

# Nonlinear Pricing Complexity and Consumer Behavior

(Exploratory) evidence from a uniquely frustrating experiment

Joshua Deutschmann, Jeffrey D. Michler, Emilia Tjernström

October 29, 2018

# Motivation: firm perspective

- Nonlinear pricing mechanisms can increase profits over linear prices. Caveat...
  - Long menus of costs  $2^k - 1$  for  $k$  goods
  - Assumes perfect knowledge of demand space
  - Assumes consumers do not make mistakes
- Real world examples
  - Cable TV providers (Crawford 2008)
  - Digital media (Shiller & Waldfogel 2011)
  - Tickets to Broadway plays (Leslie 2004)

# Motivation: behavioral perspective

- Nonlinear mechanisms can benefit consumers by offering “tailored” choices.  
Caveat...
  - People make mistakes
  - Assumes no search costs
  - Assumes no stress or cognitive costs
- Real world examples
  - Value perception & bundling (Brough & Chernev 2012)
  - Gym memberships (DellaVigna & Malmendier 2006)
  - Bandwidth & deliberation Costs (Schilbach et al. 2016; Spears 2014))

# The known unknown

- Fundamental tension in nonlinear pricing:
  - More options may  $\uparrow$  consumer surplus but also  $\uparrow$  cognitive costs,  $\uparrow$  probability of mistakes,  $\uparrow$  firm uncertainty regarding demand
- No closed-form solutions

# The known unknown

- Fundamental tension in nonlinear pricing:
  - More options may  $\uparrow$  consumer surplus but also  $\uparrow$  cognitive costs,  $\uparrow$  probability of mistakes,  $\uparrow$  firm uncertainty regarding demand
- No closed-form solutions
- How do real people respond to complex nonlinear prices?
  - Reduce performance
  - Increase drop-out
  - Increase response time
  - Welfare
- How do consumer errors affect optimal firm behavior?

# Research questions

- ① How does price complexity affect consumer choice & welfare?
- ② How do price shocks / search difficulty interact with complexity in this context?
- ③ Do these effects result in changes to optimal firm behavior?

# What we do

- Simulate optimal prices (following Chu et al. 2011; Eckalbar 2010)
- Run a lab experiment to measure choice behavior & potential errors
  - how much do participants deviate from optimal?
  - do participants do worse with complex prices?
  - does complexity cause participants to drop out of the market?
- Coming: update price simulation with participant behavior
  - how does participant behavior affect profits?

# What we do & what we find

- Simulate optimal prices (following Chu et al. 2011; Eckalbar 2010)
- Run a lab experiment to measure choice behavior & potential errors
  - how much do participants deviate from optimal? **Quite a bit!**
  - do participants do worse with complex prices? **Yep.**
  - does complexity cause participants to drop out of the market? **Looks like it.**
- Coming: update price simulation with participant behavior
  - how does participant behavior affect profits? **Don't know yet!**



# Generalized setup

- Monopolist firm selling  $N$  goods
- Consumer valuations:  $V_i = [V_{i1}, \dots, V_{iN}]$ 
  - Each valuation drawn from uniform distribution
  - Unit demand for each good
- Consumers maximize surplus:  $V_i' D_j - p_j$ 
  - $D_j$   $K \times 1$  binary vector indicating goods in bundle  $j$
  - $p_j$  price of bundle  $j$

# Pricing strategies

- Component Pricing (CP)
  - Set price for each good
  - No bundle discount offered
  - $k$  prices
- Pure Bundling (PB)
  - Set price for bundle
  - No separate sale
  - 1 price
- Mixed Bundling (MB)
  - Set price for each good
  - Set price for each combination
  - $2^k - 1$  prices
- Bundle Sized Pricing (BSP)
  - Set price for a single good
  - Set price for each bundle size
  - $k$  prices

# Experimental design

- Random reservation values for 6 goods
  - Constant for each participant throughout experiment
- 6 periods of 6 rounds each
- In each round, randomly draw:
  - Pricing scheme (CP, PB, MB, BSP)
  - Number of goods (2-5)
  - Type of goods (color)
- Prices simulated-optimal
- Interface shows cost and surplus of current selection(s)

**Valuations:**

Blue	79
Green	13
Purple	48
Orange	61

**Purchase Cost:** 0

Show Surplus

**Purchase Surplus:**

Next

You need to select an option before continuing

Color(s)	Price	Selected
Bundle: Blue, Green, Purple, Orange	\$137	<input type="checkbox"/>
Purchase nothing		<input type="checkbox"/>



Game Rules

**Valuations:**

Red	77
Blue	27
Purple	45
Orange	11
Maroon	80

**Purchase Cost:** 0

Show Surplus

**Purchase Surplus:**

Next

You need to select an option before continuing

Bundle: Blue, Purple, Maroon	\$186	<input type="checkbox"/>
Bundle: Blue, Orange, Maroon	\$161	<input type="checkbox"/>
Bundle: Purple, Orange, Maroon	\$151	<input type="checkbox"/>
Bundle: Red, Blue, Purple, Orange	\$200	<input type="checkbox"/>
Bundle: Red, Blue, Purple, Maroon	\$204	<input type="checkbox"/>
Bundle: Red, Blue, Orange, Maroon	\$193	<input type="checkbox"/>
Bundle: Red, Purple, Orange, Maroon	\$185	<input type="checkbox"/>
Bundle: Blue, Purple, Orange, Maroon	\$196	<input type="checkbox"/>
Bundle: Red, Blue, Purple, Orange, Maroon	\$207	<input type="checkbox"/>

# Treatments

## Price Shock:

- After randomly-selected rounds, extra ‘bonus’ round
- **Treatment group:** fix scheme, prices  $\uparrow$  40%
- **Control group:** fix scheme, redraw basket

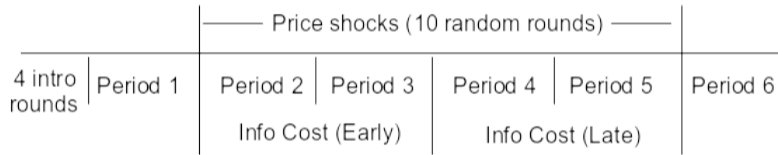
# Treatments

## Price Shock:

- After randomly-selected rounds, extra ‘bonus’ round
- **Treatment group:** fix scheme, prices  $\uparrow$  40%
- **Control group:** fix scheme, redraw basket

## Information Costs:

- Two treatment groups: **early** and **late**
- Small cost to reveal surplus of current selection





# Pre-analysis plan

- Several clear primary hypotheses, which we pre-register

# Pre-analysis plan

- Several clear primary hypotheses, which we pre-register
- Many low-weight secondary hypotheses
- It can cost more in power to pre-register a hypothesis if either of these are sufficiently small (Anderson & Magruder 2017):
  - the importance of the hypothesis,  $u_h$
  - the prior probability you assign to  $H_0$  being false,  $p_h$

# Split sample intuition (A&M, 2017)

- Imagine a main hypothesis, with power 0.8 (in full data set)
- Consider a 2nd hypothesis, same power but  $p_h$  is only 0.1
- If we correct for multiple hypothesis testing, then power on both is now 0.71
- So we sacrifice 9% power on main hyp, and gained only 7% power on second

# “Hybrid” pre-analysis plan

- Follow “hybrid” split-sample strategy
  - pre-register main hypotheses, test them in full sample
  - use 35% exploratory sample ( $N=246$ ) to try out secondary
  - update pre-registration with those secondary hypotheses that pass slightly more lenient bar

# Outcomes

## Primary: Performance

$$Y_{it} = \begin{cases} \frac{\text{surplus achieved}}{\text{max surplus available}} & \text{max surplus} > 0 \\ 1 & \text{max surplus} = \text{surplus achieved} \\ 0 & \text{otherwise} \end{cases}$$

## Secondary:

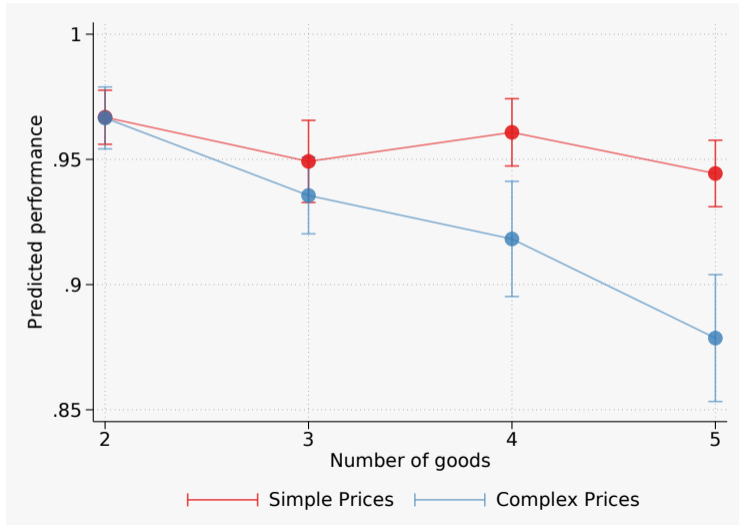
- 1 *Drop-out*: Purchasing nothing when positive surplus available
- 2 *Response time*: Number of seconds spent on decision
- 3 *Emotional response*

# Regression specification

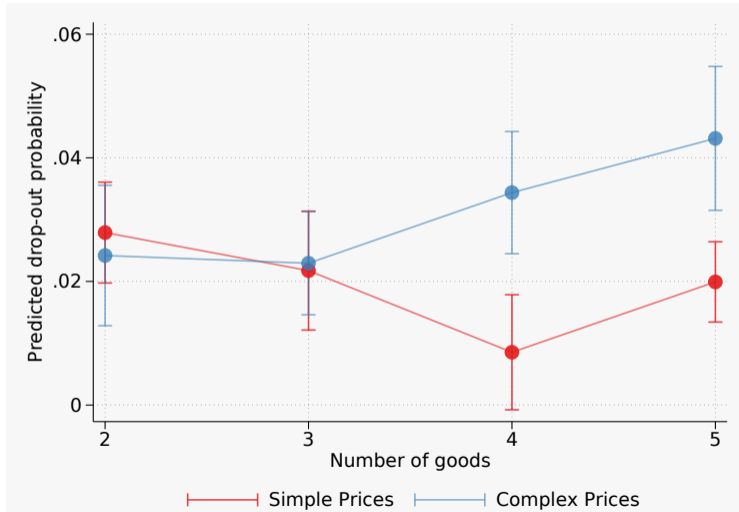
$$Y_{it} = \alpha + \beta_1 B_{it} + \beta_2 N_{it} + \beta_3 (B_{it} \times N_{it}) + \beta_4 G_{it} + \gamma_i + \lambda_t + \epsilon_{it}$$

- $B_{it}$ : complex price dummy
- $N_{it}$ : number of goods
- $G_{it}$ : other round-level game characteristics
- $\gamma_i$ : participant fixed effects
- $\lambda$ : round FE

# Performance & complexity

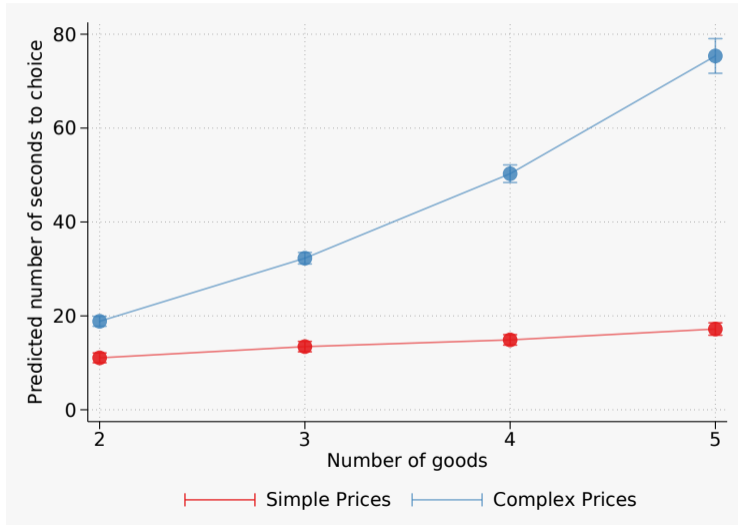


# Drop-out probability





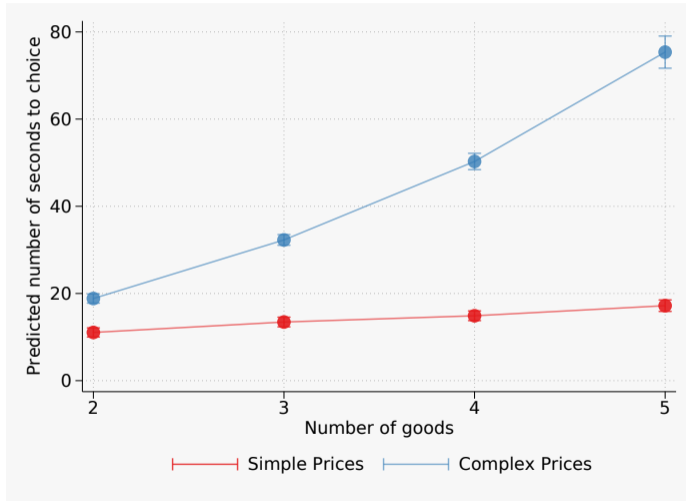
# Response time



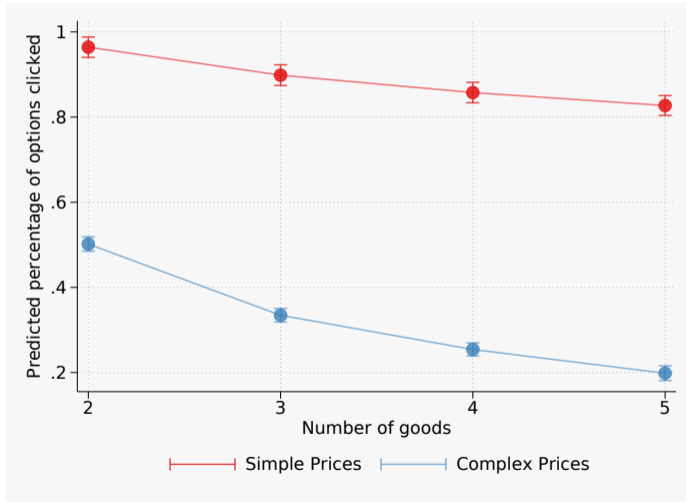
# Player behavior and performance

- First: establish that complexity affected behavior
- Then: show that behavior drives performance, instrumenting with:
  - ① Pricing scheme
  - ② Number of goods
  - ③ Information cost treatment

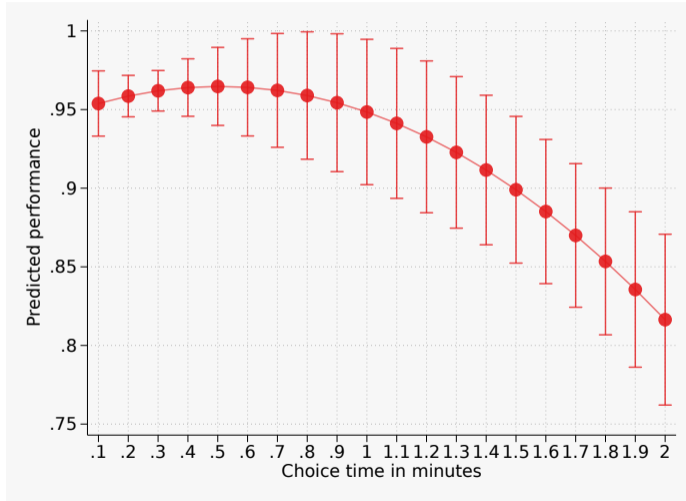
# Complexity and response time



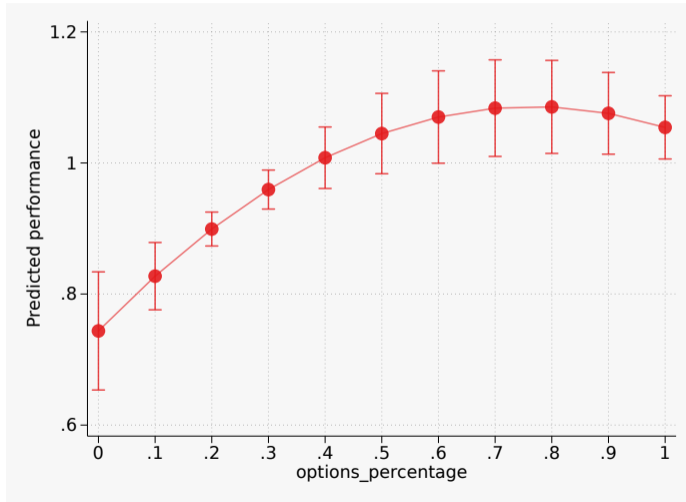
# Complexity and search



# Response time and performance



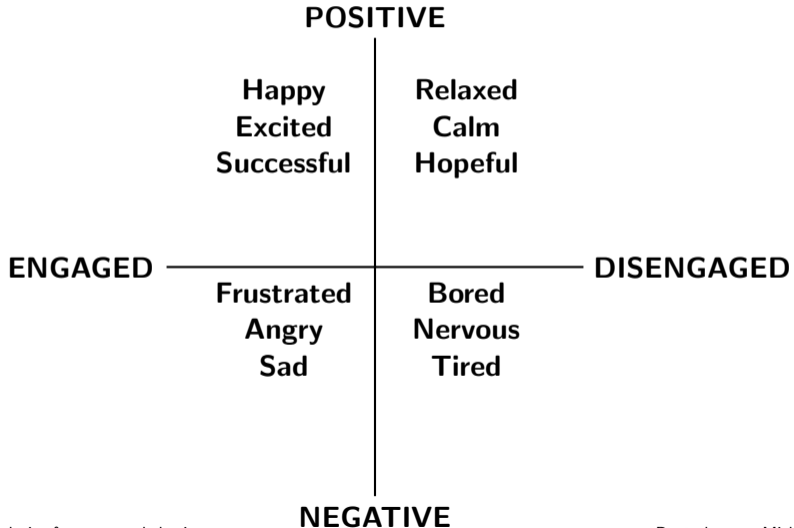
# Search and performance



# Measuring emotional responses














- We expect treatments to affect emotion
- We measure stress, cognitive load, and emotion using emojis
  - Random order
  - 13 total options, categorized along two axes:
    - **Positive/negative**
    - **Engaged/disengaged**

# Emoji diagram

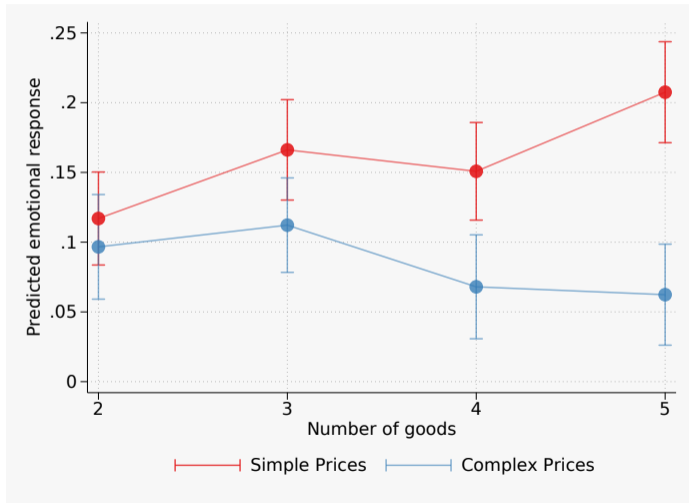




### How are you currently feeling?

Frustrated		<input type="checkbox"/>
Calm		<input type="checkbox"/>
Angry		<input type="checkbox"/>
Bored		<input type="checkbox"/>
OK		<input type="checkbox"/>
Nervous		<input type="checkbox"/>
Relaxed		<input type="checkbox"/>
Excited		<input type="checkbox"/>
Successful		<input type="checkbox"/>
Sad		<input type="checkbox"/>
Happy		<input type="checkbox"/>
Tired		<input type="checkbox"/>
Hopeful		<input type="checkbox"/>

# Positive/Negative Emotions



# Conclusion

- Exploratory analysis suggests complexity
  - Reduces performance
  - Induces drop-out
  - Increases response time
- Strong emotional responses

# Boundedly rational consumers?

Consumers clearly make mistakes but what type of mistakes?

- ① Not mistakes, failure to fully account for search costs
  - Consumers are rational; firms just needs to account for this
- ② Overconfident or biased mis-weighting of options
  - Leads to systematic distortions in demand that firms can exploit by distorting price
- ③ Fail to choose the best price due to sub-optimal search, confusion comparing bundles, or excessive inertia
  - Leads to noise in demand that is uncorrelated across consumers and may be hard for firms to fully adjust

# More work to do!

- Characterize types of non-optimal behavior
- Re-simulate optimal firm behavior based on revealed demand
  - in particular, do consumer errors change which is the profit-maximizing mechanism?

Click behavior during games

Effect of feedback between periods

Interaction between response time, performance, and drop-out