

# Manipulative consumers

Michael Richter

Baruch College, CUNY and

Royal Holloway, University of London

Nikita Roketskiy

University College London

ESSET, Gerzensee

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## Research question

- ▶ Sellers use consumer data for pricing (and product design)
- ▶ Consumers can manipulate their records at a cost

**How much is data worth to the seller?**

# Consumer data

- ▶ Data is all the records the seller has about individual consumers
  - ▶ demographics
  - ▶ past history
  - ▶ other things like social network activity, etc.
- ▶ Tabulated
  - ▶ columns are variables (or attributes)
  - ▶ table is infinitely tall (assume finite sample issues away)
- ▶ Variable is a “container”
  - ▶ Its informational content is endogenous
  - ▶ Determined by a cost of manipulation

# Main points

- ▶ Price dispersion measures the value of data
  - ▶ Data allows the seller to offer different prices to different consumers
  - ▶ Price dispersion is a simple measure that aggregates this ability
- ▶ “Richer” data (more covariates) is worth less
  - ▶ More covariates usually mean better predictive power, but...
  - ▶ ...it also makes it easier for the consumers to do arbitrage.

# General Data Protection Regulation

Personal data shall be:

- (a) processed lawfully, fairly and in a transparent manner in relation to the data subject ('lawfulness, fairness and transparency');
- ...
- (c) adequate, relevant and limited to what is necessary in relation to the purposes for which they are processed ('data minimisation');

# California Consumer Privacy Act

- (a) A business that controls the collection of a consumer's personal information shall, at or before the point of collection, inform consumers of the following:
  - (1) The categories of personal information to be collected and the purposes for which the categories of personal information are collected or used and whether that information is sold or shared.
  - ...
- (c) A business' collection, use, retention, and sharing of a consumer's personal information shall be reasonably necessary and proportionate to achieve the purposes for which the personal information was collected or processed ...

## Related works

### Manipulable data:

- ▶ Ball (2021), Frankel and Kartik (2019, 2022) - inference from manipulable data
- ▶ Eliaz and Spiegler (2021), Caner and Eliaz (2021) - IC estimators
- ▶ Deneckere and Severinov (2017), Severinov and Tam (2019), Perez-Richet and Skreta (2022), Dana, Larsen and Moshary (2023), Tan (2023), Moreno de Barreda and Safonov (2023) - m./test design
- ▶ Bonatti and Cisternas (2019), Bhaskar and Roketskiy (2021) - consumer history and price discrimination

### Market segmentation:

- ▶ Hidir and Vellodi (2020) - IC market segmentation
- ▶ Liang and Madsen (2021) - profiling and incentivizing effort
- ▶ Eilat, Eliaz and Mu (2020) - restricting informativeness of a price discrimination

### Value of data/Privacy:

- ▶ Dubé and Misra (2021) - value of personalized pricing
- ▶ Bergemann and Bonatti (2015), Bergemann, Bonatti and Smolin (2018) Segura-Rodriguez (2019) - data brokers
- ▶ Bonatti, Huang and Villas-Boas (2023)

# Consumers

- ▶ Continuum of consumers,  $C = [0, 1]$
- ▶ Willingness to pay for quality  $\tau : C \rightarrow \{t_\ell, t_h\}$
- ▶ Surplus from a transaction with the monopolist:  $s(i, q) = \tau(i)q - \frac{q^2}{2}$ ,
- ▶ Premium for quality:  $d = t_h - t_\ell$



# Monopolistic seller

- ▶ produces a variety of vertically differentiated products, quality  $q$  (at “zero” cost)
- ▶ menu pricing  $p(q)$
- ▶ can condition the menu on observables  $\alpha(i)$
- ▶ no commitment to the data practices, use all the data that is available

# Consumer data

- ▶  $\omega : C \rightarrow \{0, 1\}^K$  - consumer attributes (ex ante, exogenous, private)
- ▶  $\alpha : C \rightarrow \{0, 1\}^K$  - consumer data (ex post, endogenous, public)
- ▶  $\alpha(i)$  is chosen at a cost  $\frac{\|\alpha(i) - \omega(i)\|}{K} c$
- ▶  $\tau(i)$  is correlated with  $\omega(i)$
- ▶  $m(\cdot)$  is measure of  $\ell$ -consumers
- ▶  $n(\cdot)$  is measure of  $h$ -consumers
- ▶ two assumptions (A1, A2) on these measures

## A1 and A2, preliminary

- (A1) A balanced proportion of consumers with low and high willingness to pay for quality.
- (A2) Each of the  $K$  dimensions of consumer data represent new, cond. independent information (no duplication).

# Market segments

- ▶ Seller uses consumer data to price the products: a consumer faces prices that depend on her attributes.
- ▶ A combo of 2nd and 3rd degree price discrimination:
  - ▶ Each market segment  $S \in \mathfrak{S}$  gets its own optimal menu.
  - ▶ Firm estimates the consumer demand within the segment.
- ▶ Market segment labels  $\mathfrak{S}$
- ▶ Firm regresses attributes to market segments:

$$R : \mathfrak{A} \rightarrow \mathfrak{S}$$

## Optimal menu in segment $S$

Demand statistics:

$$h(S) = \frac{n}{m}(\{i \in C : R(\alpha(i)) = S\})$$

Consumer surplus (per  $H$ -consumer):

$$U_h(S) = \max\{0, 2d(t_\ell - h(S)d)\}$$

Profit (per  $\ell$ -consumer in  $S$ ):

$$\rho(S) = h(S)(t_\ell + d)^2 + [\max\{0, t_\ell - h(S)d\}]^2$$

**A1**

$$\bar{h} \in \left[ \frac{c}{2d^2}, \frac{t_\ell}{d} - \frac{c}{2d^2} \right].$$

## Value of consumer data

Aggregating profit across segments

**Proposition:**

$$\pi(S) - \pi^* = d^2 \underbrace{\sum_{\mathbf{a}} m(\mathbf{a}) [h(R(\mathbf{a})) - \bar{h}]^2}_{\text{Var}[h(R(\cdot))]} = \frac{1}{4} \sum_{\mathbf{a}} m(\mathbf{a}) [p_h(R(\mathbf{a})) - \bar{p}_h]^2$$

**Corollary:**  $h(R(\mathbf{a}))$  is a mean-preserving contraction of  $h(\mathbf{a})$  hence it is optimal to use all available information

$$R^*(\mathbf{a}) = \mathbf{a}$$

Value = explained variation

- ▶ Seller does a non-parametric regression of  $h$  on  $\mathbf{a}$ .
- ▶ Part of variation in “premium” demand explained by the data:

$$\sum_{\mathbf{a}} m(\mathbf{a}) [h(\mathbf{a}) - \bar{h}]^2$$

is the value of consumer data for the seller.

# Attributes

Each consumer is endowed with a vector of  $K$  binary attributes (personal data):

$$\omega(i) \in \{0, 1\}^K$$

Consumer can change the values of any attributes at a cost. If consumer  $i$  sets her attributes to  $\alpha(i) \in \{0, 1\}^K$  she pays

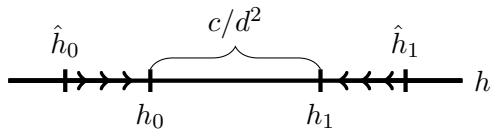
$$\frac{\|\alpha(i) - \omega(i)\|}{K} c.$$

Consumers manipulate their attributes privately before they see the prices.

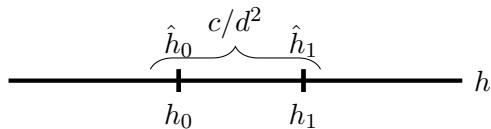


# Incentives to manipulate data, “no-arbitrage constraints”

mixed strategy



no changes to attributes



For any  $\mathbf{a}, \mathbf{b} \in \{0, 1\}^K$ :

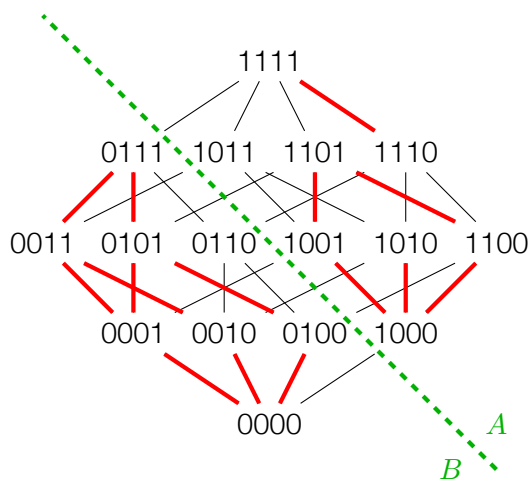
$$|h(\mathbf{a}) - h(\mathbf{b})| \leq \frac{c}{d^2} \frac{\|\mathbf{a} - \mathbf{b}\|}{K}$$

## Value of consumer data

- ▶ Value depends on correlation between data and type
- ▶ Observed data depends on consumer attributes
- ▶ We look at the **seller's best-case scenario**:

$$\begin{aligned} \max_{h(\cdot)} \quad & \sum_{\mathbf{a}} m(\mathbf{a}) [h(\mathbf{a}) - \bar{h}]^2 \\ \text{s.t.} \quad & \sum_{\mathbf{a}} m(\mathbf{a}) [h(\mathbf{a}) - \bar{h}] = 0 \\ & |h(\mathbf{a}) - h(\mathbf{b})| \leq \frac{c}{d^2} \frac{\|\mathbf{a} - \mathbf{b}\|}{K}, \text{ for all } \mathbf{a}, \mathbf{b} \in \{0, 1\}^K \end{aligned}$$

## Binding constraints



$$\sum_{\mathbf{a}} m(\mathbf{a})[h(\mathbf{a}) - \bar{h}]^2 =$$

$$\sum_{\mathbf{a} \in A} m(\mathbf{a})[h(\mathbf{a}) - h_A]^2 +$$

$$\sum_{\mathbf{a} \in B} m(\mathbf{a})[h(\mathbf{a}) - h_B]^2 +$$

$$m(A)[h(A) - \bar{h}]^2 +$$

$$m(B)[h(B) - \bar{h}]^2$$

**Lemma** The graph of binding constraints is connected.

## New attributes, new information

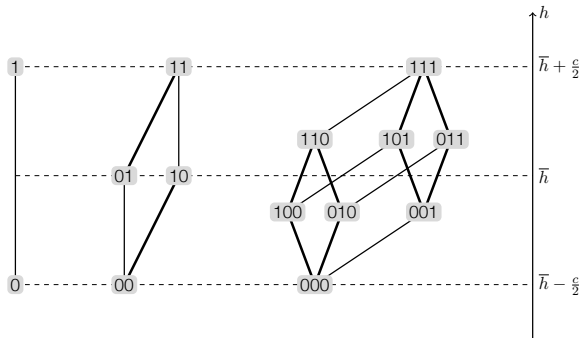
### **A2**

There exist marginal probabilities  $\mu_i : \{0, 1\} \rightarrow \mathbb{R}_+, i = 1, \dots, K$ , such that for any vector of attributes  $\mathbf{a}$  :

$$m(\mathbf{a}) = \bar{m} \prod_{i=1}^K \mu_i(\mathbf{a}_i)$$

.

With A2 we can use induction



## The main result

If A1 and A2, then the value of consumer data is

$$D = \frac{1}{K} \bar{m} \left[ \frac{c}{2d} \right]^2 \frac{\sum_{j=1}^K \mu_j(0) \mu_j(1)}{K}$$

## Scope for manipulation

The spread of  $\ell$ -consumers across attribute values:

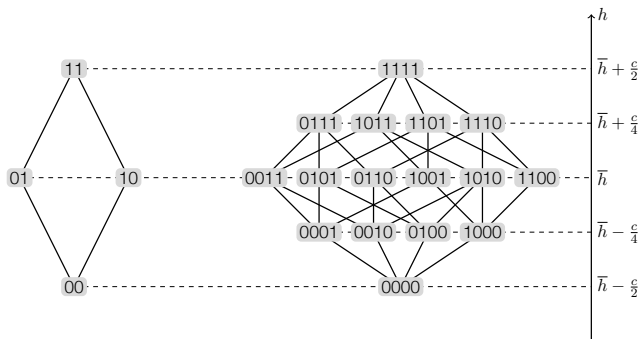
$$\frac{\sum_{j=1}^K \mu_j(0)\mu_j(1)}{K}$$

If  $\ell$ -consumers are concentrated, it is easy for the  $h$ -consumers to blend in.

# The effect of increasing $K$

$$\frac{1}{K} \bar{m} \left[ \frac{c}{2d} \right]^2$$

$$\lim_{K \rightarrow \infty} \frac{1}{2^K} \binom{K}{K/2} = 1$$





## Opaque use of data

As in Frankel and Kartik (2019, 2022) and Ball (2021):

If firm can **commit** to using single **unspecified** attribute then the value of consumer data is

$$D' = \bar{m} \left[ \frac{c}{2d} \frac{\sum_{j=1}^K \sqrt{\mu_j(0)\mu_j(1)}}{K} \right]^2$$

- ▶ For manipulation to be fruitful, consumers need to guess which attribute to manipulate
- ▶ The seller uses attribute  $j$  with prob.  $\frac{\sqrt{\mu_j(0)\mu_j(1)}}{\sum_{k=1}^K \sqrt{\mu_k(0)\mu_k(1)}} \approx \frac{1}{K}$ .
- ▶ This reduces the gain from manipulation by a factor of  $\frac{1}{K}$ .

# Conclusion

- ▶ Value of information is measured by the price variance
- ▶ Adding new (non-duplicating) variables to the data, increases both informational content and manipulation opportunities—the latter erodes value