collar_constant
	exp_school	6.548940e-02	wage_white-collar_exp_school
	exp_white-collar	1.763655e-02	wage_white-collar_exp_white-collar
	exp_white-collar_square	-4.215936e-02	wage_white-collar_exp_white-collar_square
	exp_blue-collar	3.431936e-02	wage_white-collar_exp_blue-collar
	exp_military	1.406945e-02	wage_white-collar_exp_military
	hs_graduate	-3.599855e-03	wage_white-collar_hs_graduate
	co_graduate	2.301313e-03	wage_white-collar_co_graduate
	period	9.577717e-03	wage_white-collar_period
	is_minor	-1.509984e-01	wage_white-collar_is_minor

Model options

	value
estimation_draws	200
estimation_seed	500
estimation_tau	500
interpolation_points	-1
n_periods	50
simulation_agents	5000
simulation_seed	132
solution_draws	500
solution_seed	456
monte_carlo_sequence	random
covariates	{'hs_graduate': 'exp_school >= 12', 'co_gradua...

Projects

Research projects

Economics and data

- **Biased expectations** Incorporate subjective expectations
Collaboration with DIW for SOEP-IS data collection
- Robust decisions
- Option value

Economics and data

- Biased expectations
- **Robust decisions** Account for ubiquitous uncertainties
Robust decision in light of model misspecification
- Option value

Research projects

Economics and data

- Biased expectations
- Robust decisions

- **Option value**

Schooling reform for identification and validation
Collaboration with Statistics Norway

Research projects

Computation

- **Uncertainty quantification** Capture parametric uncertainty
Assess competing policy implications
- Global optimization
- HPC implementation

Research projects

Computation

- Uncertainty quantification
- **Global optimization** Explore estimation uncertainty
Acknowledge multiplicity of local minima
- HPC implementation

Research projects

Computation

- Uncertainty quantification
- Global optimization

- **HPC implementation**

Enable increased realism and auditing of economic models
Exploit large-scale parallelism on supercomputers

Conclusion

Join us!



<http://bit.ly/ose-github>



<http://bit.ly/ose-zulip>



https://twitter.com/open_econ



<https://open-econ.org>



**Open Source
Economics**



respy



econsa

References

References

- Aguirregabiria, Victor, and Pedro Mira.** 2010. "Dynamic Discrete Choice Structural Models: A survey." *Journal of Econometrics* 156 (1): 38–67.
- Becker, Gary S.** 1964. *Human Capital*. New York City, NY: Columbia University Press.
- Bellman, Richard E.** 1954. "The theory of dynamic programming." *Bulletin of the American Mathematical Society* 60 (6): 503–15.
- Keane, Michael P., and Kenneth I. Wolpin.** 1997. "The career decisions of young men." *Journal of Political Economy* 105 (3): 473–522. [PDF p. 24]
- Keane, Micheal P, and Kenneth I Wolpin.** 1994. "The Solution and Estimation of Discrete Choice Dynamic Programming Models by Simulation and Interpolation: Monte Carlo Evidence." *Review of Economics and Statistics* 76 (4): 648–72.
- Puterman, Martin L.** 1994. *Markov decision processes: Discrete stochastic dynamic programming*. New York City, NY: John Wiley & Sons.
- White, D. J.** 1993. *Markov decision processes*. New York City, NY: John Wiley & Sons.
- Wolpin, Kenneth I.** 2013. *The Limits to Inference without Theory*. Cambridge, MA: MIT University Press.