# Why Structural Econometrics

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# Introduction

# Outline

# Goals For This Lecture

- Explain what structural econometrics is
- Show when it can be useful
- Relate it to use of models in other disciplines
- Look at one paper in detail
- Give you an intuition for structural modeling

# Why Structural Econometrics?

- Hierarchy of policy evaluations
  - P1 Evaluate effect of a policy that has been implemented
  - P2 Predict effect a policy that has been implemented in one environment would have in a different environment
  - P3 Predict the effect of a policy that has not yet been implemented (Ex-ante Evaluation)
- The main goal of structural econometrics is ex-ante Evaluation!

# Models in Economics

# Models in Economics

- Behavioral economists:
  - Conceptual tool to organize thoughts
  - Discipline thinking by mathematical rigor
  - Rationalize results of experiments
- Theorists:
  - Uncover deep truths about human behavior
  - Mechanism design
  - Welfare theorems
- Macroeconomists:
  - ?
- It's hard to tell what's a good model ...

# Structural Models

- Model = tool to predict causal effect of policies
- Can be used to design optimal policy
- Model is good if it predicts the effect reasonably well

→ Unrealistic assumptions might be OK

→ Channels of model are not always meaningful

# Models in Other Disciplines

# Example 1: Car Manufacturers

# Example

- Want to take an existing car and make it lighter
- There are many options:
  - Replace steel by lighter materials
  - Replace simple shapes by optimized profiles
  - Make materials thinner
- Each decision affects behavior in crash
- In the end, car needs to conform to standards

# How Could Safety Be Assessed?

- Experimental approach:
  - Build (a few) prototypes for each design change
  - Crash them at different speeds
  - Assess safety for passengers
- Problems:
  - Prototypes cost a lot
  - The process is very time consuming
  - We haven't even tested combinations of changes!
  - How would we ever find the optimal modifications?

# What is Actually Done?

- Develop a computer model of cars
  - Model = mapping from car to crash behavior
  - Describe shape and material of each component
  - Use properties of the materials to predict how the car reacts to a crash
  - Make simplifying assumptions for speed reasons
- Advantages:
  - Reduce the number of costly experiments
  - Try out multiple changes at a time
  - Find the optimal combination of changes!

# How Do They Know it Works?

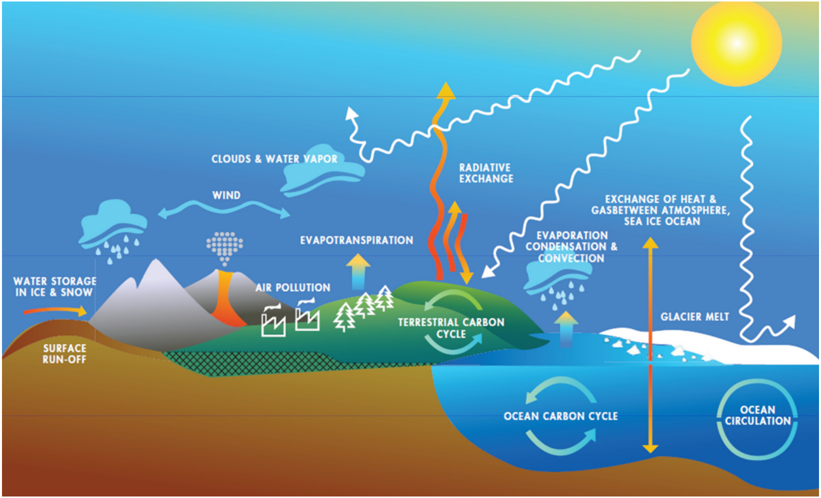
- Actually build some cars and crash them
- Simulate crashes for the same cars
- Compare the results
- i.e. go back to the experimental approach
- This is called model validation

# Example 2: Climate Science

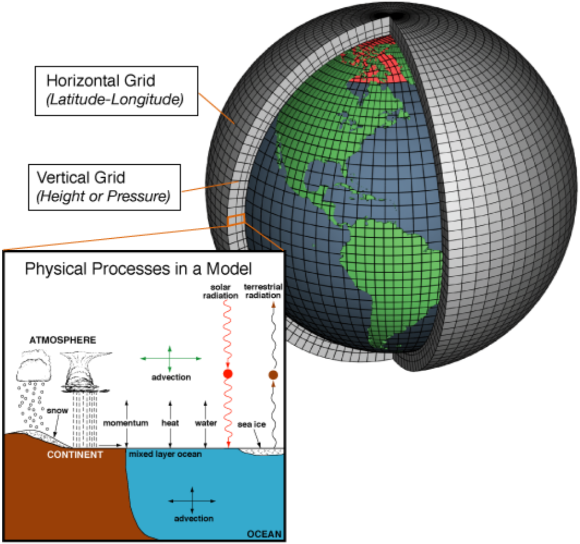
# Example

- We want to predict effect of CO2 doubling on average air temperature in Germany
- Many things to consider
  - Direct effect on atmospheric temperature
  - Some extra heat is absorbed by oceans
  - Feedback via change of ocean currents
- Experimental approach is not possible

# Conceptual Climate Model



# Abstractions and Simplifications



# Equations

- Temperature (T)
- Pressure (P)
- Winds (U,V)
- Humidity (Q)

- Conservation of momentum

  $$\frac{\partial \vec{V}}{\partial t} = -(\vec{V}\cdot\nabla)\vec{V} - \frac{1}{\rho}\nabla p - \vec{g} - 2\vec{\Omega}\times\vec{V} + \nabla\cdot(k_m\nabla\vec{V}) - \vec{F}_d$$

- Conservation of energy

  $$\rho c_{\vec{v}}\frac{\partial T}{\partial t} = -\rho c_{\vec{v}}(\vec{V}\cdot\nabla)T - \nabla\cdot\vec{R} + \nabla\cdot(k_T\nabla T) + C + S$$

- Conservation of mass

  $$\frac{\partial \rho}{\partial t} = -(\vec{V}\cdot\nabla)\rho - \rho(\nabla\cdot\vec{V})$$

- Conservation of $H_2O$ (vapor, liquid, solid)

  $$\frac{\partial q}{\partial t} = -(\vec{V}\cdot\nabla)q + \nabla\cdot(k_q\nabla q) + S_q + E$$

- Equation of state

  $$p = \rho R_d T$$

***Calculated for each grid cell at each time step***

# How to Calibrate This Model

- Divide the model into components
  - Atmospheric model
  - 2 layer ocean model
- Calibrate components by lab experiments
  - Ocean = bathtub
- Measure initial conditions as precisely as possible
  - More than 40 000 weather stations worldwide
  - Sensors to measure ocean temperature

# How Do They Know it Works?

- Validate subcomponents
- Quantify uncertainty around initial conditions
- Quantify uncertainty around lab calibrated parameters

# Summary

# Summary I

- Engineers
  - Can experiment
  - Use models to need fewer experiments
  - Calibrate and validate models with experimental data
- Climate scientists
  - Can only do very simplified experiments
  - Use models to replace real experiments
  - Calibrate and validate subcomponents

# Summary II

- In both cases, models are:
  - Extremely simplified ("all models are wrong")
  - Have a clear purpose (prediction)
  - Might be wrong but good enough for that purpose
- Economists are between the two
  - Experimentation is more difficult than for engineers
  - Macro-experiments are sometimes possible

# An Example of a Structural Model

# Background

# The PROGRESA Program

- Todd and Wolpin, 2006 evaluate the Conditional Cash Transfer (CCT) PROGRESA
- first Latin American CCT program
- Eligible mothers get cash if children go to school and health checkups
- Transfers start at 3$^{rd}$ grade and end after 9$^{th}$ grade
- Benefit increases with grade and is higher for girls

# Transfer Schedule

| | | Monthly Payment in Pesos | |
|---|---|---|---|
| School Level | Grade | Females | Males |
| Primary | 3 | 70 | 70 |
| | 4 | 80 | 80 |
| | 5 | 105 | 105 |
| | 6 | 135 | 135 |
| Secondary | 1 | 210 | 200 |
| | 2 | 235 | 210 |
| | 3 | 255 | 225 |

- For US-Dollars, divide by 10

# Hypothesized Effects of CCTs

**Positive**

- Increase human capital via school attendance
- Improve child health
- Alleviate extreme poverty

**Negative**

- Negative incentives on fertility decisions of young women

# The Field Experiment

- Random Assignment of:
  - 320 treatment villages
  - 186 control villages
- In treatment villages, about 50 % of households are eligible
- Pre-intervention data collected before March 1998
- Post-intervention data collected until end of 1999

# Policy Questions

# What Can We Learn from the Experiment?

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What is the ATT of the implemented transfer scheme on school attainment one year after the intervention if the policy is introduced as a surprise but announced to be permanent?

# And Which Can't?

- What is the most **efficient transfer scheme**?
- What is the effect of that policy if it is already **in place when people take fertility decisions**?
- What is the effect on **total school attainment**?

# Contributions of the Paper

- Answers the questions that can't be answered by the experiment
- Requires a structural model
- "no consensus on what is a reasonable model"
  - Estimate model on control group data
  - Use it to predict the effect of the experiment
  - Validate model on treatment group
- One of the first papers to address and implement model validation in a systematic way

# A Model of Schooling Choices and Fertility

# Type of Model

- Finite Horizon **Discrete Choice Dynamic Programming** (DCDP) Model
- **Intuitively**: "*a behavioral economic model that can be described as sequential discrete choice optimization problems constrained by resource limitations and imperfect information about future events.*"
- Widely applied for ex-ante policy evaluation
- Models the decision making process of individuals
- After policy, decisions change but decision making process does not!

# Choice Set

- In each period, households decide:
  - Whether to become pregnant or not
  - For each child, decide whether:
    - Child stays at home
    - Child goes to school
    - Child works and earns income
- In each fertile period there are $2 \cdot 3^n$ options, where $n$ is the number of children

# Rewards and Constraints

- Immediate utility depends on:
  - Consumption
  - Pregnancy and birth history
  - Schooling history for each child
  - Children at home
  - Distance to school
  - Shocks
- Constraints
  - Consumption = (exogenous) parent income + (endogenous) child labor income

# State Space

- **Definition**: set of all factors, known to the individual, that affect current rewards or the probability distribution of any of the future rewards.
- The state space contains:
  - Birth histories of sons and daughters
  - School histories of sons and daughters
  - Age of parents and age at marriage
  - Distance to secondary school and city
  - Current preference shocks (unobserved)
  - Types (permanent heterogeneity, unobserved)
- The state space is huge

# Identification of the Policy Effect From Observational Data

# Identification of the Policy Effect

- **Best Case**: exogenous variation in tuition costs
- **Instead**: exploit variation in child wages
- **Problem**: only observe wages if children work
- **Solution**:
  - Estimate the wage offer distribution
  - Model is identified, if there is a variable that affects wage offers but not parents' preference for schooling
  - Authors use distance to next city

Economic Assumptions

# Convenience Assumptions

- Distributional assumptions on unobservables
- Functional form assumptions on utility functions
- Not only needed for estimation, but even for identification
- Model can be estimated by maximum likelihood

# Model Validation

# What Is Meant By Validation

- In-sample goodness of fit measures can't check model's ability to predict counterfactuals
- Instead: use model to predict effects of policies not observed in the estimation sample
- Compare predictions with experimental treatment effects
- If this works, consider the model to be validated with respect to that policy question

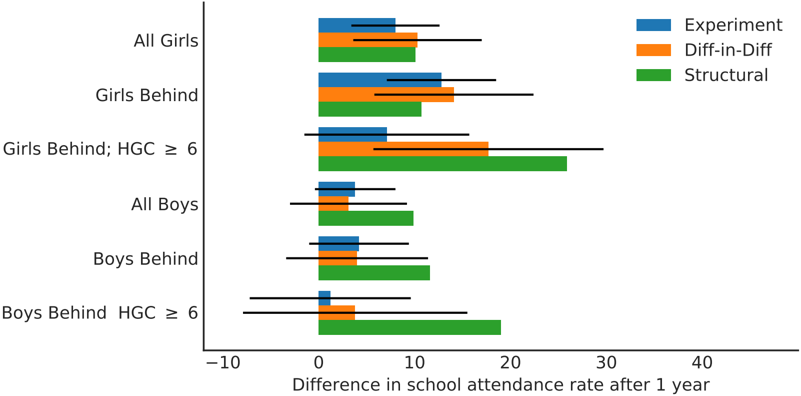
# Use the Model to Predict Treatment Effects

- Closer look at the budget constraint in the treatment group:

$$C(t) = y_p(t) + \sum_{n=1}^{N} y_n(t)\mathbb{1}_{\{\text{n works}\}} + \tau_n(t)\mathbb{1}_{\{\text{n at school}\}} \qquad (1)$$

- This can be used for counterfactual simulation
- To do so, use 200 simulation draws per family
- In what follows, this is used to:
  - Predict experimental treatment effects
  - Predict choices
  - Answer the policy questions

# Figure: Actual and predicted treatment effects



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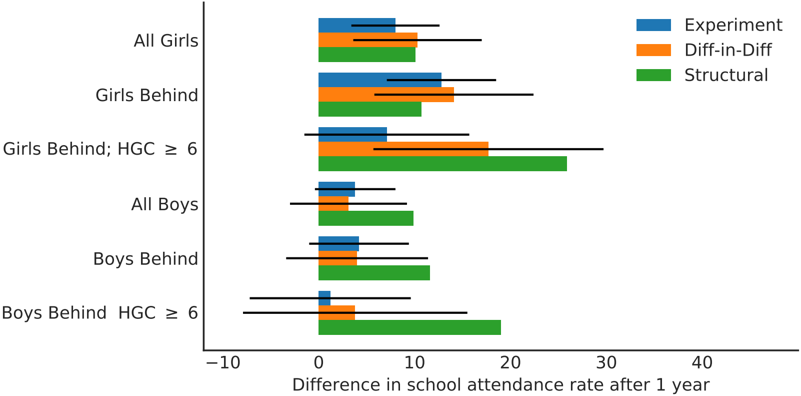
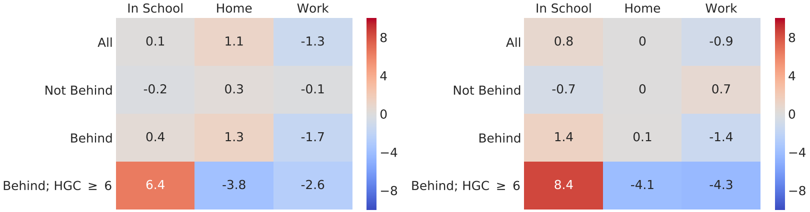



- Effects of the policy on school attendance rates after 1 year
- Children aged 12 to 15
- Bars show ±1 Standard Error

Figure: Actual And Predicted Choices

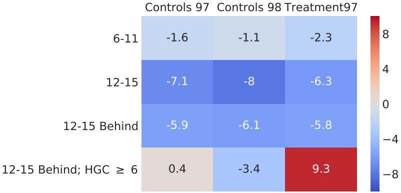



(a) Girls

(b) Boys

- Children aged 12 to 15
- Deviations between actual and predicted group percentages
- Overall pretty good!

Figure: Actual and Predicted Schooling N-Years Ahead

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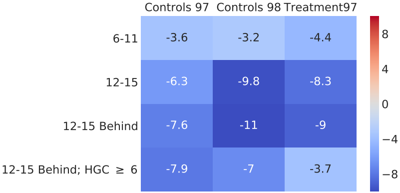
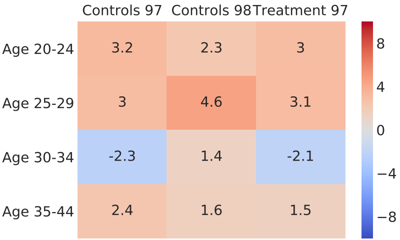



(b) Boys

- Predictions only based on household characteristics at marriage!

Figure: Actual and Predicted Pregnancy Rate N-Years Ahead




- Predictions only based on household characteristics at marriage!

# Answers to Policy Questions

# Treatment Effects in Short and Long Run

| | Girls | | Boys | |
|---|---|---|---|---|
| | Short-run effect | Long-run effect | Short-run effect | Long-run effect |
| Control group | | | | |
| 1997 | 10.9 | 11.9 | 10.7 | 12.0 |
| 1998 | 11.2 | 12.3 | 11.4 | 12.7 |
| Treatment group | | | | |
| 1997 | 11.2 | 12.3 | 11.3 | 12.4 |
| 1998 | 11.7 | 12.7 | 12.1 | 12.4 |

- Effects of the policy on school attendance rates
- Long: program is in place since marriage!
- Long effects slightly larger than short run effects

# Effects on Completed Schooling

| | Girls | | Boys | |
|---|---|---|---|---|
| | No subsidy | Subsidy | No subsidy | Subsidy |
| Mean schooling | 6.29 | 6.83 | 6.42 | 6.96 |
| % completing grade 6 or more | 75.8 | 82.2 | 78.8 | 83.3 |
| % completing grade 9 or more | 19.8 | 25.9 | 22.8 | 28.0 |

# Alternative Transfer Schedules

- The authors simulate several alternative subsidies
- A cost neutral shift of transfers towards the higher grades, makes the treatment effect about 25 % larger
- This was to be expected, since school attendance is universal in earlier grades
- **Careful**: The outcome variable is only completed schooling; Positive effects on cognitive and non-cognitive skills through other parental investments are not included!

# Summary of the Workflow

- Specify explicit economic model of decision making
- Estimate the model on data
- Use estimates to simulate effect of policies
- Model is good if it predicts policies well
- Ideally, shown by validation through a policy experiment

# Some Notes on Structural Econometrics

# Why Are Individuals Optimizing

- Reason 1: We believe in utility maximization
- Reason 2: People might behave close to optimal without optimizing
- Example:
  - A new tax policy is implemented
  - Some people find that after the change it's better to retire earlier
  - They talk to others about what worked for them
  - Over time, people converge to the optimum
  - Basic argument: Swarm intelligence

# Wouldn't Almost-Optimization be Enough?

- Lumsdaine et al., 1990 estimates three models of retirement
  1. Standard DCDP model with dynamic optimization
  2. Option value model that is similar to the DCDP model but replaces the Emax function by the maxE function and thus simplifies the computational burden considerably.
  3. A static probit model.
- Validate all three models experimentally
- 1 and 2 are equally good
- Absolutely no impact on later literature!

# Structural Econometrics and Experiments

- Experiments can help structural Economists
  - Cleaner Identification
  - Validation
  - Wolpin, 2013 discusses trade-offs
- Structural models can help experimentalists
  - Design the right experiment to identify effect of interest
  - Model helps to organize thoughts (DellaVigna, 2017)

# Structural Econometrics and Machine Learning (ML)

- Models are tools to predict effect of policies
- Machine Learning is great at prediction
- It makes less assumptions on behavior
- Why not use it instead?

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- It makes less assumptions on behavior
- Why not use it instead?
- ML predicts well as long as Data Generating Process does not change
- Structural Model uses theory to identify policy effect from surrogate variation in the data

# What can We Learn from ML

- Use (possibly non-random) holdout samples
- Cross validation techniques
- Modern Hardware (GPUs, TPUs, . . . )
- Algorithmic improvements
- Function approximation methods

# Summary

# Summary

- Economists use models for various purposes
- Conceptual Tool, discipline thinking, Understanding behavior
- Other disciplines use models as prediction tools
  - Opens the possibility to validate a model
- Structural Econometrics bridges that gap
- Simplifying assumptions are ok, as long as you validate
- Good example: Todd and Wolpin, 2006

# References I


DellaVigna, Stefano (2017). “Structural Behavioral Economics”. Future Handbook Chapter.

Lumsdaine, R.L., J.H. Stock, D.A. Wise, and National Bureau of Economic Research (1990). *Three Models of Retirement: Computational Complexity Versus Predictive Validity*. NBER working paper Nr. 3558. National Bureau of Economic Research. URL: https://books.google.de/books?id=WqsiAQAAMAAJ.

# References II


Todd, Petra E. and Kenneth I. Wolpin (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". In: *American Economic Review* 96.5, pp. 1384–1417. DOI: 10.1257/aer.96.5.1384. URL: http://www.aeaweb.org/articles?id=10.1257/aer.96.5.1384.

Wolpin, Kenneth I. (2013). *The Limits of Inference without Theory*. MIT Press. ISBN: 9780262019088. URL: http://www.jstor.org/stable/j.ctt5vjpxr.