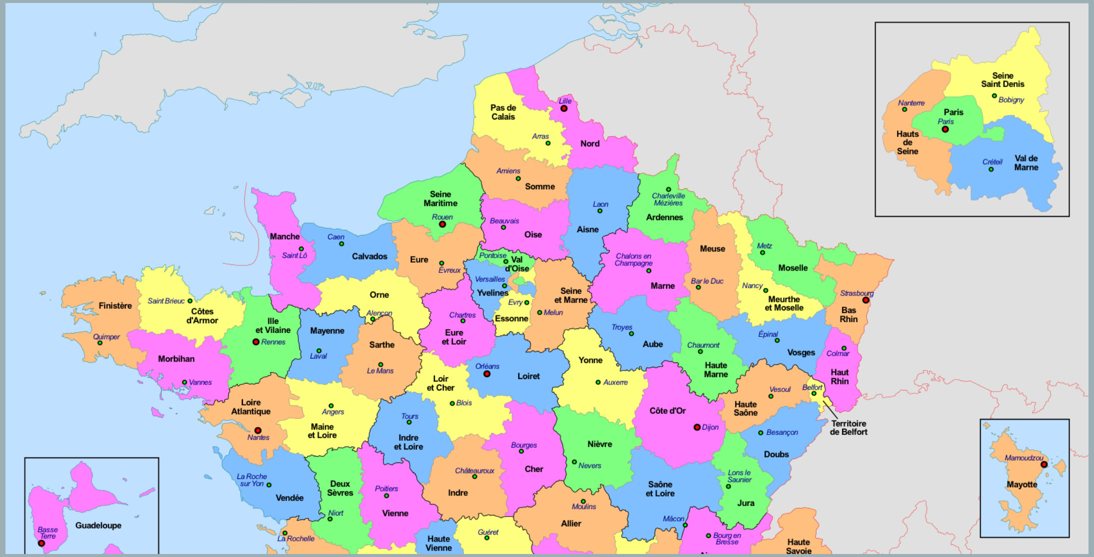
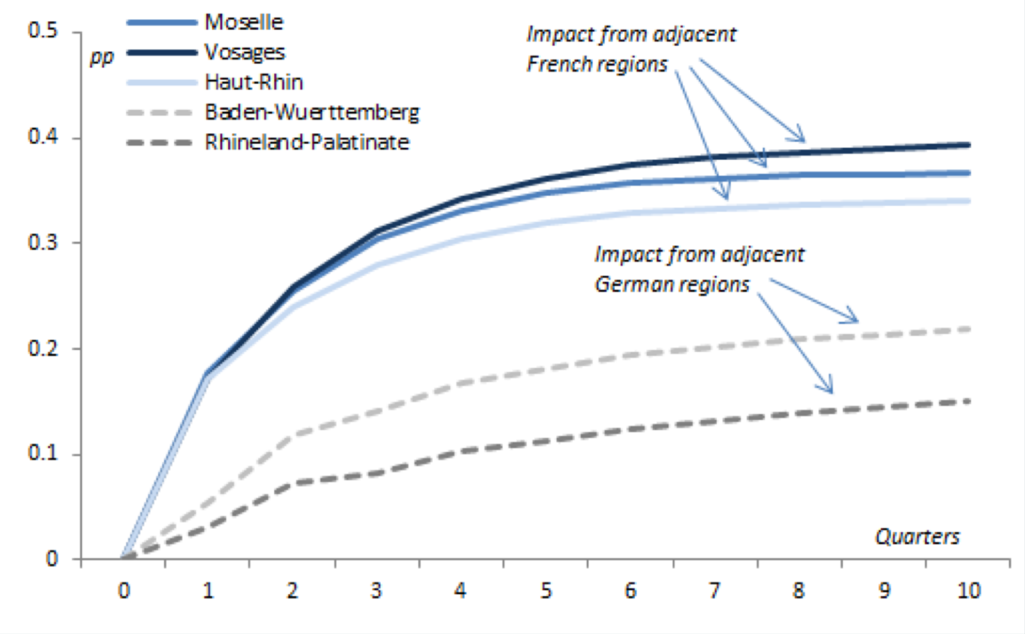
MACROECONOMICS AT THE VAMPIRE SQUID

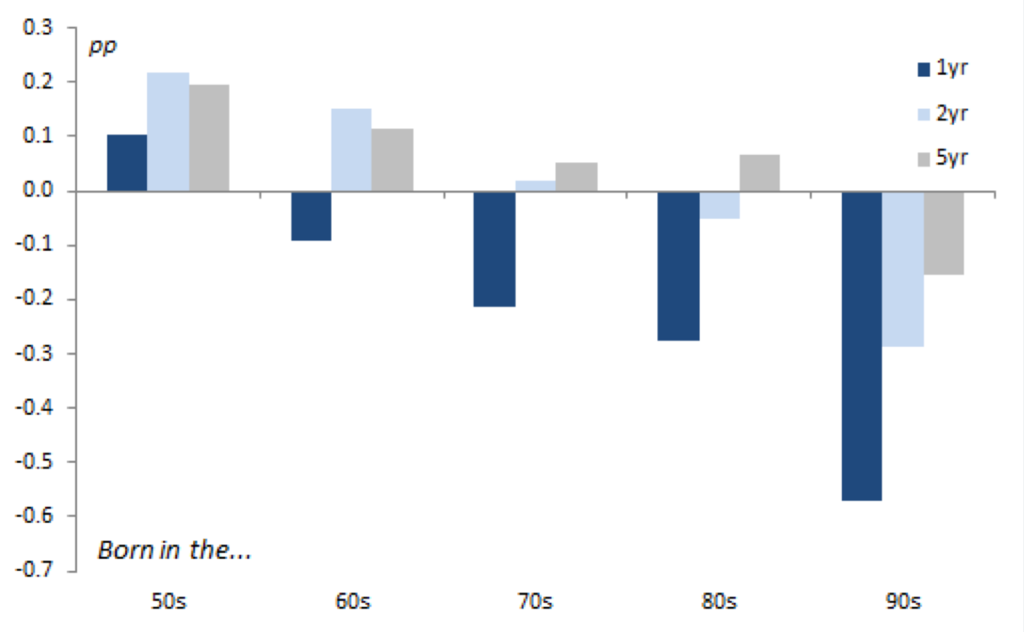


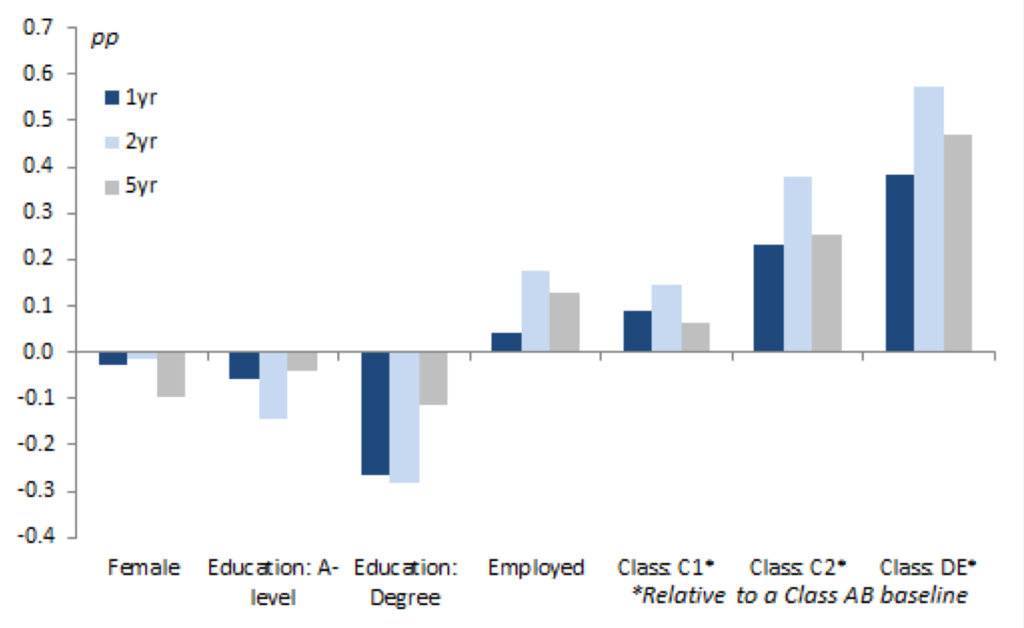
Impact on the unemployment rate of Bas-rhin of a 1 s.d. shock to regional unemployment rates



- Q: Should we model the European labour market as one labour market?
- Research design:
  - Borrow from regression discontinuity literature – reduced form, not structural
  - Regions on the borders between countries should react similarly to shocks from adjacent labour markets – regardless of the "nationality" of the shock
  - Model the change in the unemployment rate in a VECM, with adjacent regions as explanatory variables (and other controls)
- Findings:
  - Model the European labour market as separate countries – it is not well integrated across borders.

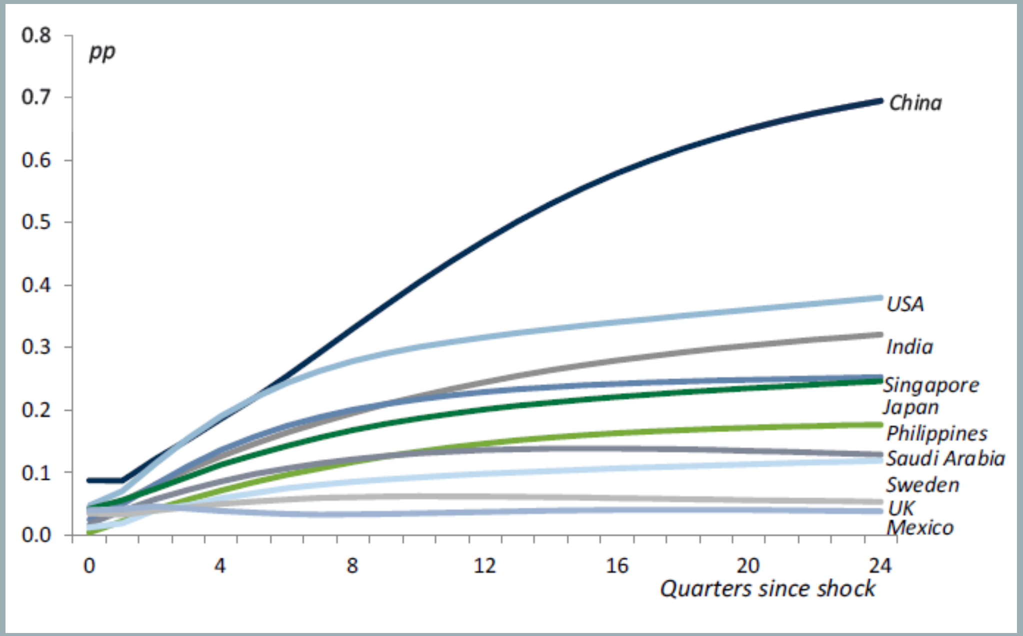
Relative to being born in the 40s, more recent generations have lower inflation expectations



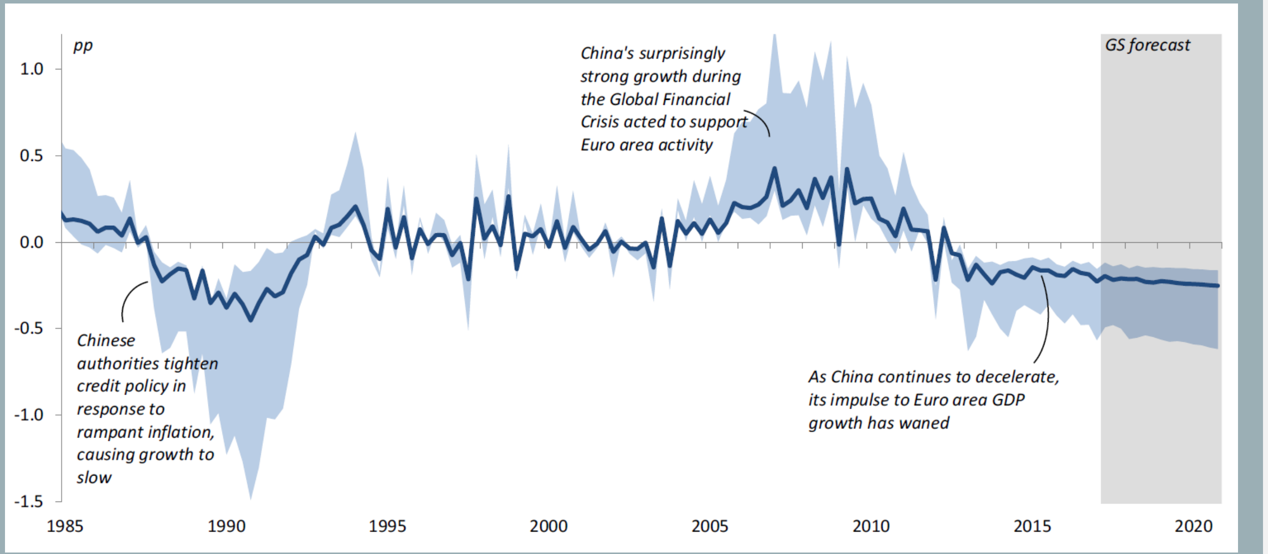


- Q: Why are inflation expectations drifting downwards?
- Research design:
  - Use micro-data from consumer expectation surveys
  - Psychology literature suggests experiences are formative in your younger years
  - Could people who lived through high inflation periods have higher inflation expectations?
- Findings:
  - Cohort matters for inflation expectations. Those who lived through high inflation in their 20s have avg. expectation 0.7pp higher than those born in the 1990s.
  - Expect the downward drift in inflation expectations to continue
  - Does this have monetary policy implications?

Impact on Euro area of a one s.e. shock to Foreign country GDP



Impulse to Euro area growth, 90% CI



- Q: What would the impact of a Chinese slowdown be on the Euro area economy?
- Research design:
  - Easy to model direct relationship. But what about general equilibrium relationship?
  - Need to incorporate channels that work through third countries, commodity prices, financial prices etc…
  - And side-step the curse of dimensionality
  - Use a GVAR:
    - Stack individual country VARs (26), with domestic endogenous variables and…
    - …global external variables that are trade-weighted and weakly exogenous
- Findings:
  - Size matters
  - Volatility matters
  - Indirect linkages matter

Good job :)

Who's up next?

AGE OF MARRIAGE, WEATHER SHOCKS, AND THE DIRECTION OF MARRIAGE PAYMENTS

Lucia Corno, Nicole Hildebrandt, Alessandra Voena

Alex Weinberg
University of Chicago

weinberga@uchicago.edu

July 19, 2018

Motivation

- 700 Million women alive today were married before age of 18
- Especially common in South Asia and Sub-Saharan Africa
    - 56% of women in South Asia
    - 42% of women in Sub-Saharan Africa
- Early marriage associated with a wide range of adverse outcomes for women and their offspring including:
    - higher rates of domestic violence
    - harmful effects on maternal, newborn, and infant health
    - reduced sexual and reproductive autonomy
    - lower literacy and educational attainment

Research Question

- Do aggregate Economic forces influence marriage decisions?
- In particular, do aggregate shocks affect rates of child marriage?
- In what direction?
  - Dowry vs. Brideweath (Brideprice)

This Paper

- Builds an equilibrium model of child marriage incorporating income shocks
- Matches drought data and survey data to test what [if any] effect a drought has on marriage decision
- Finds:
  - Africa: droughts increase the probability of child marriage
  - India: droughts decrease probability

Optimal Stopping Problem

Editor – /Users/alexweinberg/Desktop/Code/Economics/Research/Voena/alex_SellingDaughters/life_cycle_women.m

life_cycle_women.m

```matlab
%%%%TERMINAL PERIOD
%%%% daughter is already married
V1(:,T)=utility(Income_unc',gamma); %Utility of Income going forward
V0(:,T)=-Inf;                       %Already married, so V0 not an option

%%%%%%%%% periods in which daughter can no longer get married
for t = T-1:-1:ages(end)+1
    t
    %%%%%%%%%%%% calculate expectations
    ev1 = repmat((expected_value(PWeights,V1(:,t+1),1)),[I,1]); %Exp_value of V1 given income probs
    V1(:,t) = utility(Income_unc',gamma)+beta*ev1;              %utility today + expval tommorow
    V0(:,t) = -Inf;
end

%%%%%%%%%% PERIODS IN WHICH DAUGHTER CAN MARRY %%%%%%%%%%%%
for t = ages(end):-1:ages(1)
    t
    %%%%%%%%%%%% calculate expectations
    %If already sold daughter
    ev0 = repmat((expected_value(PWeights,V0(:,t+1),1)),[I,1]); %Exp_val of staying unmarried
    ev1 = repmat((expected_value(PWeights,V1(:,t+1),1)),[I,1]); %Exp_val of already married
    V1(:,t) = utility(Income_unc',gamma)+beta*ev1;              %Val_func if already married
    %%%%% if have not yet married and sell
    v1 = utility(Income_unc' + BPAmount(t),gamma)+beta*ev1;     %Val_func for period when sell
    %%%% if have not yet married and not sell
    v2 = utility(Income_unc' - scale(t),gamma)+beta*ev0;        %Val_func for all periods not sell
    Sell(:,t)=(v1>=v2);                                         %Policy function
    V0(:,t)=max(v1,v2);                                         %Val_func for not yet married
end

%%%%%%%%% ages in which daughter cannot yet marry
```

My Work

- More detailed subset of the paper in Tanzania
- Finite horizon VFI, Optimal Stopping Probelm
  1. No savings decision
  2. When to sell your daughter?
- **Answer:** Using brideweath as consumption smoothing technique to smooth consumption when facing low-income shock.
- **Policy Counterfactual:** If allow savings? Marriage age goes up because want to accrue more of the benefit daughter provides to home.

Good job :)

Who's up next?

Endogenous Health Care in Overlapping Generations Model:

Simulation for Health Care and Economy

Fiona Fan

Lightning Talk for OSM Lab
July 19, 2018

Motivation

- **Health is an overlapping generations thing – Grossman Model (Grossman, 1972)**

$$H_{t+1} = (1-\delta)(H_t + I_t)$$

- **Key Features of Model**
  - Agents in the model choose health care to consume, in addition to consumption and savings.
  - Consumption of health care at time t boosts labor productivity at time t+1 (consistent with Grossman).
  - Insurance in forms of Medicare (young people pay for old people's health insurance). Other kinda insurance could be added (Hashimoto and Tabata, 2010)
  - Production of health care VS non-health-care good.

Motivation

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  - Production of health care VS non-health-care good.

What we can learn from simulation

- With the repeal of mandate (decreased insurance), what will happen to economic growth/ labor participation rate in healthcare VS non-health-care/ consumption of health care/ consumption of non-health-care, etc?
- What effect of aging/ decreased mortality rate affect health care consumption/ spending?

Demographics

$$\omega_{1,t+1} = (1-\rho_o)\sum_{s=1}^{E+S} f_s\omega_{s,t} + i_1\omega_{1,t}, \quad \forall t \tag{1}$$

$$\begin{aligned}\omega_{s+1,t+1} &= (1-\rho_s)\omega_{s,t} + i_{s+1}\omega_{s+1,t}, \\ &\forall t \quad \text{and} \quad 1 \le s \le E+S-1\end{aligned} \tag{2}$$

$$N_t = \sum_{s=1}^{E+S}\omega_{s,t} \qquad \tilde{N}_t = \sum_{s=E+1}^{E+S}\omega_{s,t} \tag{3}$$

$$g_{n,t+1} = \frac{N_{t+1}}{N_t} - 1 \qquad \tilde{g}_{n,t+1} = \frac{\tilde{N}_{t+1}}{\tilde{N}_t} - 1 \tag{4}$$

$$n_{s,t} = \begin{cases} 1, & E+1 \le s \le E + round(\frac{2S}{3}) \\ 0.2, & s \ge E + round(\frac{2S}{3}) \end{cases} \tag{5}$$

Households

- Budget Constraints

$$n_{s,t} = n_s \tag{6}$$

$$c_{s,t} + b_{s+1,t+1} + P_t^H h_{s,t} = (1 + r_t) b_{s,t} + w_t n_{s,t} f(h_{s-1,t-1}) + \frac{BQ_t}{\tilde{N}_t} \tag{7}$$

$$U = \frac{c^{(1-\sigma)}}{1-\sigma} + \frac{h^{(1-\gamma)}}{1-\gamma} \tag{8}$$

Households

- Budget Constraints

$$n_{s,t} = n_s \tag{6}$$

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$$U = \frac{c^{(1-\sigma)}}{1-\sigma} + \frac{h^{(1-\gamma)}}{1-\gamma} \tag{8}$$

- Utility Maximization

$$\max_{\substack{\{c_{s,t+s-1},h_{s,t+s-1}\}_{s=E+1}^{E+S}, \\ \{b_{s+1,t+s}\}_{s=E+1}^{E+S-1}}} \sum_{s=E+1}^{E+S} \beta^{s-E-1}[\Pi_{n=E}^{s-1}(1-\rho_n)]U(c_{s,t+s-E-1}, h_{s,t+s-E-1}) \quad \forall s,$$

$$s.t. \quad 6 \quad \text{and} \quad 7, \quad \text{and} \quad b_{E+1,t}, b_{E+S+1,t} = 0 \quad \forall t \quad \text{and} \quad c_{s,t} \geq 0 \quad \forall s,t$$

Euler Equations

$$\frac{\partial U(c_{s,t}, h_{s,t})}{\partial c_{s,t}} = \beta(1 + r_{t+1})(1 - \rho_s)\frac{\partial U(c_{s+1,t+1}, h_{s+1,t+1})}{\partial c_{s+1,t+1}} \tag{9}$$

$$\beta(1 - \rho_s)w_t n_s \frac{\partial f(h_{s,t})}{\partial h_{s,t}} \frac{\partial U(c_{s+1,t+1}, h_{s+1,t+1})}{\partial c_{s+1,t+1}} = P_t^H \frac{\partial U(c_{s,t}, h_{s,t})}{\partial c_{s,t}} + \frac{\partial U(c_{s,t}, h_{s,t})}{\partial h_{s,t}} \tag{10}$$

$$\forall t, \text{ and } E + 1 \leq s \leq S - 1$$

Each system has $S - 1$ Euler equations.

Firm

$$Y_t^H = A^H(e^{g_y} L_t^H) P_t^H \tag{11}$$

$$Y_t^N = A^N (K_t)^\alpha (e^{g_y} L_t^N)^{(1-\alpha)} \tag{12}$$

$$\max_{L_t^H} \quad P_t^H A^H (e^{g_y} L_t^H) - w_t^H L_t^H$$

$$\max_{K_t^N, L_t^N} \quad A_t^N (K_t^N)^\alpha (e^{g_y} L_t^N)^{(1-\alpha)} - (r_t^N + \delta) K_t^N - w_t^N L_t^N$$

Prices

$$r_t = \alpha A_N \left(\frac{L_t^N}{K_t}\right)^{(1-\alpha)} - \delta \tag{13}$$

$$w_t^H = w_t^N = A_N(1-\alpha)\left(\frac{K_t}{L_t^N}\right)^{\alpha_N} \tag{14}$$

$$P_t^H = \frac{w_t}{A_H} \tag{15}$$

Market Clearing

$$K_t = \sum_{s=E+2}^{E+S} (\omega_{s-1,t-1} b_{s,t} + i_s \omega_{s,t-1} b_{s,t}) \tag{16}$$

$$L_t^N + L_t^H = \sum_{s=E+1}^{E+S} \omega_{s,t} n_s f(h_{s-1,t-1}) \tag{17}$$

Market Clearing

$$K_t = \sum_{s=E+2}^{E+S} (\omega_{s-1,t-1} b_{s,t} + i_s \omega_{s,t-1} b_{s,t}) \tag{16}$$

$$L_t^N + L_t^H = \sum_{s=E+1}^{E+S} \omega_{s,t} n_s f(h_{s-1,t-1}) \tag{17}$$

$$Y_t^N = C_t + I_t - \sum_{s=E+2}^{E+S} i_s \omega_{s,t} b_{s,t+1} \quad \text{where} \tag{18}$$

$$I_t = K_{t+1} - (1-\delta) K_t \quad \text{and,}$$

$$C_t = \sum_{s=E+1}^{E+S} \omega_{s,t} c_{s,t}$$

$$Y_t^H = \sum_{s=E+1}^{E+S} \omega_{s,t} h_{s,t} \tag{19}$$

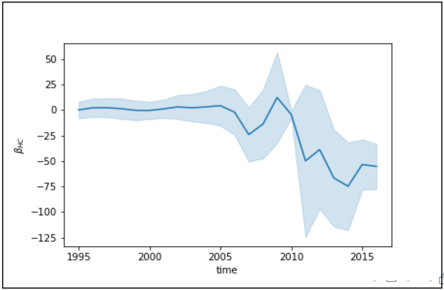
$$BQ_t = (1 + r_t) \sum_{s=E+2}^{E+S} \rho_{s-1} \omega_{s-1,t-1} b_{s,t} \tag{20}$$

Calibration and Simulation

Calibrations

- ζ_s: OCED data on increase in productivity VS health care spending/capita
- ρ, f, i: US Census data

Figure: Boost of Productivity by Healthcare over Time in OECD countries



Good job :)

Who's up next?

WILSON SHEEHAN

LAB FOR ECONOMIC OPPORTUNITIES

UNIVERSITY OF NOTRE DAME

Padua Pilot

Preliminary Results from a Randomized Control Trial

Background

- P.Is: James Sullivan & William Evans
- Co-Founders of Wilson-Sheehan Lab for Economic Opportunities
  - Research Question: Which innovative anti-poverty programs in the U.S. programs have the greatest potential to reduce domestic poverty?
  - Method: Impact evaluation through randomized control trial
  - Partners: Charities & Local Government

Key Components of Padua

- Holistic, wrap-around case management
- Low caseload and two-person service teams
- Detailed needs assessment (~6 hours of interviews)
- Customized service plan
- Financial assistance
- Two-year "treatment"

Eligibility

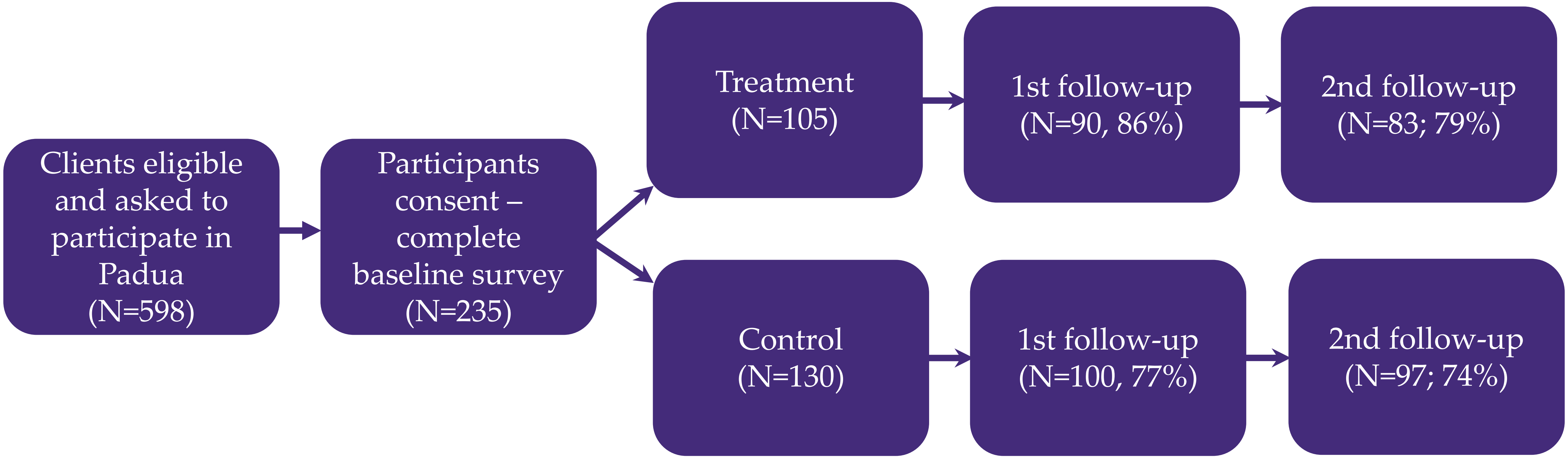
- Live in Tarrant County, TX
- At least 1 person aged 18-55 in HH willing/able to work
- Current income below the living wage for area
- Have not received services in past 30 days from CCFW
- Agree to do baseline survey
- Able to receive services in English or Spanish

	Summer/ Fall 2015	Summer/ Fall 2016	Summer/ Fall 2017	Summer/ Fall 2018	Summer/ Fall 2019
Cohort 1	Enrollment	1st Follow-up	2nd Follow-up		
Cohort 2		Enrollment	1st Follow-up	2nd Follow-up	

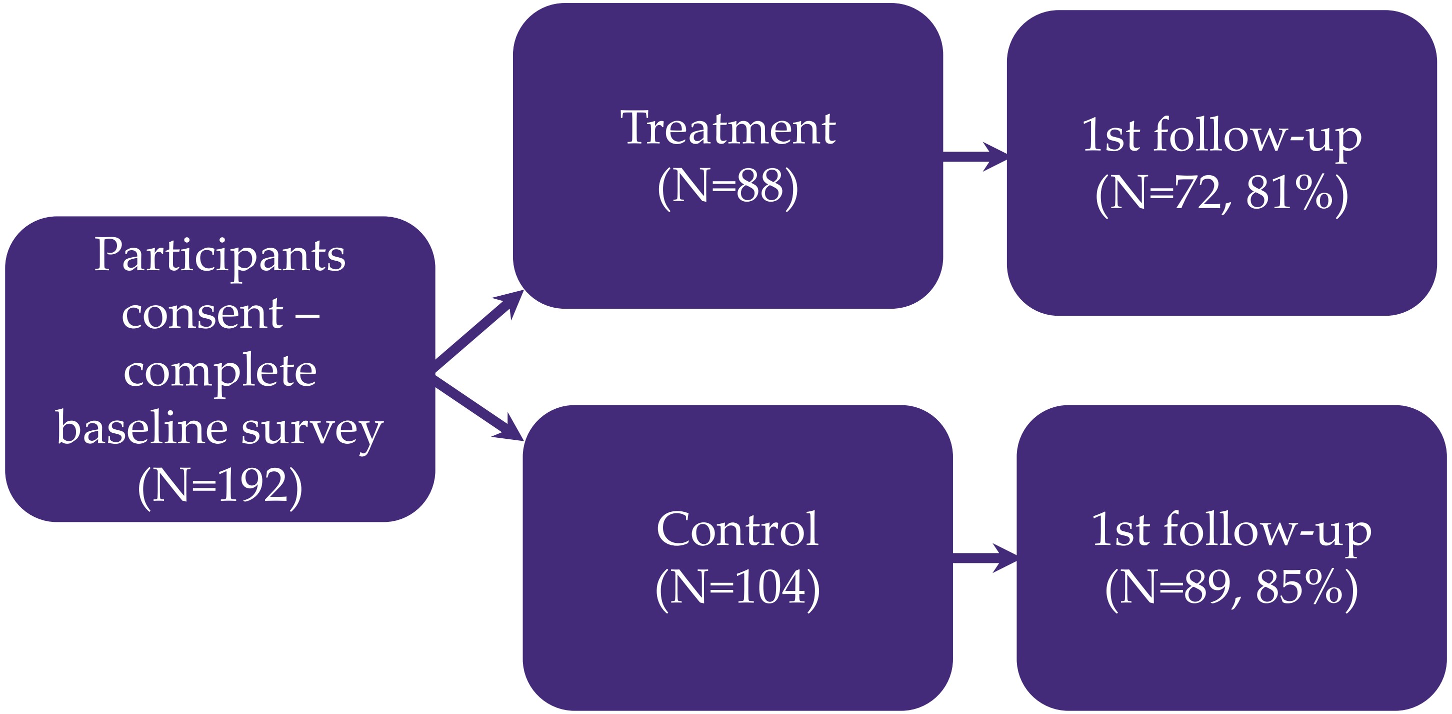
Completed

In the field now

Cohort 1 Timeline



Cohort 2 Timeline



Results in three areas

- Labor market outcomes
- Debt & Savings
- Use of government programs

Caveats

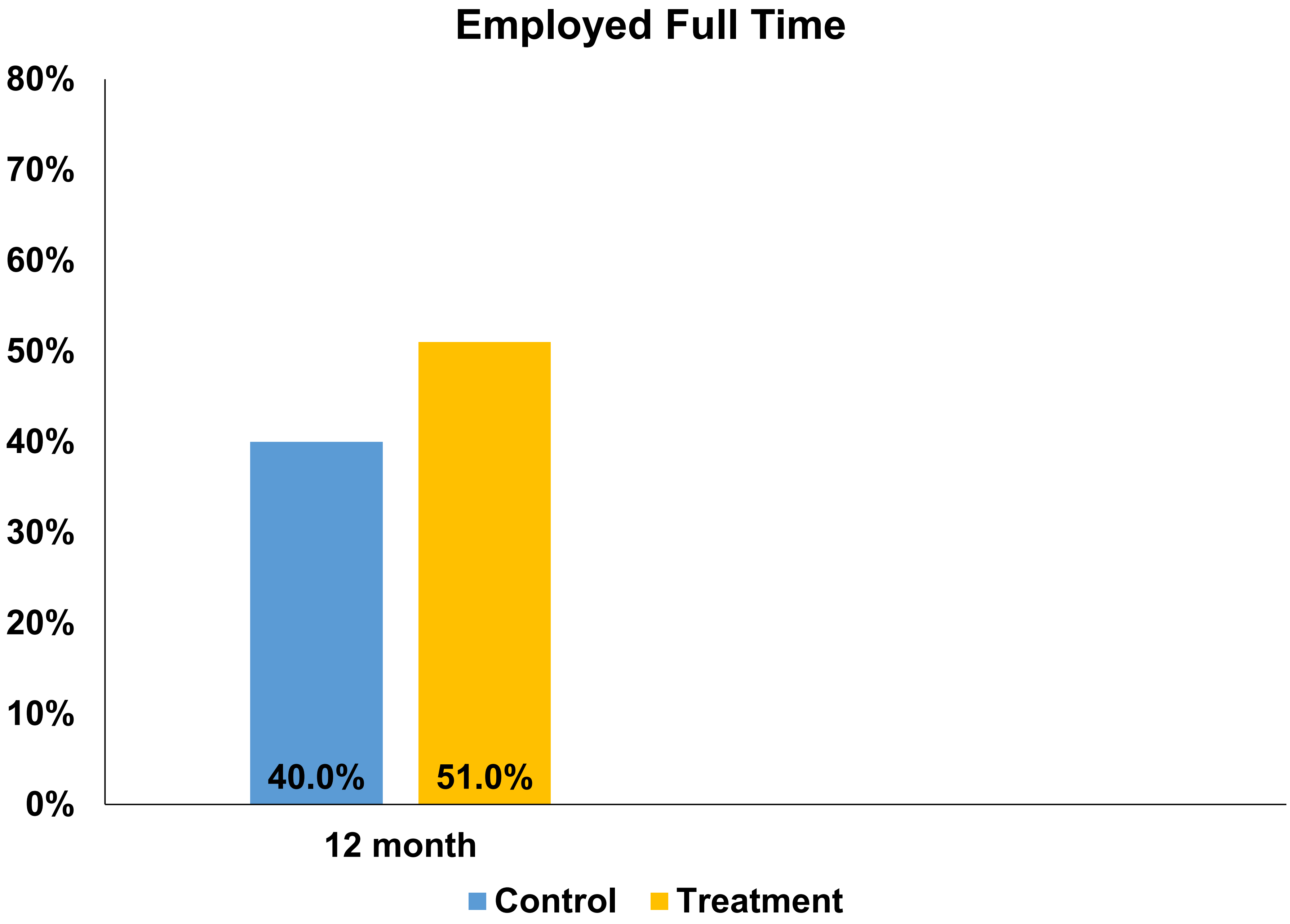
- Two-year follow-up
  - But only half the sample
- One-year data for all participants
  - But only half of the treatment is completed
- That said, results are encouraging
  - Consistency both across/within domains
  - In 12 and 24 month results
- Some puzzling results

You will not see math in these slides

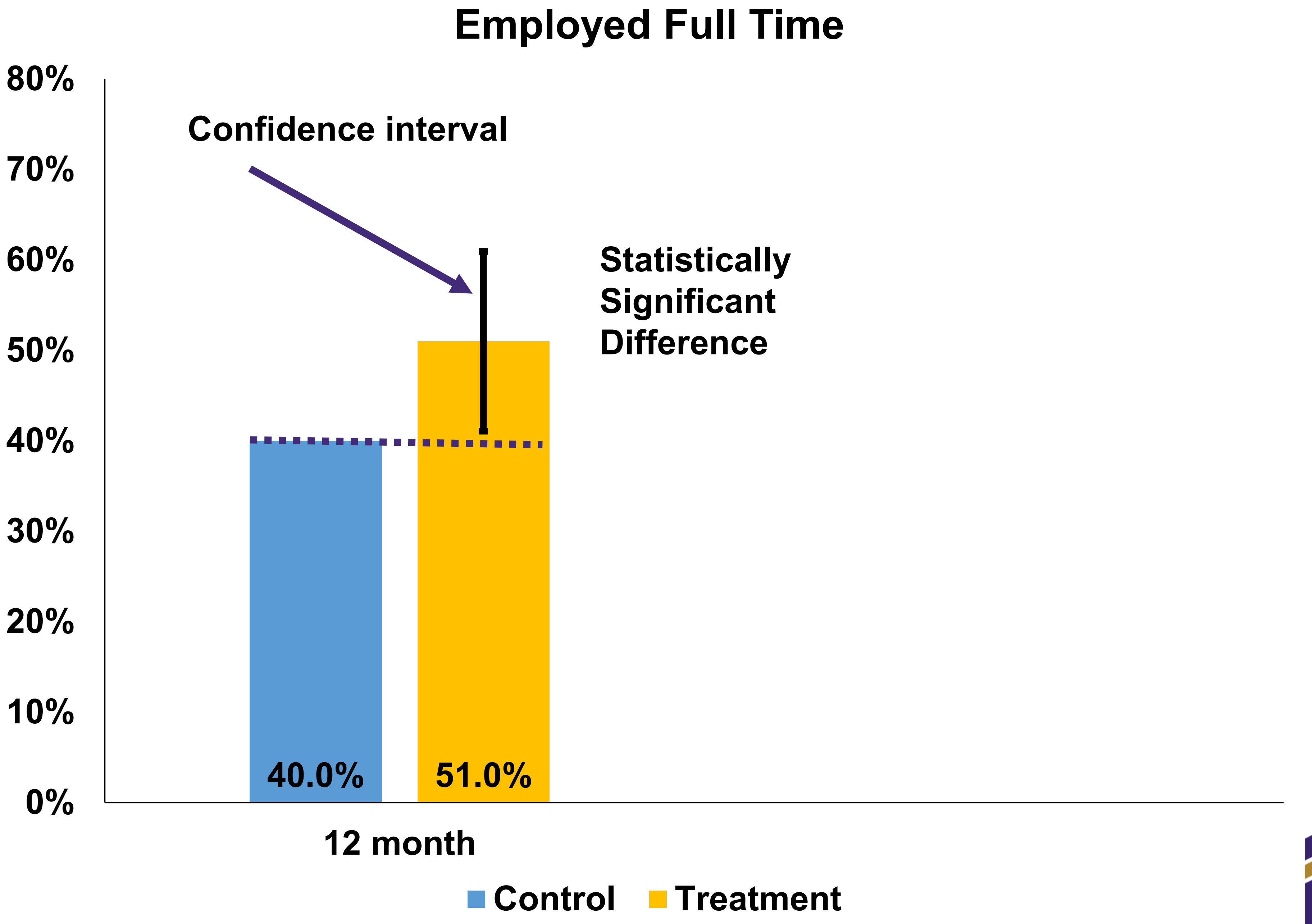
- I know, this is very sad.
- Very different from what we’ve been doing in the boot-camp
- 2 different ways of “setting up a laboratory”
- You don’t even really need multiple regression
  - If assignment is truly random, treatment effect is simply the difference between treatment group mean and control group mean

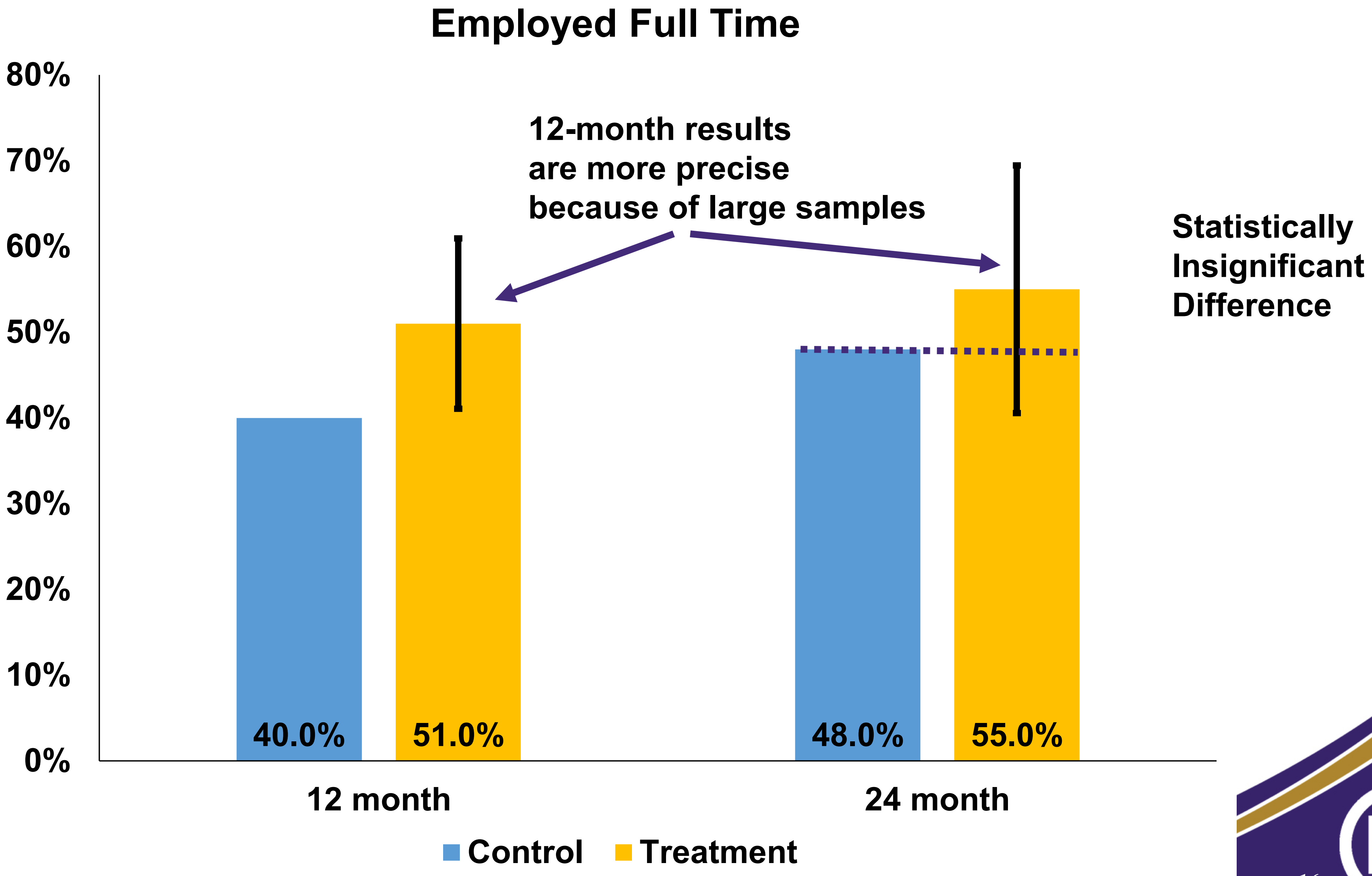
Employment and Earnings

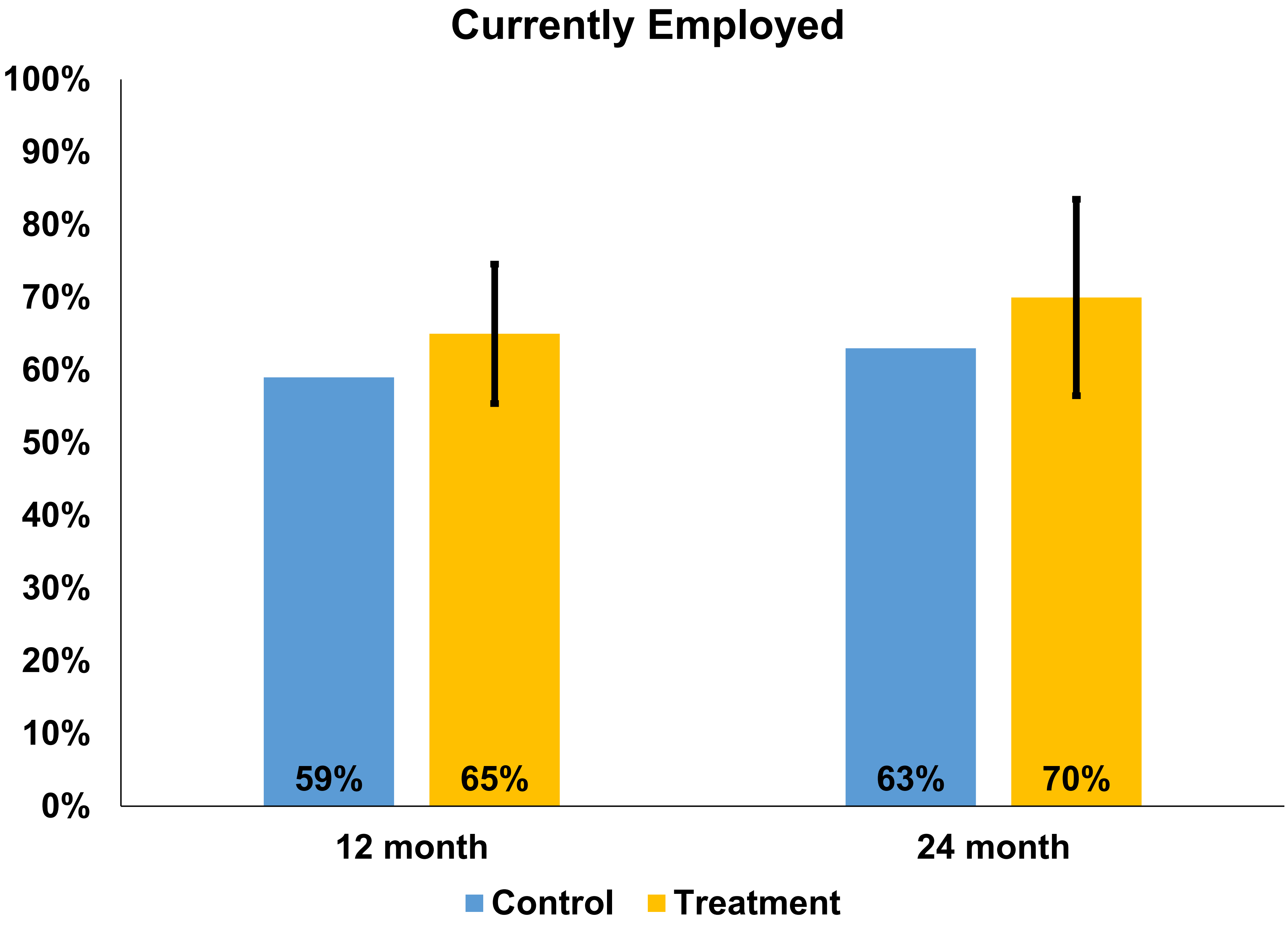
How to read the graphs



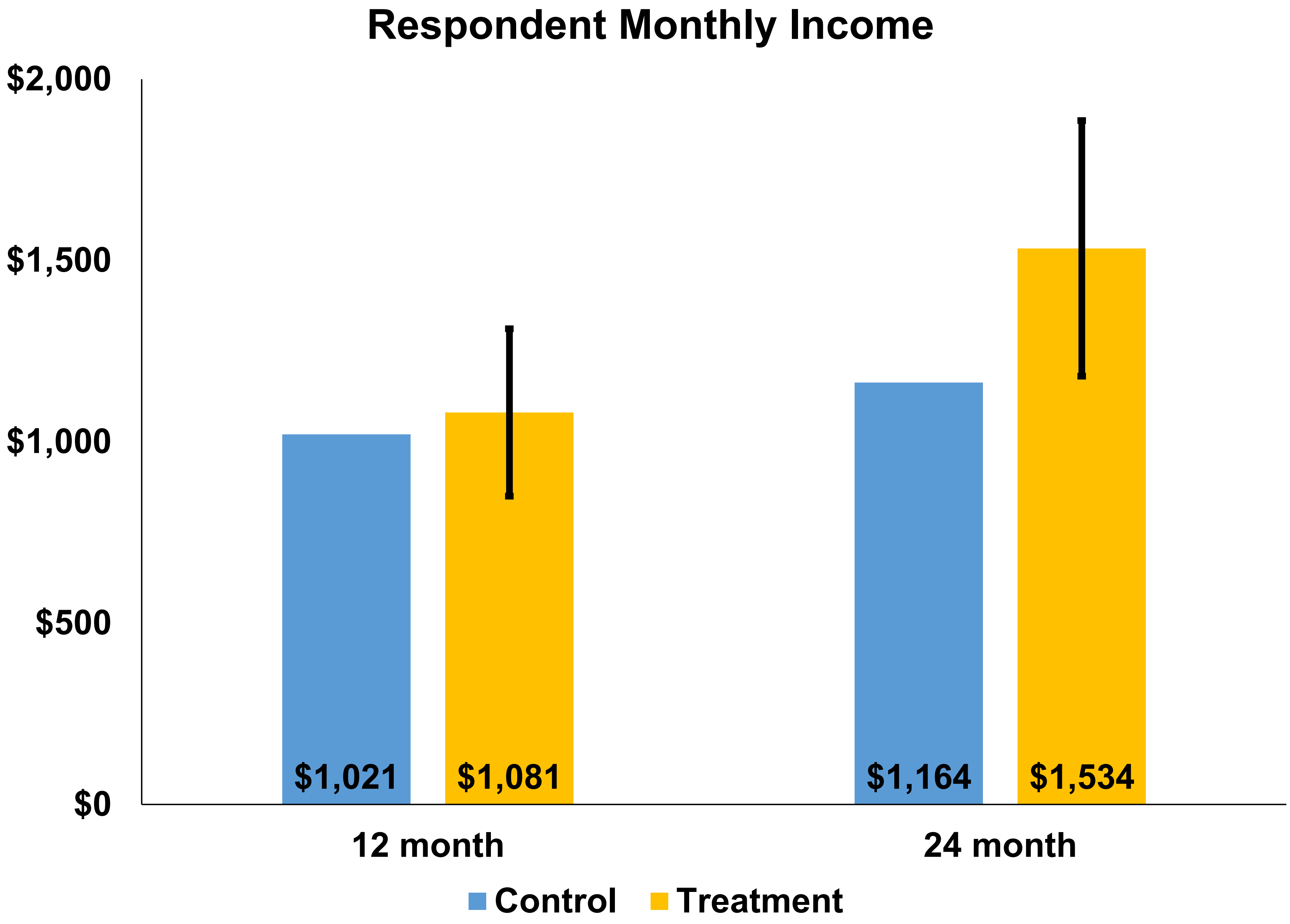
Employed Full Time
80%
70%
60%
50%
40%
30%
20%
10%
0%
40.0%
51.0%
12 month
Control
Treatment


Employed Full Time
80%
70%
60%
50%
40%
30%
20%
10%
0%
Confidence interval
Statistically
Significant
Difference
40.0%
51.0%
12 month
Control
Treatment


Employed Full Time
80%
70%
60%
50%
40%
30%
20%
10%
0%
12-month results
are more precise
because of large samples
Statistically
Insignificant
Difference
40.0%
51.0%
48.0%
55.0%
12 month
24 month
Control
Treatment

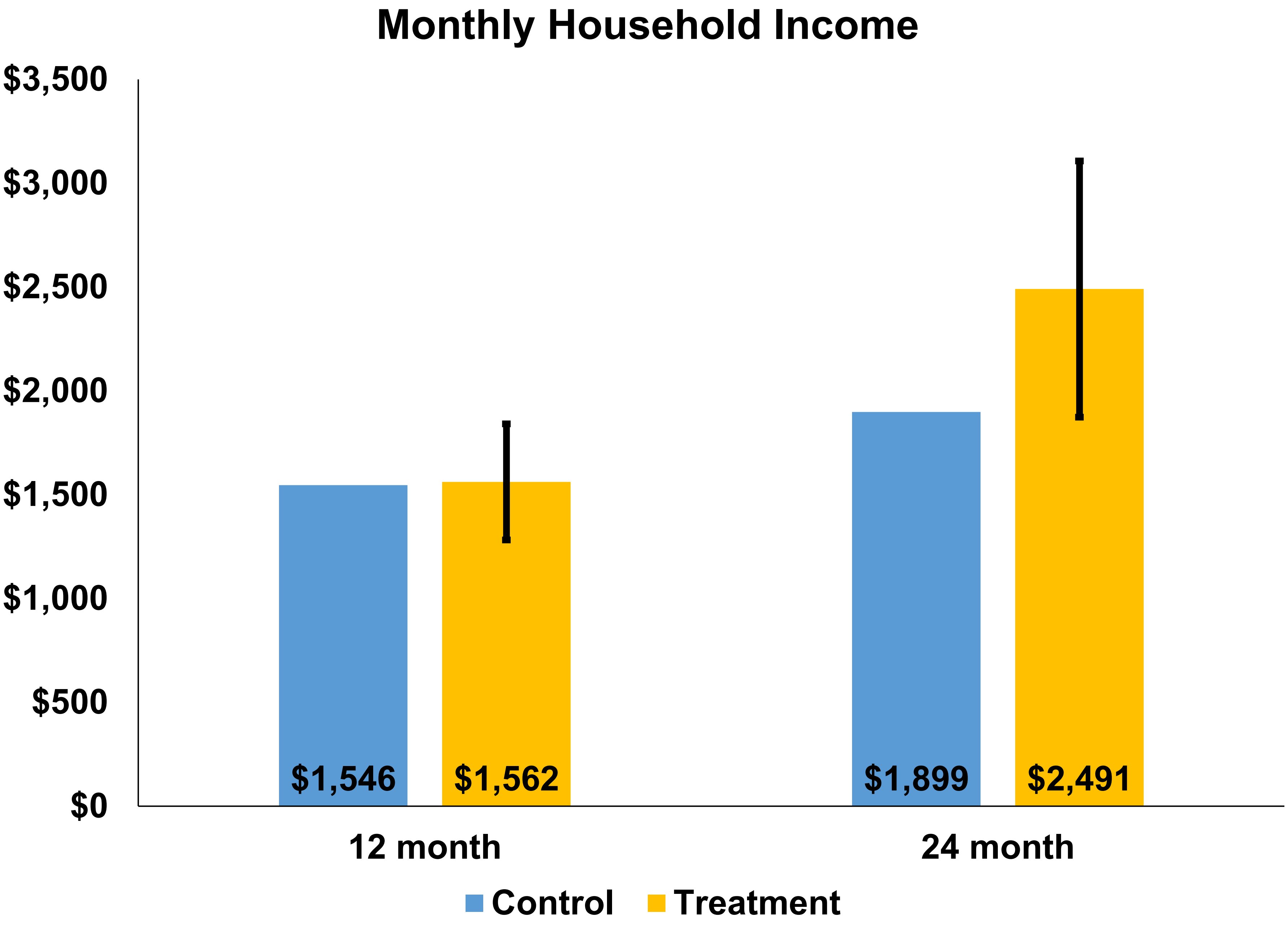


Currently Employed
100%
90%
80%
70%
60%
50%
40%
30%
20%
10%
0%
59%
65%
63%
70%
12 month
24 month
Control
Treatment


Respondent Monthly Income
$2,000
$1,500
$1,000
$500
$0
$1,021
$1,081
$1,164
$1,534
12 month
24 month
Control
Treatment

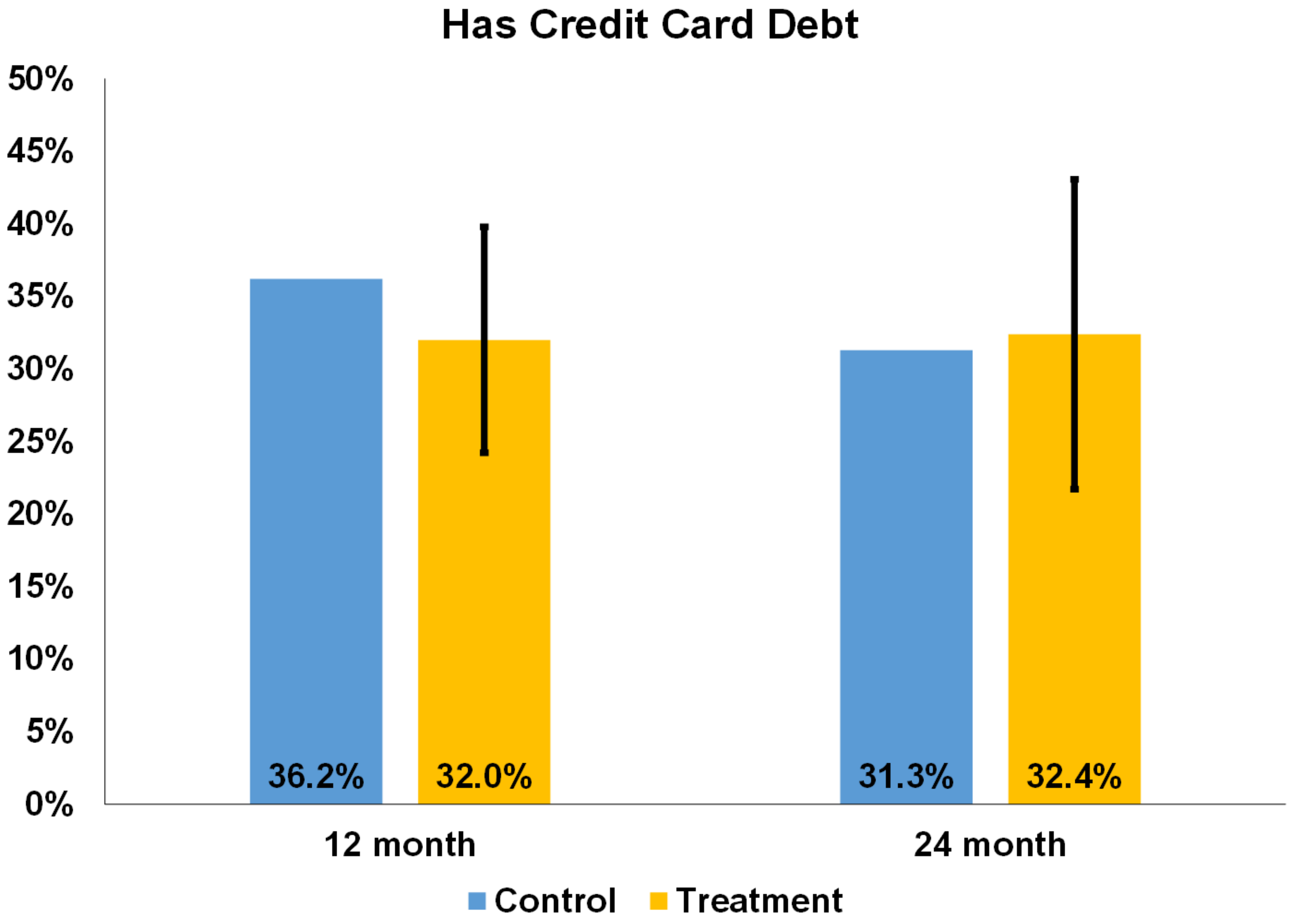
Change in earnings

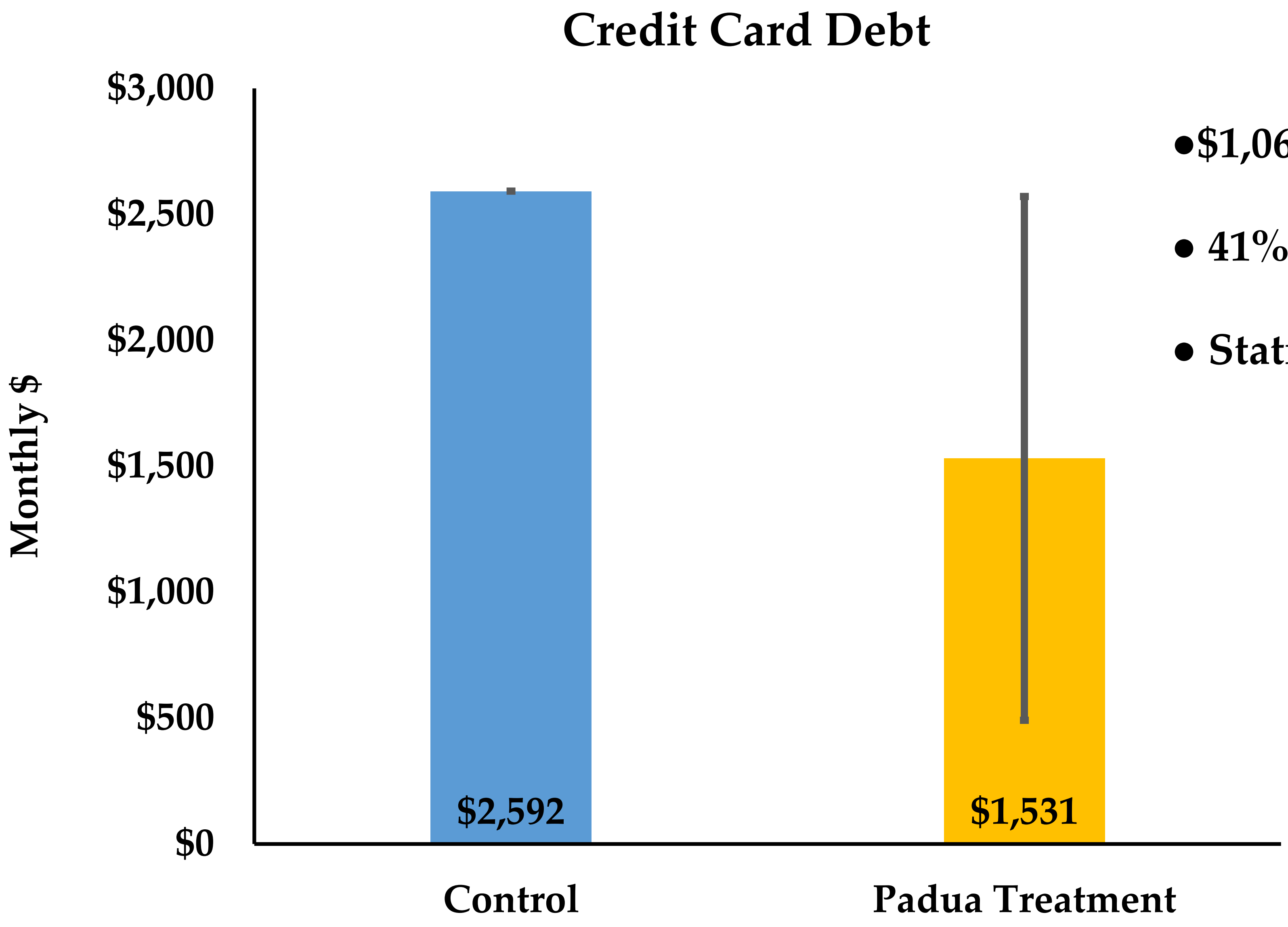
- 50% is due to increased work
- 26% is due to longer work weeks
- 24% is due to higher earnings
- None of these results are statistically significant



Monthly Household Income
$3,500
$3,000
$2,500
$2,000
$1,500
$1,000
$500
$0
$1,546
$1,562
$1,899
$2,491
12 month
24 month
Control
Treatment

Debt and savings


Has Credit Card Debt
50%
45%
40%
35%
30%
25%
20%
15%
10%
5%
0%
36.2%
32.0%
31.3%
32.4%
12 month
24 month
Control
Treatment



- $1,061 ↓ in spending
- 41% drop
- Statistically significant

Social program use

- Some decline in program participation
  - But not large, not statistically significant

- May be too early to tell

Thanks!

Good job :)

Who's up next?

USING PUBLICLY AVAILABLE SATELLITE IMAGERY AND NEURAL NETS TO ADDRESS DATA SCARCITY IN DEVELOPING ECONOMIES

By Cooper Nederhood

DATA POOR DEVELOPING ECONOMIES

- Developing economies lacking official economic measures
- Satellite data is widely available
  - Higher resolution than other economic statistics
  - Worldwide coverage
  - Low marginal cost
- Modern computer vision techniques to analyze images
- Jean et al (2016) “Combining satellite imagery and machine learning to predict poverty”

SATELLITE DATA – LANDSAT

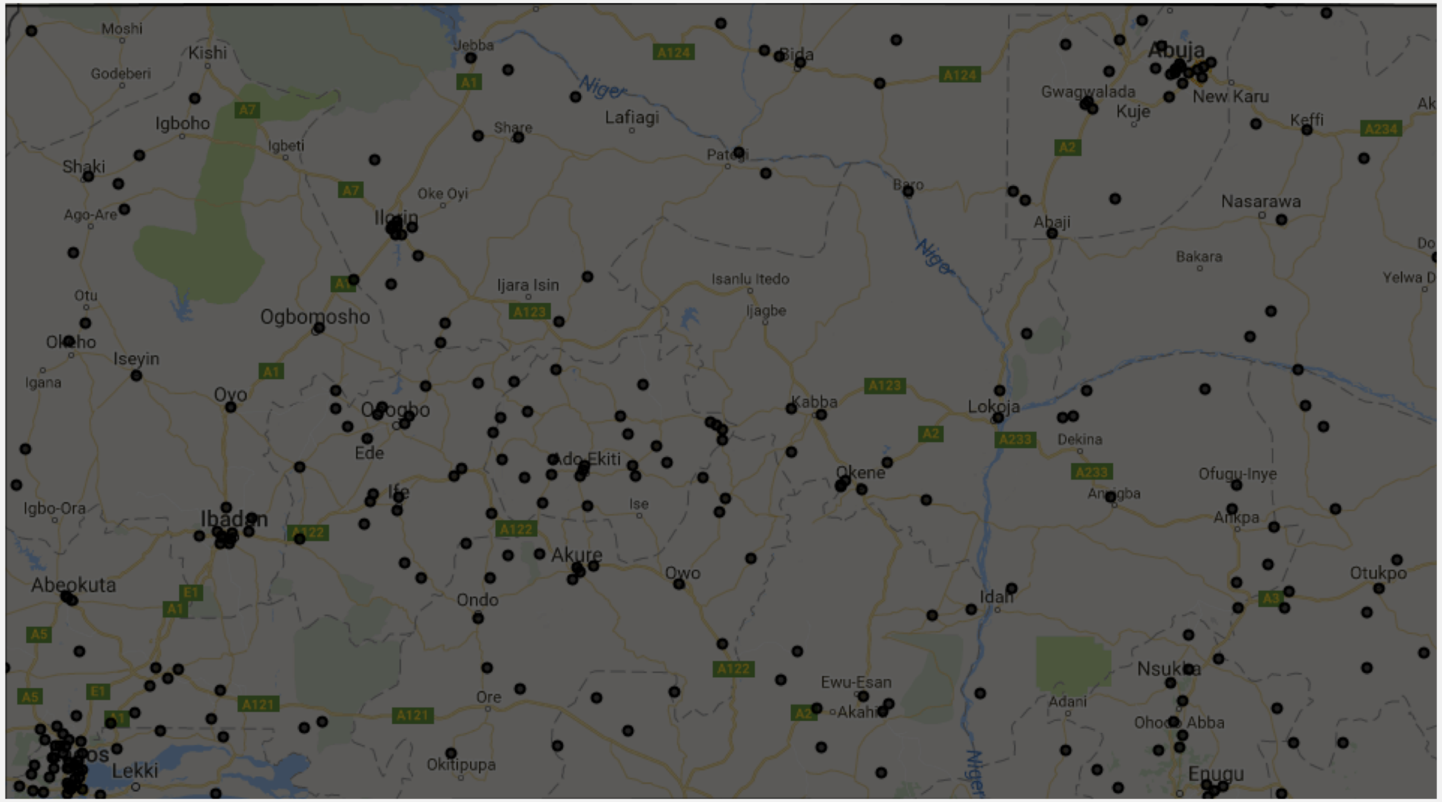
- Available from 1972 to today
- 30 meter resolution (medium resolution)
- Cover entire Earth's surface every two weeks
- Access through Google Earth Engine API
  - Goldblatt et al, 2016

GROUND TRUTH DATA – DHS SURVEY

- “Demographic and Health Survey”
- Includes Wealth Index, composite index
- Nigeria

DHS SURVEY LOCATIONS

- DHS survey locations across Nigeria
  - The wealth index is the "Y" variable
- The corresponding satellite image above is the "X" variable



NOT ENOUGH DATA FOR MODEL TRAINING

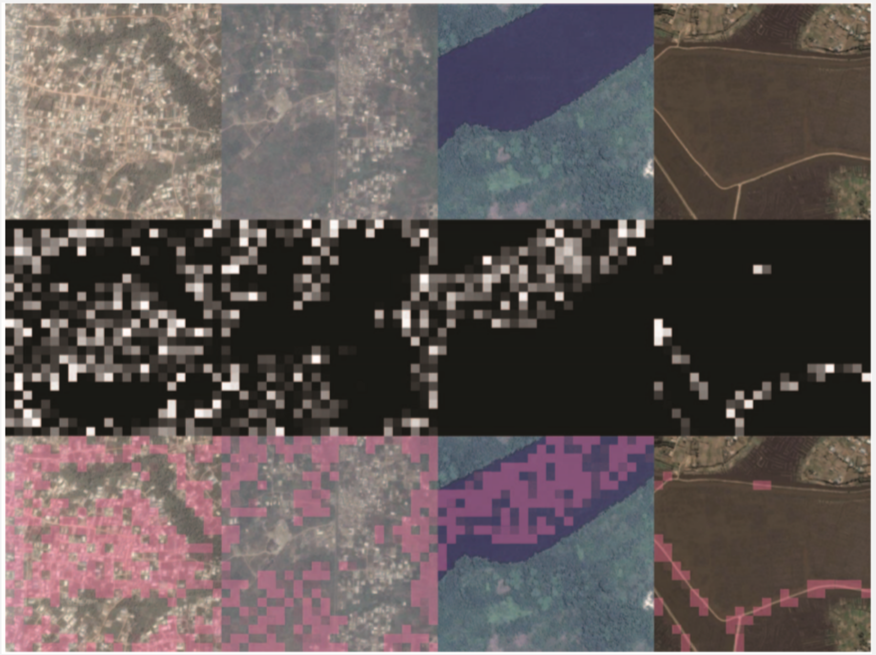
- Use convolutional neural nets to identify features in the satellite image
- Models have > 1 million parameters
- We have 279 survey locations ☹
- NEED INTERMEDIARY STEP WITH LOTS OF DATA

SOLUTION?? => TRANSFER LEARNING

- Essentially transitive property
- Learn A~B and B~C, where A~B is data rich
- The intermediary is to train CNN to identify ***nighttime luminosity*** given satellite images

CONVOLUTIONAL NEURAL NETWORK

- Deep neural network used in computer vision
- Learns to identify image features relevant to economic activity
- Transfer learning from ImageNet
- Jean et al (2016) "Combining satellite imagery and machine learning to predict poverty"
- Banerjee et al (2017) "On monitoring development using high resolution satellite images"



TRANSFER LEARNING STEPS

- Step #1: CNN learns to predict luminosity given satellite images
- Step #2: Use the ‘features’ (essentially a low-dimensional summary of the image) as regressors in a ridge regression on the wealth index

RESULTS TO DATE

- 3 CNN
  - Small (34 x 34) pixel images trained from scratch
  - Large (128 x 128) pixel images trained from scratch
  - Transfer (128 x 128) pixel images based on weights from ImageNet
- Run on Google Cloud Computing ft 3 NDVIDIA tesla K80 GPU’s
- Ridge regression has cross-validated R2 of .4

PROBLEMS, CAVEATS, FUTURE, ETC

- I (basically) don’t know how to train neural nets (yet)
- Data is highly imbalanced
- Medium resolution images complicate transfer learning from typical high-resolution image detection
- To expand to time-series, you have multiple image frames per sequence – essentially this is now a video classification task

Good job :)

Who's up next?

Myopia in Dynamic Spatial Games

Shane Auerbach
Lyft

Rebekah Dix
UW-Madison

July 18, 2018

Motivation and Outline

Dynamic games of spatial competition on graphs can be used to model ride-sharing and taxi markets.

- Develop a model of games of dynamic spatial competition on graphs using tools from computational geometry
- Model agents that adhere to myopic best response (MBR) and examine the relationship between MBR and efficiency in games
- Apply model to study ride-sharing and make policy recommendations to ride-sharing platforms regarding how to reduce passenger wait-times

Model: Overview

In a dynamic game of spatial competition on a transportation network T, Lyft drivers sequentially choose their locations on a transportation network with the objective of maximizing their market shares

- Agents: Lyft drivers
  - Objective of Agents: Maximize market share
  - Objective of Social Planner: Minimize passenger wait-times
- Environment: Transportation network T, which consists of roads and intersections
- Timing: Dynamic game in which agents sequentially choose locations on the network (turn order can either deterministic or random)

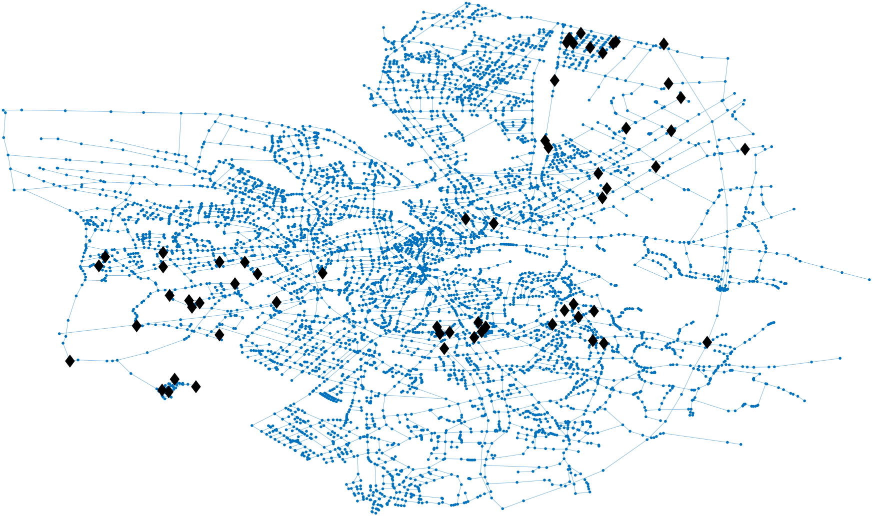


Figure 1: Initial allocation of 60 drivers in Oldenburg; $\xi(s_1) = 2.02$

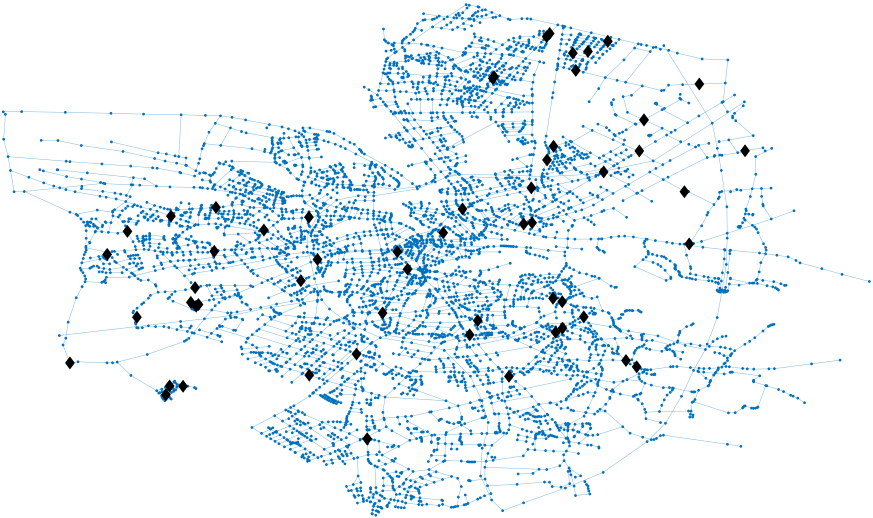


Figure 2: Final allocation of 60 drivers in Oldenburg; $\xi(s_{5000}) = 0.55$

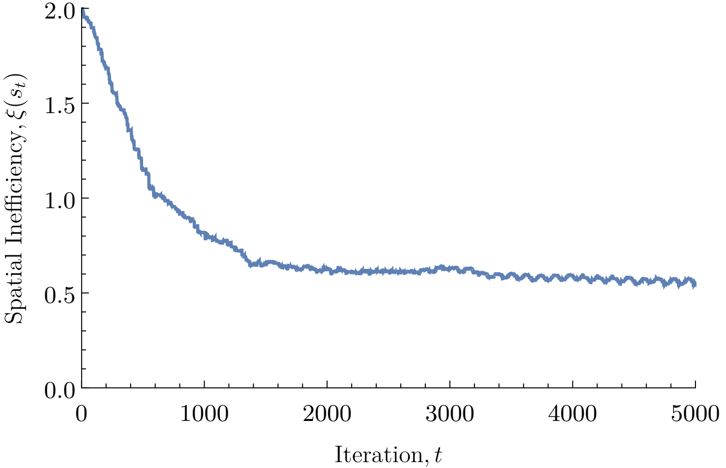


Figure 3: Spatial inefficiency along dynamic path of simulation with $T = 5000$

Application to Ride-Sharing Platforms

- MBR algorithm generally leads to large decreases in spatial inefficiency
  - Valuable for stochastic environments
- These results suggest that ride-sharing services may benefit from allowing idle drivers to observe the locations of other idle drivers on the spatial network, thus allowing drivers to compete spatially for passengers.
- Because the MBR algorithm generally decreases expected consumer wait-times, we believe that ride-sharing services may wish to allow drivers to see other nearby drivers and assist them in best responding to their neighbors.

Good job :)

Who's up next?

Smart SDFs

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Overview

1. SDF Intro
2. Parametric SDFs
3. Nonparametric SDFs

Stochastic Discount Factor

- Market with N assets. Sequence random vectors of prices $\{p_t\}$ taking values on $\mathbb{R}^N$
- Formally $\{p_t\}$ is a sequence of random vectors defined on a Filtered Probability Space $(\Omega, \mathcal{I}, \{\mathcal{I}_t\}, \mathbb{P})$

SDF

A SDF between period t and $t+1$ is a random variable $m_{t,t+1} > 0$ a.s. such that:

$$p_t = \mathbb{E}_t[m_{t,t+1} p_{t+1}].$$

SDF - Economic justification

- Axioms of rational behaviour under uncertainty (completeness, transitivity, continuity, independence) $\implies$ agents maximize Expected Utility [Von Neumann, Morgentern (1947)].
- Agent maximizes expected life-time utility from consumption:

$$\max_{\{c_t\},\{\theta_t\}} \mathbb{E}_0 \left[\sum_{t=0}^{\infty} \beta^t U(c_t;\gamma) \right]$$
$$\text{s.t.} \qquad c_t + p_t^T \theta_t = p_t^T \theta_{t-1}$$

where $\{\theta_t\}$ is a sequence of portfolio weights.

- First-order condition wrt θ_t and Law Iterated Expectations $\implies$

$$p_t = \mathbb{E}_t \left[\beta \frac{U'(C_{t+1};\gamma)}{U'(C_t;\gamma)} p_{t+1} \right]$$

SDF - Financial justification

Assumptions

1. p_{t+1} are $\mathcal{I}_{t+1}$ measurable with finite conditional (on $\mathcal{I}_t$) second moment.
2. There exist a linear pricing functional $\pi_{t,t+1} : p_{t+1} \mapsto p_t$ conditioned on $\mathcal{I}_t$ and satisfies a conditional continuity restriction.
3. There is no arbitrage in the market: if $0 \neq p_{t+1} \geq 0$ a.s., then $p_t > 0$ a.s.

Fundamental theorem of Asset Pricing

Given the previous assumptions, the Riesz representation theorem implies

$$p_t = \pi_{t,t+1}(p_{t+1}) = \mathbb{E}_t[m_t p_{t+1}]$$

where $m_t > 0$ a.s. random variable.

SDF - Cox's justification

Cox

All models are wrong, but some of them are useful.

Useful?

- Any asset pricing model (CAPM, Fama-French 3-factor model, ecc.) is a particular specification of the SDF
- SDF incorporates time discounting, preferences, risk discounting, ecc. (Specify a SDF model to identify these features)
- SDF carries information on economic outlook. "High" SDF $\Longrightarrow$ "bad" economic outlook
- Trading strategy: sell financial portfolio replicating the SDF (see later)

Parametric SDFs

Economic specifications

$m_{t,t+1} = m(Y_{t+1}; \alpha)$ where Y_{t+1} are relevant state variables and α is a vector of parameters.

- Time-separable preferences with CRRA utility

$$m_{t,t+1} = \beta (c_{t+1}/c_t)^{-\gamma}, \qquad \alpha = (\beta, \gamma)$$

- Time-nonseparable Epstein-Zin preferences

$$m_{t,t+1} = \beta^{\lambda} (c_{t+1}/c_t)^{-\gamma\lambda} (R^*_{t+1})^{\lambda-1}, \qquad \alpha = (\beta, \gamma, \lambda)$$

Parametric SDFs

Financial specifications

- Linear factor models:

$$m_{t,t+1} = \phi_0 + \phi_1^T F_{t+1}, \qquad \alpha = (\phi_0, \phi_1^T)$$

  - CAPM: $F_t = R_t^m$
  - Fama French 3-factor model: $F_t = (R_t^m, SMB_t, HML_t)^T$

- Exponentially affine factor models:

$$m_{t,t+1} = \exp(\phi_0 + \phi_1^T F_{t+1})$$

note that $m_{t,t+1} > 0$ a.s.

Parametric SDFs

Estimation

Two-step GMM estimator

$$\hat{\alpha}_T = \arg\min_{\alpha}\ \hat{g}_T(\alpha)^T \hat{V}_T^{-1} \hat{g}_T(\alpha)$$

where $\hat{g}_T(\alpha) = \frac{1}{T}\sum_{t=1}^{T-1} g(p_{t+1}, p_t, z_t; \alpha)$,

$$g(p_{t+1}, p_t, z_t; \alpha) = z_t \otimes (m_{t,t+1}(\alpha) p_{t+1} - p_t),$$

z_t is a vector of instruments and $\hat{V}_T$ is a consistent estimator of V_0

Nonparametric SDF - Hansen et al. 1990s

Assumptions

- $m, p' \in L_2$, $p \in L_1$
- *no arbitrage opportunities: if* $\theta^T p' \geq 0$ *and* $\theta^T p'$ *has positive probability, then* $\theta^T p > 0$.
- *no redundancies in the securities: if* $\theta^T p' = \theta^{*T} p'$ *and* $\theta^T p = \theta^{*T} p$, *then* $\theta = \theta*$.

Proposition

Consider

$$\inf_{m \in L_2,\ m \geq 0} \{ \ \mathbb{E}[m^2/2] \ : \ p = \mathbb{E}[mp'] \ \},$$

$$\max_{\theta \in \mathbb{R}^N} \{ \ \theta^T p/2 - \mathbb{E}[(\theta^T p')^{+2}/2] \ \}.$$

Then

$$m^* = \theta^{*T} p'$$

Nonparametric SDF - Contribution

Assumptions

- *$p \in L_1$, $m \in L_a$ and $p_i' \in L_b$ for each security i, where a and b are Hölder conjugate*
- *there exits SDF $\bar{M} > 0$ a.s. such that $\|\mathbb{E}[mp'] - p\| < \lambda$*

Proposition

Consider

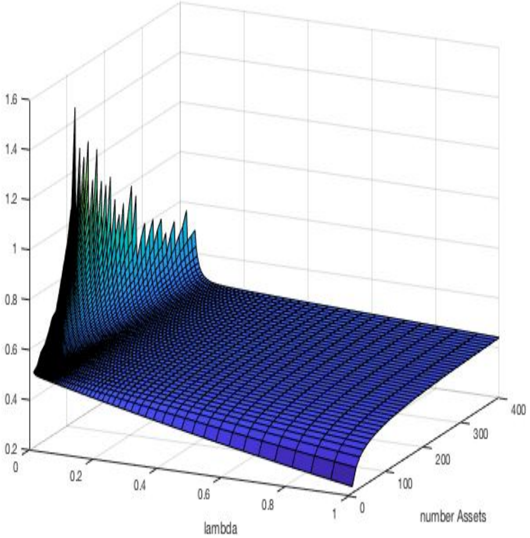
$$\inf_{m \in L_a,\ m \geq 0} \left\{ \mathbb{E}[\phi(m)] \ : \ \left\|\mathbb{E}[mp'] - p\right\| \leq \lambda \right\},$$

$$\max_{\theta \in \mathbb{R}^N} \left\{ \theta^T p - \phi_+^c(\theta^T p') - \lambda \left\|\theta\right\|^* \right\}.$$

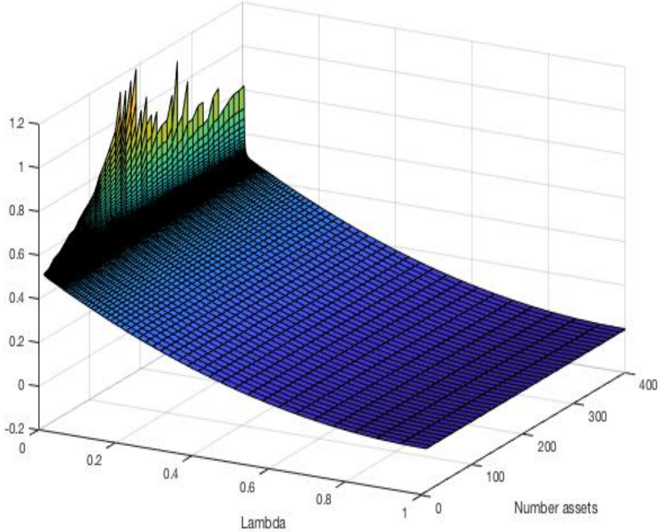
Then

$$m^* = (\phi_+^c)'({\theta^*}^T p')$$

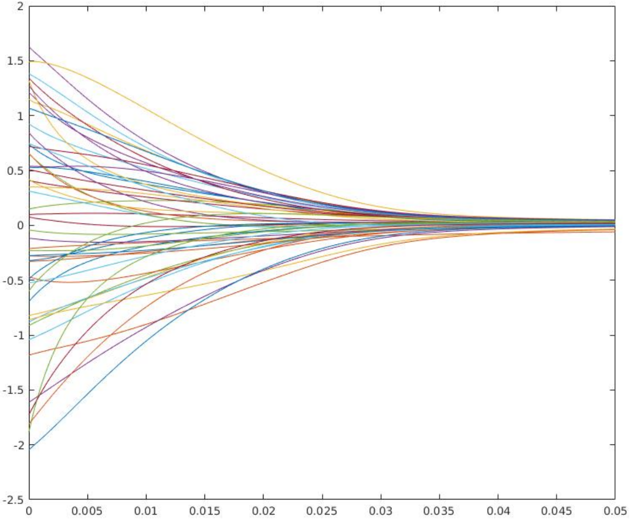
Optimal value l_2



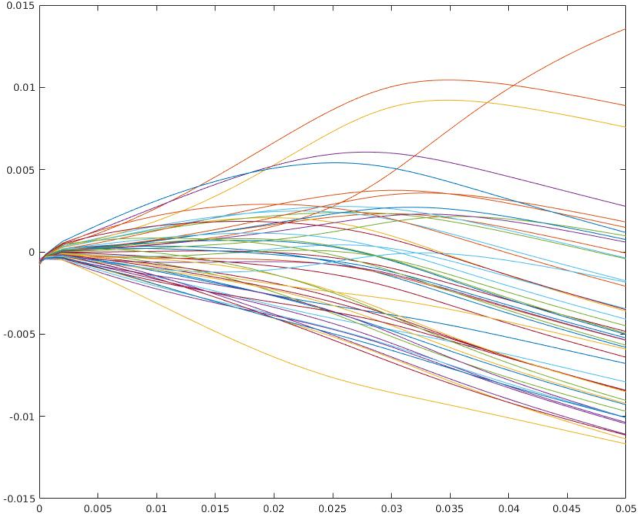
Optimal value l_1



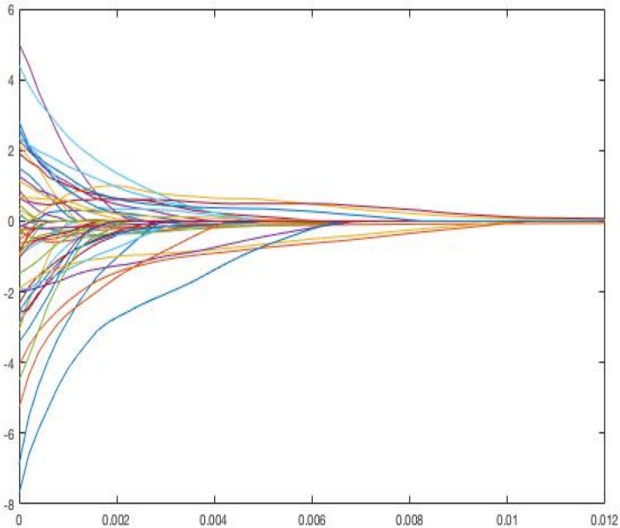
Weights l_2


2
1.5
1
0.5
0
-0.5
-1
-1.5
-2
-2.5
0
0.005
0.01
0.015
0.02
0.025
0.03
0.035
0.04
0.045
0.05

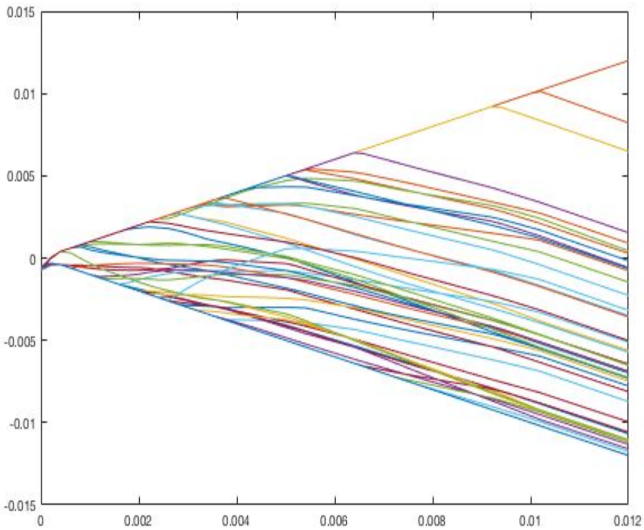
Pricing errors l_2



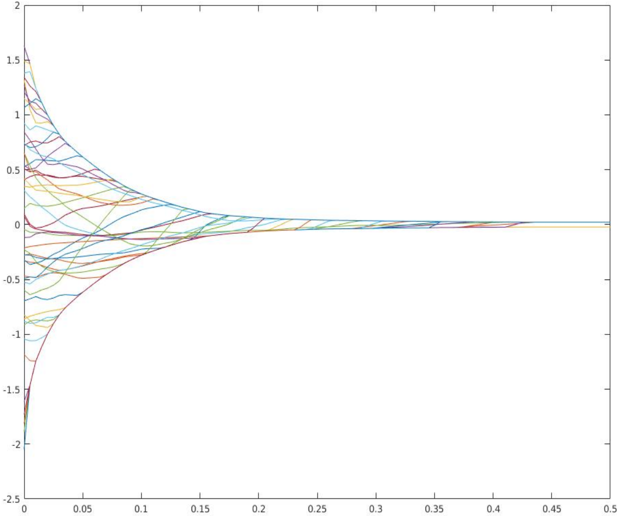
Weights l_1



Pricing errors l_1



Weights l_∞



Pricing errors l_∞