

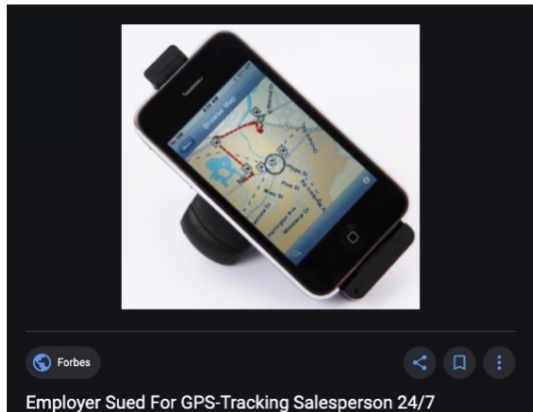
# Valuing Intrinsic and Instrumental Preferences for Privacy

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## What Are Intrinsic & Instrumental Preferences for Privacy?



**Intrinsic:** taste, right

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Forbes

Employer Sued For GPS-Tracking Salesperson 24/7

**Intrinsic:** taste, right



**Instrumental:** expected economic outcome from revealing one's type

# Why Empirically Separate the Two?

## 1. Intrinsic & instrumental preferences induce different selection patterns

*Instrumental preference only:*

- Consumers who do not share  $\Rightarrow$  “low type”  
e.g. risky drivers can be more concerned about revealing their private info

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*Heterogeneous intrinsic + instrumental preference:*

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e.g. if safer drivers intrinsically dislike sharing location info more

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## 2. Intrinsic—utility primitive; instrumental—endogenous

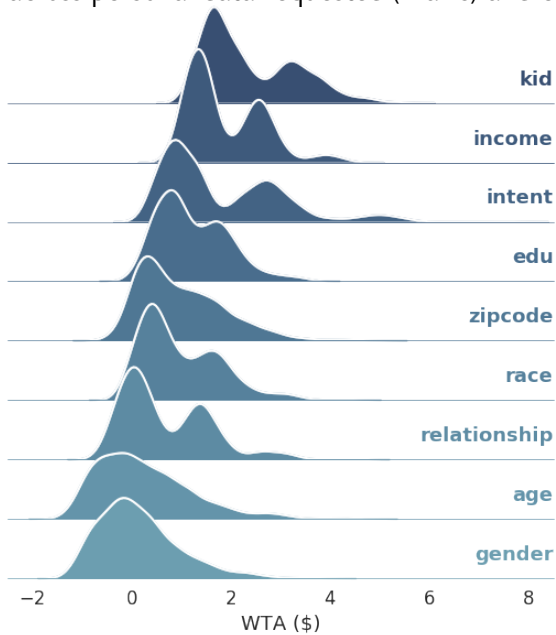
- Instrumental preferences respond to changes in firm’s data collection & usage practices, e.g. due to new regulation

# This Paper

1. Use an experiment to separately measure intrinsic & instrumental preferences
  - Revealed preference, in dollar terms; heterogeneity across demographics
  - Structurally estimate *intrinsic preference* & *belief on instrumental outcome* as primitives
2. Demonstrate the empirical selection pattern driven by the coexistence of the two preference types
3. Evaluate methods for firms & researchers to address privacy-induced selection

## Result 1: Intrinsic Preferences are Highly Heterogeneous

WTA distribution across personal data requested (Y-axis) and consumers (X-axis)





## Result 2: Instrumental Preference Matches Actual Outcome

- Consumer belief on the instrumental outcome determines the magnitude of instrumental preference
  - E.g. if risky drivers are unaware that firm uses driving data to customize premium, then instrumental preference = 0
- Estimation result shows that consumer beliefs are consistent with actual payoff qualitatively & quantitatively

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  - Actual payment:  $w = 2$  vs. Consumer belief estimates:

| Model        | 1. No Heterogeneity |              | 2. Heterogeneous $c$ |              | 3. Heterogeneous $c$ & $\delta$ |              | 4. Heterogeneous $c$ & $\beta$ |              |
|--------------|---------------------|--------------|----------------------|--------------|---------------------------------|--------------|--------------------------------|--------------|
|              | mean                | 95% CI       | mean                 | 95% CI       | mean                            | 95% CI       | mean                           | 95% CI       |
| $w_{income}$ | 2.00                | [0.15, 3.87] | 2.12                 | [0.11, 3.99] | 2.02                            | [0.14, 3.92] | 1.90                           | [0.04, 3.88] |
| $w_{intent}$ | 2.63                | [1.07, 3.88] | 1.94                 | [0.38, 3.76] | 1.97                            | [0.29, 3.77] | 1.90                           | [0.35, 3.70] |

## Result 3: Intrinsic & Instrumental Jointly Determines Selection Pattern

Classical prediction: *low types are more willing to hide*

**Result shows two opposite cases** (for different personal data requested)

1. Classical prediction rejected
  - Reason: high types have higher intrinsic preferences; magnitude dominates instrumental
2. Classical prediction confirmed
  - Reason: intrinsic preference heterogeneity independent of consumer type

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**Takeaway:** need to measure heterogeneity & correlation between the two preference components to understand the empirical selection pattern

# Implication

Separating intrinsic & instrumental preferences for privacy can help us

1. **Measure privacy preferences** by understanding how much they respond **endogenously** to ways that the firm uses data
2. **Improve methods to collect & analyze consumer data** by understanding its **selection** pattern

# Experiment Design

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## Stage 1: Collect Full Data

### Participants complete survey sent by UChicago

- Smartwatch preference questions (camouflage)
- Personal questions → contents of personal data
  - Gender, age, edu, income, relationship, number of children, zipcode, race, digital product preference

1

2

## Stage 2: Collect Privacy Choices & Shared Data

1

Participants receive data sharing request



2

Treatments (factorial):

- **Compensation (price for data):**  
Gift card value:  $\{\$0; \$10, \$20, \$50\} \times 1\%$
- **Instrumental Incentive:**  
{on, off}



## Treatment Variation to Identify Model Primitives

$U(\text{protect data}) - U(\text{share data}) = \text{intrinsic utility} + \text{instrumental utility} - \text{compensation}$

### Compensation (price for data):

- Same for each datapoint **regardless of what the firm learns about you**
- Translate privacy preferences to dollar terms

### Instrumental Incentive:

- Payoff that **depends on what the firm learns about you based on data shared**
- Separate instrumental utility from intrinsic

## Treatment Group Payment Scheme

Your winning probability is determined both by the baseline probability and by the adjustment terms. The baseline winning probability is calculated as follows:

$$\text{Baseline probability of winning} = \text{Number of boxes checked} \times 1\%$$

This baseline probability is then adjusted to encourage response sharing from the customer group that Odde intends to serve, as shown in the following chart:

|  |                                |                             |                              |
|--|--------------------------------|-----------------------------|------------------------------|
| Income   | < \$50,000                     | \$50,000 – \$75,000         | > \$75,000                   |
| <b>Adjustment</b>  | <b>-2%</b>                     | <b>Unchanged</b>            | <b>+2%</b>                   |
| Plan to purchase any digital device in the next 3 months | Somewhat or extremely unlikely | Neither likely nor unlikely | Somewhat or extremely likely |
| <b>Adjustment</b>  | <b>-2%</b>                     | <b>Unchanged</b>            | <b>+2%</b>                   |

Data

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# Sample Source and Size

## Participant: Qualtrics Panel

- Typical source when firms estimate demand before product launch
- Lower bounds of population-level intrinsic preferences; alleviate the gap by
  - Stratified sampling using US census demographics
  - Characterize heterogeneity using observables

## Sample Size:

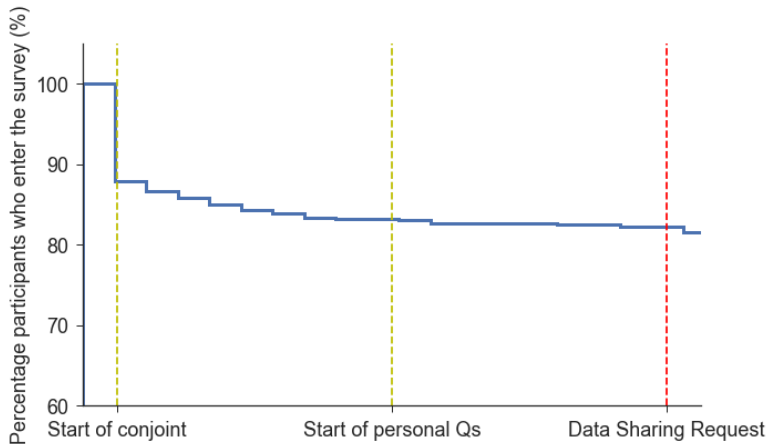
- 4,142 enter the survey; 2,583 qualified complete responses

## Demographics of Final Sample

|                         | Variables                  | Experiment Sample | 2018 Census |
|-------------------------|----------------------------|-------------------|-------------|
|                         | Female                     | 65.31%            | 50.80%      |
|                         | Married                    | 47.39%            | 51.16%      |
|                         | Have young kids            | 24.78%            | –           |
|                         | Mean age                   | 47.60 (16.89)     | 45.9 (–)    |
| Education               | High school degree or less | 47.00%            | 39.93%      |
|                         | College degree             | 40.65%            | 48.67%      |
|                         | Master's degree or higher  | 11.39%            | 11.40%      |
| Race                    | White                      | 71.27%            | 76.60%      |
|                         | Black                      | 15.37%            | 13.40%      |
| Annual Household Income | \$25,000 or less           | 21.99%            | 20.23%      |
|                         | \$25,000 to \$50,000       | 29.54%            | 21.55%      |
|                         | \$50,000 to \$100,000      | 30.12%            | 28.97%      |
|                         | \$100,000 or more          | 13.55%            | 29.25%      |
| No. Observations        |                            | 2,583             | –           |

- More female, fewer with college degree, fewer in high-income bucket

## Attrition Pattern



- Most attrition occurs at the start; not induced by concern about personal Qs

# Model

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## Conceptual Model

**Firm** wants: personal data  $\longrightarrow$  consumer's "type"  $\longrightarrow$  targeted payoff  
may offer (type-invariant) compensation to encourage data sharing

**Consumer** chooses protect vs. share data: protect iff

$$U(\text{protect}) - U(\text{share}) > 0 \iff \text{intrinsic utility} \\ + \underbrace{\text{payoff by hiding his type} - \text{payoff from disclosing his type}}_{\text{instrumental utility}} \\ - \text{compensation} > 0$$



## Estimation Model & Identification

$$U(\text{not share } k) - U(\text{share } k)$$
$$= \underbrace{c_k}_{\text{intrinsic}} + 1_{instr} \cdot 1_{k \in \{1,2\}} \cdot \underbrace{\beta \cdot p \cdot w_k \cdot \left( \widehat{E}[d_k | s_k = 0] - \widehat{E}[d_k | s_k = 1, d_{ik}] \right)}_{\text{instrumental}} - \underbrace{\beta \cdot p}_{\text{compensation}} + \epsilon_{ik}$$

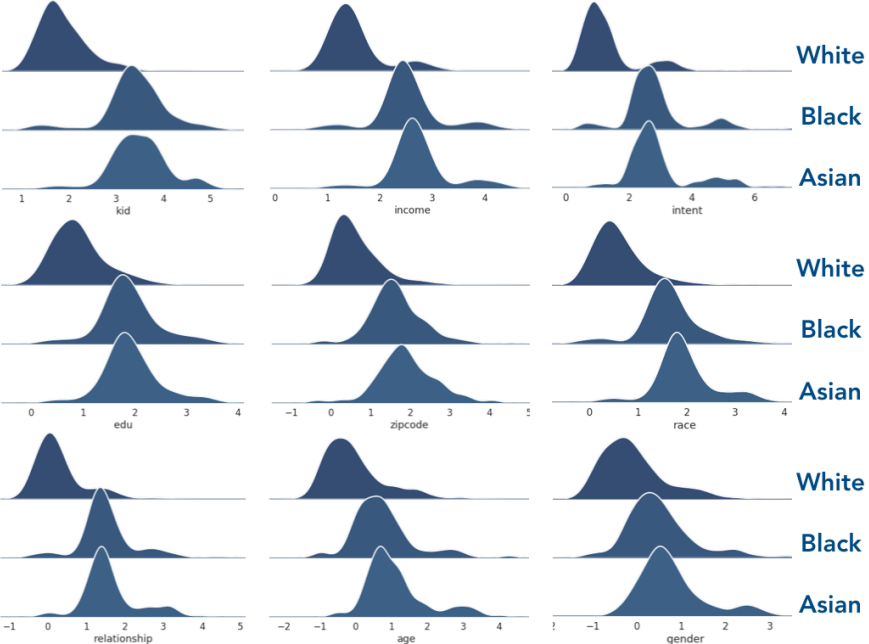
Results converted to dollar space to address scale invariance problem

- $c_k$ : utility intercept in the control group
- $\beta$ : response to different amounts of compensation
- $w_k$ : how different types react differently to instrumental incentives
- $\delta_{k0}, \delta_{k1}$ : response to instrumental incentives that is common across types

# Intrinsic Preferences

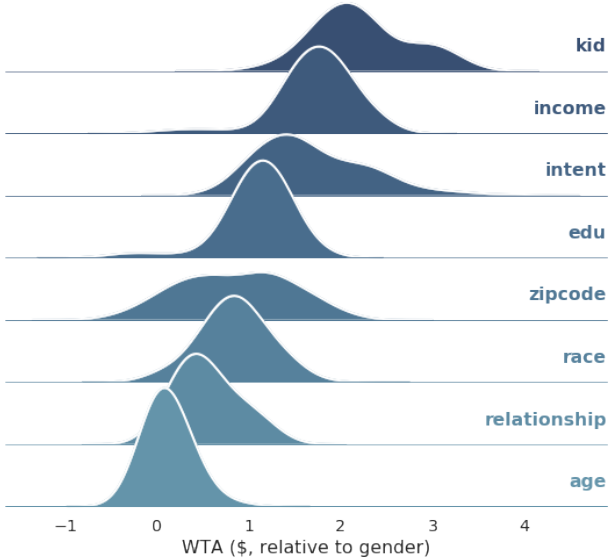
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# Intrinsic Preference: Non-Whites Higher than Whites



# Intrinsic Preference: Heterogeneous Even within Individual

Dollar Value of Intrinsic Preferences Relative to Individual Preference to Protect Gender Info



# Experiment Replication

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## Replicate Experiment in the Field

- A treatment where consumers are given \$\$\$ to get “ground truth”
- Separate intrinsic & instrumental in other treatments—Challenge: instrumental incentive hard to be removed
  - Vary intensity of instrumental incentive to measure consumer belief; project choices to 0 instrumental case, assuming belief stays constant