Bounding Demand Elasticities with Unobserved Choice Set Heterogeneity

Gregory S. Crawford
University of Zürich
and CEPR

Rachel Griffith
University of Manchester
CEPR and IFS

Alessandro Iaria
CREST and IFS

Oslo and Budapest February 2016

Motivation

- Estimating parameters of demand is one of primary applications in economics
- Typically relies on revealed preference arguments
  - we observe someone choosing A over B and therefore infer they prefer A to B
  - revealed preference arguments rely on knowledge of choice sets (we need to know that you **could have** chosen B if you instead preferred B to A)
    - *If there exist only an apple and an orange, and an orange is picked, then one can definitely say that an orange is revealed preferred to an apple. In the real world, when it is observed that a consumer purchased an orange, it is impossible to say what good or set of goods or behavioral options were discarded in preference of purchasing an orange. In this sense, preference is not revealed at all in the sense of ordinal utility.* (Koszegi and Rabin (2007, AER))

Motivation

Many reasons to believe people face heterogenous choice sets

- limited or rational (in)attention
  - Masatlioglu et al (2012, *AER*); Manzini and Mariotti (2014, *Econometrica*); Matejka and McKay (2015, *AER*)
- firm strategies
  - Eliaz and Spiegler (2011, *REStudies*)
- time constraints
  - Reutskaja, Camerer, and Rangel (2011, *AER*)
- limited information or search
  - Sovinsky (2008, *Econometrica*); De Los Santos et. al (2012, *AER*)
- self control problems and commitment

Motivation

Choice Set Heterogeneity

- GOOD: variation in choice sets helps identification of preferences
  - if choice set heterogeneity is **observed** and **exogenous** to individual preferences (Berry, Levinsohn, and Pakes, 1995)
- BAD: it may cause bias in estimates of parameters of demand model
  - if individual's choice sets are unobserved (by the econometrician)

Our Contribution

- Show that unobserved choice set heterogeneity generally causes bias in estimates of preference parameters
- Propose empirical solutions that rely on
  - assumptions about evolution/stability of choice sets over time or across individuals
    - assumptions weaker than having to identify the complete choice set
    - we are likely to have economic intuition over them
  - logit demand (common in literature)
- Allows us to
  - point identify preference parameters under plausible assumptions about behaviour
  - obtain bounds on price elasticities

Relationship to literature

- Theoretical literature
  - provides foundations for heterogeneous choice sets and for separate identification of choice sets and preferences
- Empirical economics and marketing literatures
  - typically assumes a model of choice set formation or that observe true choice set
  - we accommodate unobserved choice sets, show how we can recover preferences without needing to formulate a model of choice set formation
- Econometrics literature on identification of preferences in logit demand models
  - McFadden (1978), Chamberlain (1980)

Our Contribution

- Emphasize:
  - if we **observe true choice sets** then we should use that information, and all is well in the world
  - if we have a **well specified model of choice set formation** that we are happy we can estimate then we should use that information, and all is well in the world
  - we are considering the (common) situation where neither of these is true

Intuition: bias from misspecified choice set

- Three products, $j \in \{1, 2, 3\}$
  - consumer i most prefers $j = 1$
  - define indirect utility $\mathscr{U}_{ij} = \boldsymbol{\beta} \boldsymbol{X}_j + \varepsilon_{ij}$
  - $\mathscr{U}_{i1} > \mathscr{U}_{i2} > \mathscr{U}_{i3}$
- if i has true choice set $CS_i^{\star} = \{2, 3\}$
  - i.e. option $j = 1$ is not available
  - we observe consumer choosing 2
- if we estimate assuming $CS_i = \{1, 2, 3\}$
  - then in estimation we infer $\mathscr{U}_{i2} > \mathscr{U}_{i1}$ and $\mathscr{U}_{i2} > \mathscr{U}_{i3}$
- assumed preference ordering violates i's true ordering
  - leads to $E\left[\widehat{\boldsymbol{\beta}}\right] \neq \boldsymbol{\beta}$

Examples

- Demand for specific food products
  - unlikely consumers consider all products on each shop
- Food deserts
  - do poorer households eat poor nutritional quality food because don't have access to good foods or because preferences for less nutritious foods
  - i.e. if faced with the full choice of all products, would they choose higher nutritional quality foods
- Demand for video games
  - some games are available only on XBox One and some only on PS4
  - many consumers are likely to only consider games for which they already have the console
- Wider applicability
  - occupation choice constrained by education/training

Intuition: our solution

- We propose a solution that relies on
  - assumptions on the **evolution** of choice sets
    - allow us to identify demand parameters from “sufficient” sequences of choices that contain the sequence chosen and definitely lie within the consumer’s true (unobserved) choice set
  - logit model
    - logit form allows us to “difference out” the consumer’s true, unobserved-to-the-econometrician, choice set
  - independence of idiosyncratic demand shocks and choice set formation process

  - alternative assumptions on the evolution of choice sets lead to different sufficient sequences
  - assumptions on the evolution of choice sets are much weaker than having to specify the choice set itself

Examples

- Demand for specific food products
  - experience goods, products purchased in the (recent) past are in the choice set
- Food deserts
  - constraint arises due to transport costs, households living next door (with similar demographics) face the same (unobserved) choice of stores
- Demand for video games
  - high switching costs due to investment in platform; consumers owning the same type of console have the same choice set (conditional on demographics)
- Occupation choice
  - human capital matching model; people with same degree have same set of occupations open to them

Model preliminaries

- Market with $j = 1, \ldots, J$ products
- $i = 1, \ldots, I$ *consumer types*
- for each type, $t = 1 \ldots, T$ *choice situations*
  - with panel data, i is an individual; t is a time period
  - with cross-section data, i is a type of consumer, t are the different individuals facing the same choice set
- i's choice sequence, $Y_i = (Y_{i1}, \ldots, Y_{iT})$

Model preliminaries

- In t, consumer type i is matched to choice set $CS^{\star}_{it}$
- We are interested in the consequences of mistakenly imputing to (i, t) a superset of choices, S_t
  - that includes options that were not in CS^{*}_{it}
    - i.e., $CS^{*}_{it} \subseteq S_t, \forall i, t$
    - (for notational convenience assume S_t the same for all i, but not important)
- Let
  - the **incorrectly assumed** set of possible choice sequences: $\mathcal{S} = \times_{t=1}^{T} S_t$
  - the **true** set of possible choice sequences: $\mathcal{CS}^{\star}_i = \times_{t=1}^{T} CS^{\star}_{it}$
    - by construction the choice (Y_i) is in the choice set ($CS^{\star}_i$), $Y_i \in \mathcal{CS}^{\star}_i$

Model preliminaries

- The probability of facing $\mathcal{CS}_i^\star = c$ and making a sequence of choices, $Y_i = j$, is

$$\Pr\left[Y_i = j, \mathcal{CS}_i^\star = c \,\middle|\, \theta, \gamma \right] = \Pr\left[Y_i = j \,\middle|\, \mathcal{CS}_i^\star = c, \theta \right] \Pr\left[\mathcal{CS}_i^\star = c \,\middle|\, \gamma \right]$$

- Preferences given by θ and γ
  - θ and γ can have common elements

- This captures two features of behavior:
  - $\Pr\left[Y_i = j \,\middle|\, \mathcal{CS}_i^\star = c, \theta \right]$: consumer preferences for products given the choice set they are matched to
  - $\Pr\left[\mathcal{CS}_i^\star = c \,\middle|\, \gamma \right]$: matching of consumers to their (unobserved) choice set

Logit assumption

- Let indirect utility for i in t:

$$U_{ijt} = V_{ijt}\left(X_{it}, \theta\right) + \varepsilon_{ijt}, \quad j \in CS^{\star}_{it}$$

- We assume
  - ε_{ijt} is distributed Type I Extreme Value *conditional* on the specific sequence of choice sets to which i is matched

- Thus for any c

$$\Pr\left[Y_i = j \middle| \mathcal{CS}^{\star}_i = c, \theta\right] = \prod_{t=1}^{T} \frac{\exp\left(V_{ijt}\left(X_{it}, \theta\right)\right)}{\sum_{m \in CS^{\star}_{it} = c_t} \exp\left(V_{imt}\left(X_{it}, \theta\right)\right)}$$

Logit assumption

- While a strong assumption, it is one that is uniformly made in both economics and marketing
  - Economics: BLP(1995, p864-868), Conlon and Mortimer (2013, eq (13)), Goeree (2008, p1025)
  - Marketing: Bronnenberg and Vanhonacker (1996, p165), Draganska and Klapper (2011, p660)
- We are working on extending methods here to
  - nested logit and non-logit demand, a promising topic for future research
  - mixed logit (random coefficient) models, challenging but may be feasible

Bias

- If econometrician incorrectly specifies choice from a superset, $\mathcal{S} = s = \times_{t=1}^{T} s_t$:

$$\Pr\left[Y_i = j \middle| \mathcal{S} = s, \tilde{\theta} \right] = \prod_{t=1}^{T} \frac{\exp\left(V_{ijt}\left(X_{it}, \tilde{\theta}\right)\right)}{\sum_{m \in S_t = s_t} \exp\left(V_{imt}\left(X_{it}, \tilde{\theta}\right)\right)}$$

- This causes bias

$$\begin{aligned}\Pr\left[Y_i = j \middle| \mathcal{S} = s, \theta \right] &= \underbrace{\Pr\left[Y_i = j \middle| \mathcal{CS}_i^\star = c, \theta \right]}_{\text{The true model}} \underbrace{\Pr\left[Y_i \in \mathcal{CS}_i^\star = c \middle| \mathcal{S} = s, \tilde{\gamma} \right]}_{\text{Bias}} \\ &= \prod_{t=1}^{T} \frac{\exp\left(V_{ijt}\left(X_{it}, \theta\right)\right)}{\sum_{m \in CS_{it}^\star = c} \exp\left(V_{imt}\left(X_{it}, \theta\right)\right)} \frac{\sum_{m \in CS_{it}^\star = c} \exp\left(V_{imt}\left(X_{it}, \theta\right)\right)}{\sum_{r \in S_t = s_t} \exp\left(V_{irt}\left(X_{it}, \theta\right)\right)}\end{aligned}$$

Bias

- Estimation based on $\mathcal{S}$ will be biased if $\Pr\left[\, Y_i \in \mathcal{CS}_i^{\star} = c \middle|\, \mathcal{S} = s, \theta\right]$ is important
  - this is the probability that *i*'s choices will belong to $\mathcal{CS}_i^{\star} = c$ when *i* is faced with the larger choice set
  - i.e. if, when facing the choice set $\mathcal{S} = s$, *i* would make a choice *not* in $\mathcal{CS}_i^{\star} = c$
  - i.e. if we include alternatives in estimation that *i* really likes but were not chosen because they were not available

Our solution strategy

- Make assumptions about the evolution or stability of choice sets to allow us to identify "sufficient sets" of choices that
    - contain consumer's observed choices
    - lie within the consumer's true unobserved choice sets
- we also need that logit demand shocks (ε_{ijt}) are independent of choice set (though θ and γ can have elements in common)
- Show that logit preferences allow us to
    - "difference out" consumer's true, unobserved-to-the-econometrician, choice sets
    - identify preferences based on variation in price and other product characteristics among the products in the sufficient set

General solution intuition

- We use
  - the observed choice sequence Y_i
  - plus assumption(s) over the **evolution/stability** of choice sets over t within i
- to construct a *set* of choice sequences $f(Y_i) \subseteq CS_i^\star$
  - if assumption correct (and logit), then $f(Y_i)$ is a "sufficient set" for $\mathcal{CS}_i^\star$
- Following McFadden (1978)
  - we can consistently estimate preferences using this subset of choices, $\Pr[Y_i = j | f(Y_i), \theta]$

General solution proof

$$\Pr\left[Y_i = j | f(Y_i) = r, \theta\right] = \frac{\Pr\left[f(Y_i) = r | Y_i = j, \theta\right] \Pr\left[Y_i = j | \mathcal{CS}_i^\star = c, \theta\right]}{\Pr\left[f(Y_i) = r | \mathcal{CS}_i^\star = c, \theta\right]}$$

$$= \frac{\Pr\left[f(Y_i) = r | Y_i = j, \theta\right] \Pr\left[Y_i = j | \mathcal{CS}_i^\star = c, \theta\right]}{\sum_{k \in \mathcal{S}} \underbrace{\Pr\left[f(Y_i) = r | \theta, Y_i = k\right]}_{\text{Equals 1 if } k \in r \text{, 0 else}} \Pr\left[Y_i = k | \mathcal{CS}_i^\star = c, \theta\right]}$$

$$= \frac{\prod_{t=1}^{T} \frac{\exp\left(V_{ijt}(X_{it}, \theta)\right)}{\sum_{v \in CS_{it}^\star = c} \exp\left(V_{ivt}(X_{it}, \theta)\right)}}{\sum_{k \in f(k) = r} \prod_{t=1}^{T} \frac{\exp\left(V_{ikt}(X_{it}, \theta)\right)}{\sum_{v \in CS_{it}^\star = c} \exp\left(V_{ivt}(X_{it}, \theta)\right)}} \quad CS_{it}^\star \text{ drops out}$$

$$= \frac{\prod_{t=1}^{T} \exp\left(V_{ijt}(X_{it}, \theta)\right)}{\sum_{k \in f(k) = r} \prod_{t=1}^{T} \exp\left(V_{ikt}(X_{it}, \theta)\right)}$$

Sufficient sets

- In order to implement our solution, we need to identify useful “sufficient sets” that satisfy two criteria:
  - contain the chosen sequence, Y_i
  - lie within the consumer’s true (unobserved) choice set
- To do this we make assumptions on the **evolution** of choice sets

Sufficient sets - examples

- An individual's choice set is stable for two (or more) periods, i.e. $CS^{\star}_{it} = CS^{\star}_{it-1}$
  - use the set of products a consumer purchased over those periods as the sufficient set
- Fixed-Effect logit, Chamberlain (1980)
  - relies on differencig
  - allows for very general individual heterogeneity
  - however does not allow us to identify the non-time varying elements of θ, so e.g. can't identify elasticities
- Full-Purchase-History logit
  - uses same sufficient set but does not difference, so time varying elements of θ are identified
  - but does not accomodate individual heterogeneity

Example

- Assume that from $\underline{T}$ to $\overline{T}$, $CS_{it}^{\star} = CS_{i\underline{T}}^{\star}, \forall i, t$
  - (not essential that common across individuals)
  - (an individual can have multiple spells)
- Suppose two choice situations with true unobserved choice set $CS_{i1}^{\star} = CS_{i2}^{\star} = \{1, 2, 3\}$
  - $\Rightarrow \mathcal{CS}_i^{\star} \equiv \{1, 2, 3\} \times \{1, 2, 3\} = \{(1, 1), (2, 2), (3, 3), (1, 2), (2, 1), (1, 3), (3, 1), (2, 3), (3, 2)\}$
- Suppose observed choices are: $Y_i = (1, 3)$

Fixed Effect Logit (FE)

- Let utility be defined

$$U_{ijt} = \eta_i + \delta_j + \beta X_{it} + \varepsilon_{ijt}, \quad j \in CS^{\star}_{it}$$

- Fixed-Effect logit
  - relies on switches to identify parameters
  - uses all possible permutations of the observed sequence of choices as the sufficient set
  - $f_{FEL}\left(Y_i\right) \equiv \{(1,3),(3,1)\}$

$$\Pr\left[\, Y_i = (1,3) \mid \beta, \{(1,3),(3,1)\}\right] = \frac{\exp\left(X_{i11}\beta\right)\exp\left(X_{i32}\beta\right)}{\exp\left(X_{i11}\beta\right)\exp\left(X_{i32}\beta\right) + \exp\left(X_{i31}\beta\right)\exp\left(X_{i12}\beta\right)}$$

- η_i and δ_j difference out, so not identified

Full Purchase History Logit (FPH)

- Can't accomodate η_i so let utility be defined

$$U_{ijt} = \delta_j + \beta X_{it} + \varepsilon_{ijt}, \quad j \in CS^{\star}_{it}$$

- The FPH logit uses all combinations of the products as the sufficient set
  - $f_{FPHL}(Y_i) \equiv \{(1,1),(3,3),(1,3),(3,1)\}$

$$\begin{aligned}
&\Pr[Y_i = (1,3)|\theta, \{(1,1),(1,3),(3,1),(3,3)\}] \\
&\quad = \frac{\exp(\delta_1 + X_{i11}\beta)}{\exp(\delta_1 + X_{i11}\beta) + \exp(\delta_3 + X_{i31}\beta)} \times \frac{\exp(\delta_3 + X_{i32}\beta)}{\exp(\delta_1 + X_{i12}\beta) + \exp(\delta_3 + X_{i32}\beta)}
\end{aligned}$$

Past-Purchase History logit (PPH)

- If we assume product is an experience good
  - an individual's choice set increases (over some period of time) as they experience new goods
- Past-Purchase History logit uses the products purchased between $\underline{T}$ and t as the sufficient set
  - $f_{PPHL}(Y_i) \equiv \{(1,1),(1,3)\}$

$$\Pr[Y_i = (1,3)|\theta, \{(1,1),(1,3)\}] = 1 \times \frac{\exp(\delta_3 + X_{i32}\beta)}{\exp(\delta_1 + X_{i12}\beta) + \exp(\delta_3 + X_{i32}\beta)}$$

Inter-Personal Logit (IP)

- A group of individuals face the same choice set
  - re-interpret i and t: i is now a consumer type, t are different individuals making independent choices from the same choice set
- Inter-Personal logit uses all combinations of the products as the sufficient set
- $f_{IP}\left(Y_i\right) \equiv \left\{\left(1,1\right),\left(3,3\right),\left(1,3\right),\left(3,1\right)\right\}$

$$\Pr[Y_i = (1,3)|\theta, \left\{\left(1,1\right),\left(1,3\right),\left(3,1\right),\left(3,3\right)\right\}]$$
$$= \frac{\exp(\delta_1 + X_{i11}\beta)}{\exp(\delta_1 + X_{i11}\beta) + \exp(\delta_3 + X_{i31}\beta)} \times \frac{\exp(\delta_3 + X_{i32}\beta)}{\exp(\delta_1 + X_{i12}\beta) + \exp(\delta_3 + X_{i32}\beta)}$$

Sufficient Sets: comments

- Which assumption on the evolution of choice sets is most appropriate will depend on the application and the economic environment

- and the empirical usefulness of the assumption will depend on available data

- with panel data we can combine assumptions, and for example use the intersection of purchase history (PH) and inter-personal (IP) sufficient sets

Elasticity Bounds

- While our methods enable us to point-identify preference parameters θ...
  - we cannot point-identify elasticities
- Why not?

$$\xi_{jj} = \beta_{\mathrm{p}} \mathrm{p}_j \left(1 - \frac{\exp\left(\boldsymbol{\beta X}_j\right)}{\sum_{l \in CS^\star} \exp\left(\boldsymbol{\beta X}_l\right)} \right) \qquad \xi_{jk} = -\beta_{\mathrm{p}} \mathrm{p}_k \left(\frac{\exp\left(\boldsymbol{\beta X}_k\right)}{\sum_{l \in CS^\star} \exp\left(\boldsymbol{\beta X}_l\right)} \right)$$

  - elasticities are functions of the full choice set, $CS_i^\star$, which are not observable without imposing more structure/further assumptions about the choice set formation process
  - how far can we get with out imposing anything else?

Elasticity bounds

- We can construct *bounds* on elasticites
- For any sufficient set, e.g. $s \in \{FE, FPH, PPH, IP\}$
  - $f_s(\boldsymbol{y}_i) \subseteq CS_i^\star \subseteq \mathcal{S}$
  - these allow us to bound the denominator of the "true" logit choice probability:

$$\sum_{k \in f_s(\boldsymbol{y})} \exp(\beta \boldsymbol{X}_{ik}) \leq \sum_{k \in CS^\star} \exp(\beta \boldsymbol{X}_{ik}) \leq \sum_{k \in \mathcal{S}} \exp(\beta \boldsymbol{X}_{ik}).$$

Elasticity Bounds

- When $\beta_{\text{p}} < 0$, we get the following bounds on the own price elasticity:

$$\underbrace{\beta_{\text{p}} \text{p}_j \left(1 - \frac{\exp\left(\boldsymbol{X}_j \boldsymbol{\beta}\right)}{\sum\limits_{k \in f_s(\boldsymbol{y})} \exp\left(\boldsymbol{X}_k \boldsymbol{\beta}\right)} \right)}_{\text{Lower (in absolute value) Bound}} \leq \xi_{jj} \leq \underbrace{\beta_{\text{p}} \text{p}_j \left(1 - \frac{\exp\left(\boldsymbol{X}_j \boldsymbol{\beta}\right)}{\sum\limits_{k \in \mathcal{S}} \exp\left(\boldsymbol{X}_k \boldsymbol{\beta}\right)} \right)}_{\text{Upper (in absolute value) Bound}}$$

Elasticity Bounds

- What elasticity are we interested in?
- If we never observe *i* purchasing *j* then we don't know whether *j* is currently in *i*'s choice set
  - the lower (absolute) bound is 0
- We can:
  1. assume *j* is not in *i*'s choice set, and that an incremental change in price will not move *j* into consumer *i*'s choice set:
     - use $j \in f_s$
  2. assume *j* is either in *i*'s choice set, or that an incremental change in price will move *j* into consumer *i*'s choice set
     - use $j \in f_{s+j}$

Elasticity Bounds

- Probability i buys j
  1. conditional on j observed in sufficient set

$$P\left[y_{itj} = j \middle| f_s = r\right] = \begin{cases} \frac{exp\left(\widehat{\beta}_1 p_{tj} + \widehat{\beta}_2 d_{ij} + \sum_k \widehat{\beta}_3 k x_{kj}\right)}{\sum_{l \in f_s} exp\left(\widehat{\beta}_1 p_{tl} + \widehat{\beta}_2 d_{il} + \sum_k \widehat{\beta}_3 k x_{kl}\right)} & \text{if } j \in f_s \\ 0 & \text{if } j \notin f_{ss} \end{cases}$$

  2. assuming j is in true consideration set

$$P\left[y_{itj} = j \middle| f_s = r, j \in CS^*_{it}\right] = \frac{exp\left(\widehat{\beta}_1 p_{tj} + \widehat{\beta}_2 d_{ij} + \sum_k \widehat{\beta}_3 k x_{kj}\right)}{\sum_{l \in f_{s+j}} exp\left(\widehat{\beta}_1 p_{tl} + \widehat{\beta}_2 d_{il} + \sum_k \widehat{\beta}_3 k x_{kl}\right)}$$

- I'll use second in what I present in the slides to follow

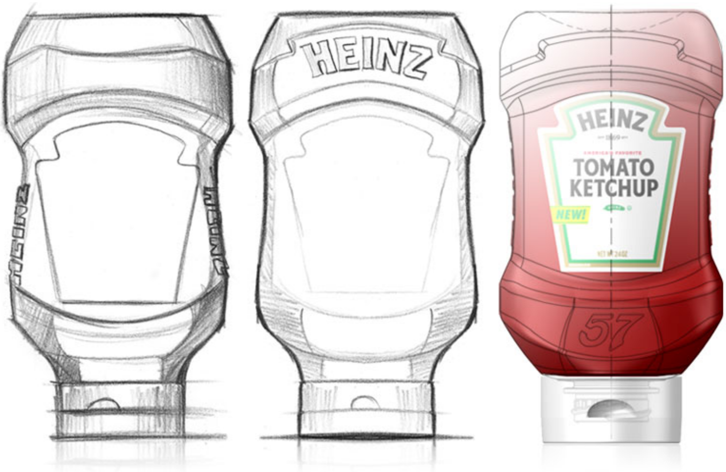
Application

- We present an application where we know the true choice set, and where we observe a period of time when we know that a product that many people prefer is not in their choice set
- in this application we know the choice set, so we don't need to use our estimator
- we use it as an example of how it can be used, if one did not know the true choice set
- we are trying to illustrate the consequences of incorrect choice set specification and how we can fix it
- (we also do this with a Monte Carlo simulation)

Application: introduction of a new ketchup product

A Design Flaw

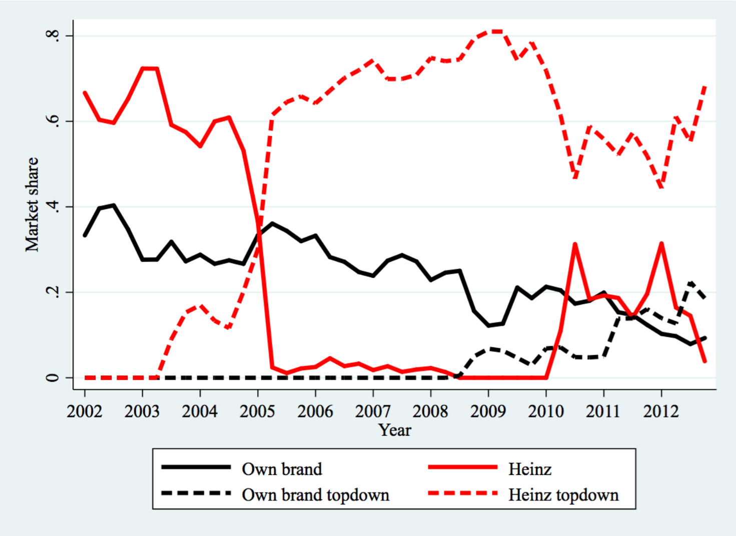
An innovation



Application Overview

- We estimate household demand for ketchup in the UK grocery market between 2002 and 2012
  - Heinz is the dominant brand, with 40-60% market share
  - Heinz introduced the top-down format in July 2003
  - Heinz top-down became the most popular variety, though some households never purchased it
  - Heinz top-down lost market shares starting in April 2010, due to entry of store own-brand top-down formats
    - evidence that some consumers value the top-down characteristic, while others don't

Ketchup: Brand market shares



Ketchup: Data

- Household level data on ketchup purchases
  - All purchases, longitudinal data
  - Product characteristics, e.g.,
    - Price, glass or plastic bottle, pack-size, etc.
  - Where household lives
  - Where stores are located
- Choice sets change over time due to the introduction of the new products
  - We observe in each t which products are available
- Use to investigate consequences of choice set misspecification and whether proposed fixes work

Ketchup: products Asda

Product	purchases	in PH choice set		Mean MS
			and in fascia	
Asda Asda pls 700g	785	3706	2528	2.2
Asda Asda pls 1000g	1677	5238	3444	4.6
AsdaTD Asda pls 1000g	643	1231	850	1.8
Heinz Asda pls 700g	452	2025	1524	1.2
Heinz Asda pls 1000g	835	2775	1819	2.3
Heinz Asda pls 1300g	1026	5936	3963	2.8
HeinzTD Asda pls 500g	1213	6091	4286	3.4
HeinzTD Asda pls 700g	1144	5495	3861	3.2
HeinzTD Asda pls 900g	1516	5718	3773	4.2
HeinzTD Asda pls 1200g	961	3621	2452	2.7

Ketchup: products Morrisons

Product	purchases	in PH choice set		Mean MS
			and in fascia	
Morr Morr pls 700g	379	2330	1218	1.0
Heinz Morr pls 500g	192	515	380	0.5
Heinz Morr pls 700g	360	1838	1189	1.0
Heinz Morr pls 1000g	230	1224	789	0.6
Heinz Morr pls 1300g	1065	5118	2705	2.9
HeinzTD Morr pls 500g	1087	5691	3245	3.0
HeinzTD Morr pls 700g	920	3890	2539	2.5
HeinzTD Morr pls 900g	460	2618	1730	1.3
HeinzTD Morr pls 1200g	1162	3960	2333	3.2

Ketchup: products Sainsburys

Product	purchases	in PH choice set	and in fascia	Mean MS
Sain Sains pls 500g	326	1540	1089	0.9
Sain Sains pls 700g	916	4160	2641	2.5
Sain Sains pls 1000g	993	3329	2009	2.7
SainTD Sains pls 600g	57	120	91	0.2
SainTD Sains pls 900g	79	172	122	0.2
Heinz Sains pls 500g	121	401	262	0.3
Heinz Sains pls 700g	237	1726	1115	0.7
Heinz Sains pls 1000g	420	1710	1227	1.2
Heinz Sains pls 1300g	739	4084	2668	2.0
HeinzTD Sains pls 500g	1076	4403	2862	3.0
HeinzTD Sains pls 700g	1105	4552	2908	3.1
HeinzTD Sains pls 900g	363	2041	1263	1.0
HeinzTD Sains pls 1200g	531	2104	1416	1.5

Ketchup: products Tesco

Product	purchases	in PH choice set		Mean MS
			and in fascia	
Tesco Tesco pls 500g	400	459	437	1.1
Tesco Tesco pls 700g	1163	5085	3843	3.2
Tesco Tesco pls 1000g	2470	6723	4859	6.8
Tesco Tesco pls 1100g	98	201	169	0.3
TescoTD Tesco pls 500g	84	134	121	0.2
TescoTD Tesco pls 700g	23	60	53	0.1
Heinz Tesco pls 500g	53	152	120	0.1
Heinz Tesco pls 700g	613	2719	1815	1.7
Heinz Tesco pls 1000g	799	3285	2418	2.2
Heinz Tesco pls 1300g	997	6806	4774	2.8
HeinzTD Tesco pls 500g	1990	7574	5329	5.5
HeinzTD Tesco pls 700g	1893	7488	5387	5.2
HeinzTD Tesco pls 900g	1186	6036	4156	3.3
HeinzTD Tesco pls 1200g	1310	4804	3235	3.6

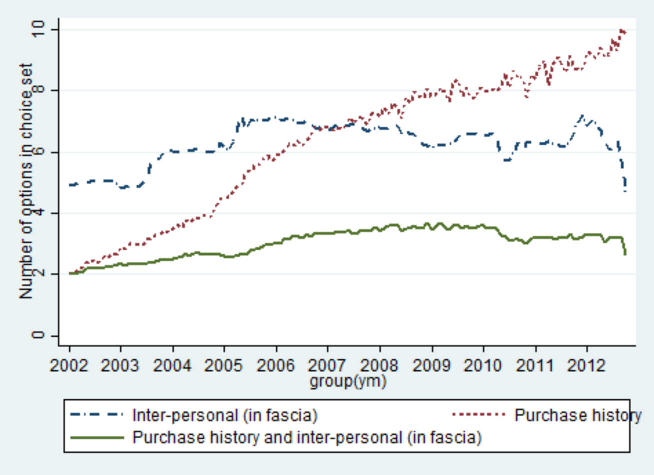
Ketchup: Sufficient sets

I'll show results from four sufficient sets today:

- Superset of the universal choice set ($\mathcal{S}$)
  - all 47 products
- Inter-Personal (IP)
  - products that at least one consumer is observed purchasing in the chain the household chose to shop in on that day
- (Past) Purchase History (PH)
  - all products that household has purchased in the past
- Inter-Personal (Past) Purchase History (IPPH)
  - (IP) $\times$ (PH)

Mean number of options in sufficient sets

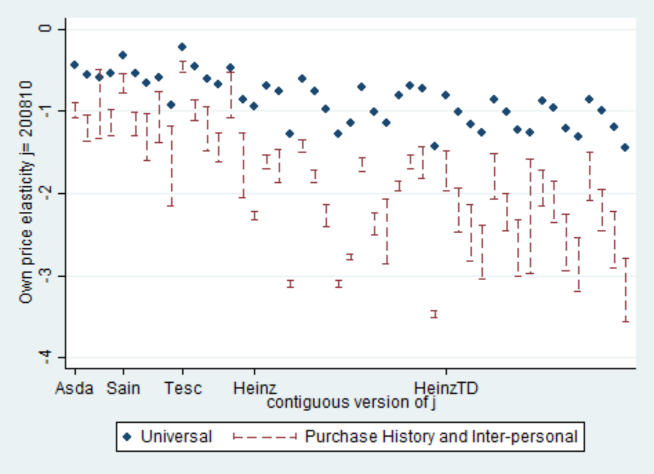
Mean number of options in sufficient sets



Ketchup

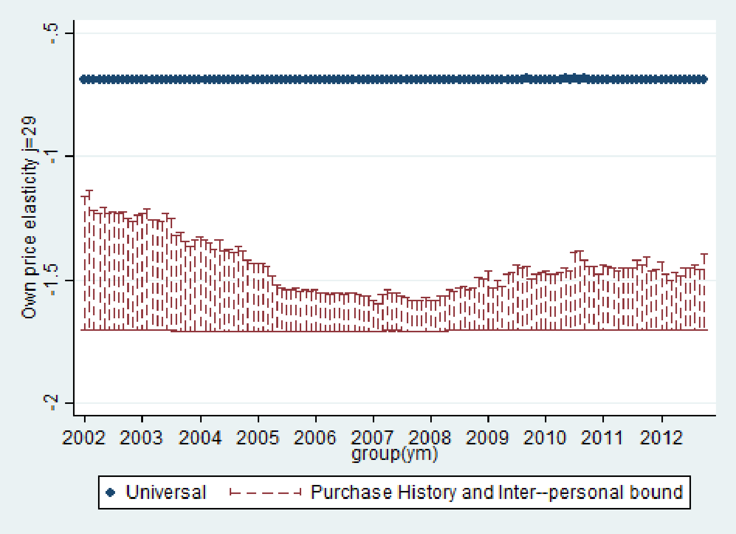
	Universal	Interpersonal (in fascia)	Purchase History (alone)	Purchase History × IP	Chamberlain FE T=4	Chamberlain FE T=8
price	-0.613	-1.395	-1.011	-1.496	-1.69	-1.49
	(0.016)	(0.020)	(0.023)	(0.025)	(0.04)	(0.03)
distance	-0.149	-0.151	-0.035	-0.036		
	(0.002)	(0.002)	(0.002)	(0.002)		
	...	...	...	...		
topdown	0.661	0.512	2.944	1.498		
	(0.014)	(0.020)	(0.027)	(0.030)		
	...	...	...	...		
N	1951816	936020	244248	160562		
(*it*)	41528	41528	41528	41528		
(*i*)	2391	2391	2391	2391	2391	2391
number of options (j) in households choice set						
mean	47	23	6	4		
minimum	47	15	2	2		
maximum	47	28	23	14		
choice sequences					9020	5115

Own price elasticities, October 2008

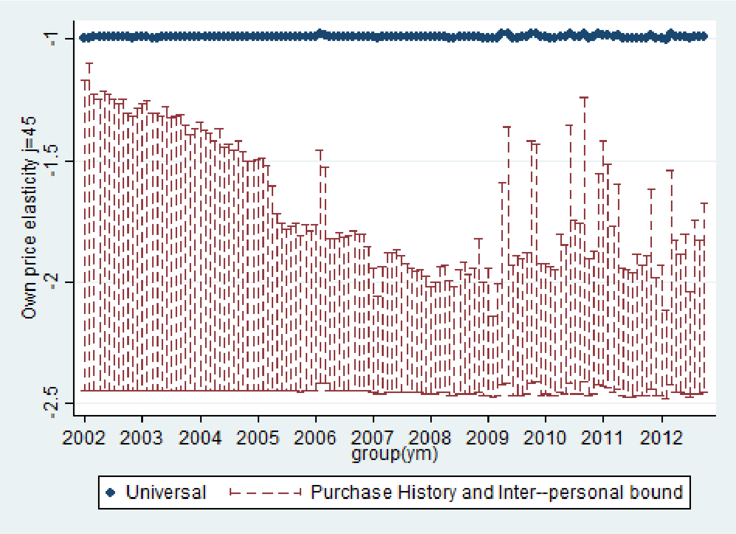


- Average: Universal -0.87; PHIP: [-1.53, -2.11]

Heinz 700g plastic, at mean price



Heinz 700g topdown, at mean price



Conclusions

- There is a lot of interest in understanding consumer behaviour in situations where they face constrained and heterogenous choice sets
  - it isn't always possible to specify how choice sets are determined
- We address the consequences of unobserved choice set heterogeneity on demand estimation
  - show that it generally causes bias
  - propose a method to
    - consistently estimate demand parameters
    - bound estimated demand elasticities
  - Based on
    - logit demand
    - assumptions about **evolution** of choice sets, that allows us to identify "sufficient sets" of choices
  - Estimable on both cross-section and panel data

Conclusions

- We show that it matters in an application
  - coefficient estimates biased (towards zero)
  - elasticities using universal choice set estimates often lie outside our bounds
- Next steps in this paper:
  - provide further intuition for assumptions on evolution of choice sets, and possible testing procedures
- Future work:
  - extend to Nested Logit and (simple) Random Coefficients
    - E.g, with discrete distributions of support
  - see if we can extend methods to allow us to learn about individual's (unobserved) choice sets