Choice, Welfare, and Market Design:

An Empirical Investigation of Feeding America's Choice System

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January 25, 2023

Motivation

- Many organisations must allocate heterogeneous objects that arrive stochastically
  - Council houses to tenants
  - Donor kidneys to transplant patients
  - Contracts to contractors
  - Food to food banks

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- In this paper I study the allocation of food to food banks:
  - Food bank networks receive truckloads of various types of food and must decide which food bank to send it to
  - How important is it to allow food banks to choose the types of food they receive?

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  - Food bank networks receive truckloads of various types of food and must decide which food bank to send it to
  - How important is it to allow food banks to choose the types of food they receive?

- The benefits of choice depend on **heterogeneity** in match values
  - $\rightarrow$ Estimating the degree of heterogeneity is key to welfare analysis

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- Before 2005 food banks were offered food at random
  - Different **food banks** want different **types of food** at different **points in time**
  - What they want is determined by what they do not receive from local donors

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- **Research Question:** How does welfare compare under the two systems?

  → What factors are driving this difference?

  → Could other food bank networks benefit from adopting a similar system?

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- **Empirical strategy**:
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  - Counterfactuals: Compare allocations under the current and previous regimes

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- **Solution:**
  - Structurally estimate a dynamic multi-object auction model (solves 1 & 2)
  - Use a Bayesian approach to numerically integrate over unobserved stocks (solves 3)
    $\rightarrow$ "data augmentation": Infer changes in stocks from changes in bids

Preview of Findings

- Preferences and Heterogeneity:
  1. Large heterogeneity across food banks and across different types of food
  2. Evidence of heterogeneity within food banks over time due to variation in stocks

- The Importance of Choice:
  1. Equivalent to a 17.1% increase in the supply of food, or 50 tons each day
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- The key reason? Batching
  - The Auction System allocates many loads simultaneously in batches
  - The Old System allocated sequentially - each load allocated before the next arrived

    → Most other food bank networks allocate food sequentially

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Contribution and Related Literature

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1. Empirical: I examine how food banks benefit from choice over their allocations
   - **Empirical Market Design**: [*school choice*] Agarwal and Somaini (2018) Kapor et al (2020), Akbarpour et al (2022) [*teacher allocation*] Combe et al (2022), Bobba et al (2022) [*medical match*] Agarwal (2015), [*spectrum allocation*] Fox & Bajari (2013)
   - **Empirical Dynamic Matching**: [*public housing*] Thakral (2016), Waldinger (2022), van Dijk (2022), [*kidney allocation*] Agarwal et al (2020), Agarwal et al (2021), [*hunting permits*] Reeling & Verdier (2022), [*foster care*] Robinson-Cortés (2019)
   - **Food banks**: Prendergast (2017 & 2022), Walsh (2015), Bazerghi et al (2016)

   → I use a long panel of food bank bidding data to estimate a structural model with rich, unobserved, and time varying, heterogeneity

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2. Methodological: I estimate an empirical auction model with unobserved states
   - **Empirical Auctions**: [*single object*] Guerre et al (2000) [*dynamic auctions*] Jofre-Bonet & Pesendorfer (2003), Backus & Lewis (forthcoming), [*multi-object auctions*] Cantillon & Pesendorfer (2006), Gentry et al (2022) [*both*] Altmann (WP)
   - **Identification**: Berry & Compiani (2022), Connault (2016), Hu & Shum (2012), Arcidiacono & Miller (2011), Kasahara & Shimotsu (2009)

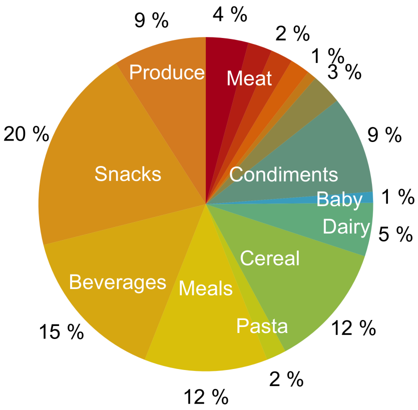
   → I present an identification strategy using observed shifters of the unobserved states

Outline

1. Institutions and Data
2. Model and Identification
3. Estimation and Results
4. Counterfactuals

Feeding America

- Feeding America work with 200 food banks across the country
- They provide food to feed 130,000 people each day
- Distributing 100,000 tons of food to food banks each year



Feeding America

The Auction System (2005 - present):

- Each load is put to auction, in a simultaneous FPSB format

- Food banks place bids on loads using a fake currency - ‘shares’
  - Daily allocations of fake money are determined by local poverty
  - fake money can be saved, and interest free credit is available
  - Negative bids are allowed, down to $-2000 \rightarrow$ this helps shift undesirable loads
  - The (fake) money supply varies with the food supply to keep prices constant

Data

Two sources of data are used:

1. Bidding Data
   - Information on every auction from 2014-2017
   - The goods included in each lot
   - The location of each lot
   - Identities and bids of both winning and losing bidders

2. Food bank data
   - Catchment areas, local population data and poverty rates

$\rightarrow$ I do not have data on stocks, local donations, or food sent to food pantries

Outline

Stylised Facts

The model needs to incorporate 3 key observed facts:

1. Heterogeneity
   - Systematic differences in behaviour across food banks and over time [Graphs]
     $\rightarrow$ Evidence of persistent and time-varying **unobserved heterogeneity**

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   - After winning a lot, the probability of bidding on a similar lot falls by 25%
   - Anecdotal evidence that food banks are forward looking and patient

     → Evidence we need a **Dynamic** auction framework [Graphs]

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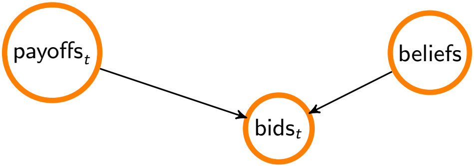
     → Evidence we need a **Dynamic** auction framework Graphs

3. Negative prices and infrequent bidding
   - 21% of bids are negative, and the average bidder only bids on 2% of lots

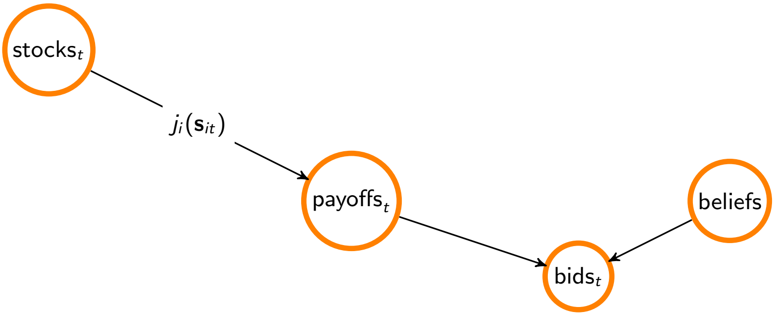
     → Evidence of **storage costs**

The Model



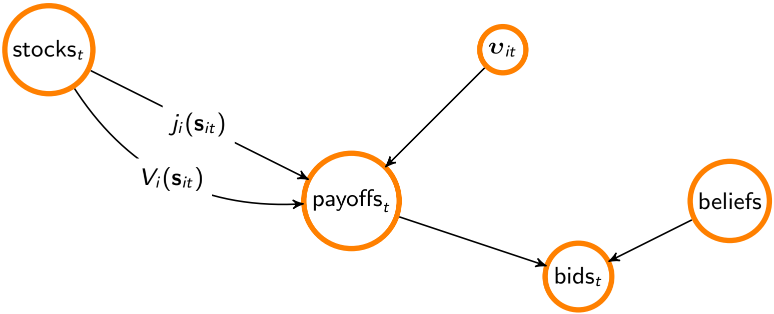
- Food banks bid in repeated rounds of simultaneous first price auctions Model details
  - → Independent private values, endogenous entry into auctions, risk neutral bidders
  - → Payoffs are Quasi-linear in fake money

The Model



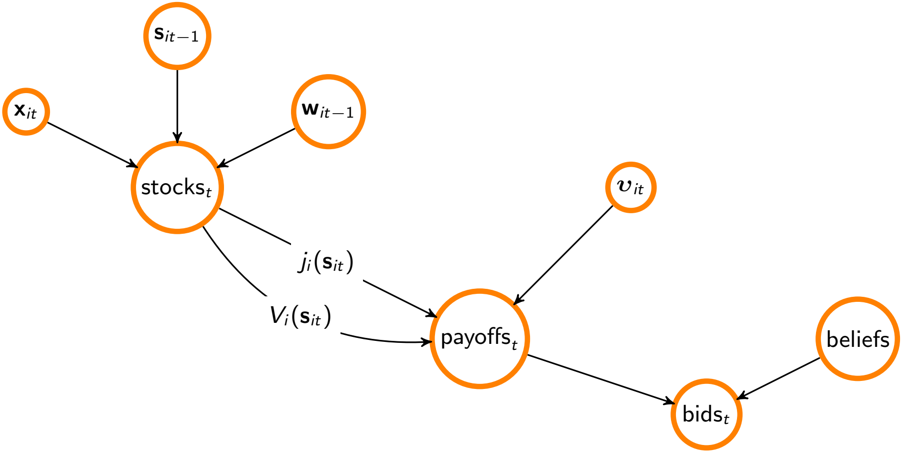
- If a food bank ends the period with stocks $\mathbf{s}_i$, they receive pay-off $j_i(\mathbf{s}_i)$ Model details
  - $\rightarrow$ This depends on stock by subcategory and by storage type
  - $\rightarrow$ This captures the utility of holding food to give it out, and storage costs

The Model

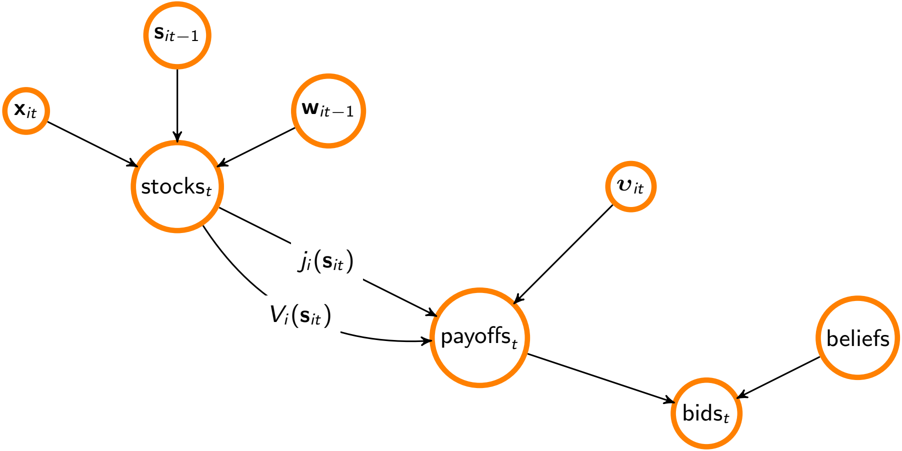


- $V_i(\mathbf{s}_i)$ gives the continuation value: expected future payoffs given ending in state $\mathbf{s}$
- If they win lot l they also receive lot specific idiosyncratic pay-off $\upsilon_{itl} \sim F^{\upsilon}$
  - $\rightarrow$ This captures transportation costs and unmodelled variation in lot attributes

The Model



- I assume a stock process: $\mathbf{s}_{it} = \mathbf{s}_{it-1} + winnings_{it-1} + \mathbf{x}_{it}$
  - $\rightarrow$ $\mathbf{x}_{it}$ = local donations minus food distributed to local pantries ($\mathbf{x}_{it} \sim F_i^x$)
  - $\rightarrow$ This is not a random walk: $\mathbf{w}_{it-1}$ responds to $\mathbf{s}_{it-1}$ to prevent stocks dropping too low



- **Equilibrium**: I focus on Markov Perfect Equilibrium
  - $\rightarrow$ This ensures strategies only depend on $\mathbf{s}_t$, not on t itself
  - $\rightarrow$ Essentially, this is a stationarity assumption

Details

The Food Bank's Problem

Sum over possible outcomes a

Bellman Equation:

$$W_i(\boldsymbol{\upsilon}_i, \mathbf{s}_i) = \max_{\mathbf{b}} \left\{ \sum_l \Gamma_l(b_l)(\upsilon_{il} - b_l) + \sum_a P_a(\mathbf{b})[j_i(\mathbf{s}_i^a) + \beta V_i(\mathbf{s}_i^a)] \right\}$$

$P(\text{win lot } l | b_l)$

Combination probability

$= E_{\boldsymbol{\upsilon}_{it+1}, \mathbf{s}_{t+1}}[W_i(\boldsymbol{\upsilon}_i, \mathbf{s}_i) | \mathbf{s}^a]$

Key:

- b_l = bid on lot l
- $\mathbf{s}_i$ = i's stocks
- $\mathbf{s}_i^a$ = i's hypothetical stocks
- υ_{il} = lot specific value
- $j_i(\mathbf{s}_i)$ = flow payoffs
- $V_i(\mathbf{s}_i)$ = continuation value
- β = discount factor

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- **First Order Conditions:**

$$0 = \frac{\partial \Gamma_l(b_l^*)}{\partial b_l}(\upsilon_{il} - b_l^*) - \Gamma_l(b_l^*) + \sum_a \frac{\partial P_a(\mathbf{b}^*)}{\partial b_l}[j_i(\mathbf{s}_i^a) + \beta V_i(\mathbf{s}_i^a)]$$

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- **Inverse Bid System:**

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Are the model primitives $\{j_i(\mathbf{s}_i), F_i^x\}_i$ identified from our data?

- In short, identification is a major challenge, particularly due to...

  $\rightarrow$ Unobserved state

  $\rightarrow$ Simultaneous auctions

  $\rightarrow$ Repeated auctions

  $\rightarrow$ Reservation prices

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- However, in the paper I prove identification using 2 sources of variation:

1. Using observed variation in the size and composition of lots Reduced Form

   $\rightarrow$ This pins down $j_i(\mathbf{s}_i)$

2. Using observed variation in winnings Reduced Form

   $\rightarrow$ This pins down $F_i^{\mathbf{x}}$

Proof Outline

Outline

- The standard estimation procedure comes from Jofre-Bonet & Pesendorfer (2003)
  1. Estimate the distribution of equilibrium bids
  2. Write $V(\mathbf{s})$ as a function of this distribution
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- However, we can write V as a function of bids and a correction term

  $\rightarrow$ This correction is just a (linear) function of $j + \beta V$

1. Estimate equilibrium beliefs: Γ & P

Details

→ We then return to the Inverse Bid Function:

$$\upsilon_l(\mathbf{b};\mathbf{s}_i) = b_l + \frac{\hat{\Gamma}_l(b_l)}{\partial\hat{\Gamma}_l(b_l)/\partial b_l} - \sum_a \frac{\partial\hat{P}_a(\mathbf{b})/\partial b_l}{\partial\hat{\Gamma}_l(b_l)/\partial b_l}\left[j_i(\mathbf{s}_i^a) + \beta V_i(\mathbf{s}_i^a)\right]$$

3 Step Estimation Procedure

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2. Estimate F_i^x, F_i^υ, and $k_i(\mathbf{s}_i) = j_i(\mathbf{s}_i) + \beta V_i(\mathbf{s}_i)$ (Details shortly)

   $\rightarrow$ This uses the Inverse Bid Function, as well as the Transition Process

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3. Disentangle j_i and V_i Details

   - Write $V_i(\mathbf{s})$ as a function of F_i^x and $k_i(\mathbf{s})$:

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Estimating F_i^x and $k_i(\mathbf{s})$

Details

- I make parametric assumptions on F_i^x and $k_i(\mathbf{s}_i)$:
  - F_i^x is normal, with mean $\boldsymbol{\mu}_i$ and variance Σ_i
  - $k_i(\mathbf{s}_i)$ is quadratic in $\mathbf{s}_i$ (Linear Demand Curves)

- The general idea behind estimation:
  1. Observe how behaviour changes with the available lots, or around a recent win
  2. Consider other changes in bidding behaviour...
     ...and find the change in stocks that rationalise this behaviour

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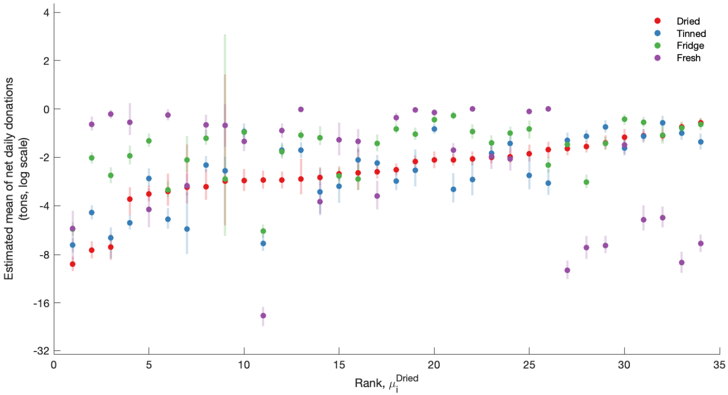
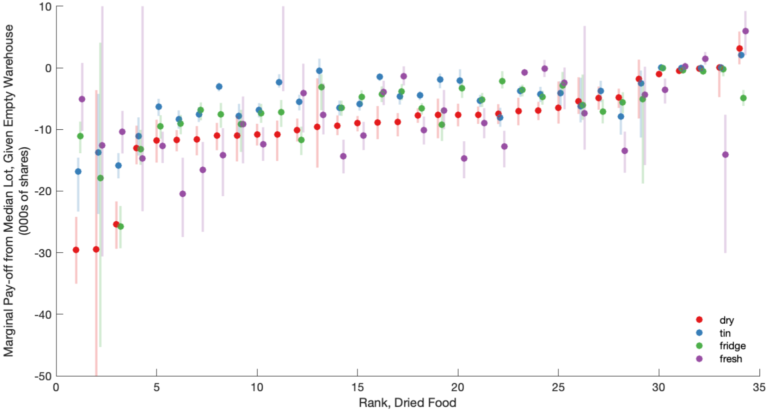
- Estimated using a Gibbs Sampler: Details
  1. *k-step*: Given draw of $\{\mathbf{s}_t\}_T$, sample k
     $\rightarrow$ Regress available lots and $\mathbf{s}$ on bids
     $\rightarrow$ This relationship arises from the inverse bid system
  2. *s-step*: Given draw of k, sample $\{\mathbf{s}_t\}_T$ and hence F^x
     $\rightarrow$ Employs the Carter-Kohn Algorithm
     $\rightarrow$ Infer changes in stocks from changes in bids
  3. repeat

Estimated mean net donations ($\mu_i = \hat{E}[\mathbf{x}_{it}]$)



Note: Plot shows estimated mean net local donations by food bank × food type, sorted across food banks by estimate for Dried food (red). Error bars give 95% credible intervals. See $\hat{\Sigma}$

Estimated Marginal Flow Payoff $\nabla j_i(\mathbf{s}_i)$



Note: Plot shows estimated marginal flow pay-off from receiving an average lot by food bank $\times$ food type, evaluated when stocks are empty. Estimates are sorted across food banks by estimate for Dried food. 95% credible intervals are plotted. See $\hat{k}$

Outline

Mechanisms

I consider 3 mechanisms:

1. The Auction System
2. The Old System
   - Food banks queue, get offered a load, then go to the back of the queue
   - Due to time constraints each load could only be offered to ≈ 10 food banks
3. Random Allocation (benchmark)

- For each mechanism I need to solve for the Markov Perfect Equilibrium

  $\rightarrow$ Find the fixed point between Accept/Reject decisions and beliefs

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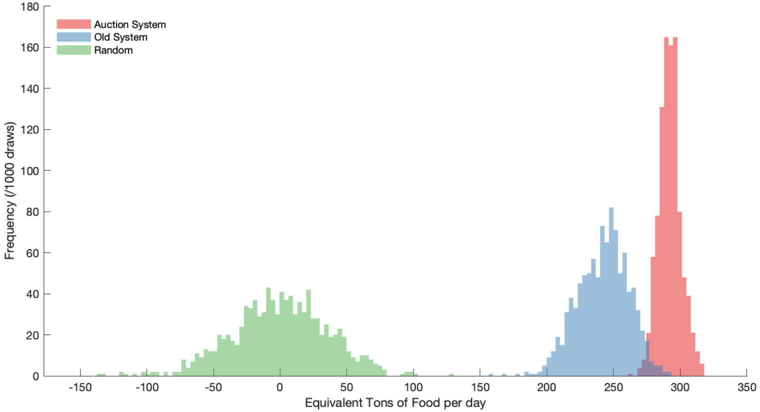
- For each mechanism I need to solve for the Markov Perfect Equilibrium

  $\rightarrow$ Find the fixed point between Accept/Reject decisions and beliefs
- Consider Welfare in terms of Consumer Surplus, measured in virtual currency
  - The money supply varies with the food supply to ensure prices remain constant

  $\rightarrow$ Hence we can translate welfare into equivalent increase in the food supply

Welfare



Note: Plot shows the posterior distribution of welfare under each mechanism. Evaluated over 1000 draws from the posterior distribution of parameters. Welfare is measured relative to the mean of the Random allocation. On average, welfare increased by 50 tons of food per day, representing a gain of 17.1% relative to the Old System.

Where does this benefit come from?

- More food allocated Histogram

  → On average 9% more food is allocated under the Auction System

- Less distance travelled Histogram

  → On average lots are allocated 29% closer under the Auction System

Where does this benefit come from?

- More food allocated [Histogram]

  → On average 9% more food is allocated under the Auction System

- Less distance travelled [Histogram]

  → On average lots are allocated 29% closer under the Auction System

- 81.5% of the welfare change comes from reduced storage costs

  → They seem to accept food that doesn't meet their most pressing needs...

  ... then don't have room to accept food that does meet these needs later

  → They accept food that other food banks might value more

- Equity? [Plot]

  → On average 85% of food banks achieve higher welfare under the Auction System

Welfare decomposition

I consider two more allocation mechanisms:

- Old System, working down the queue offering each load to **every** food bank
- An **Efficient** sequential mechanism

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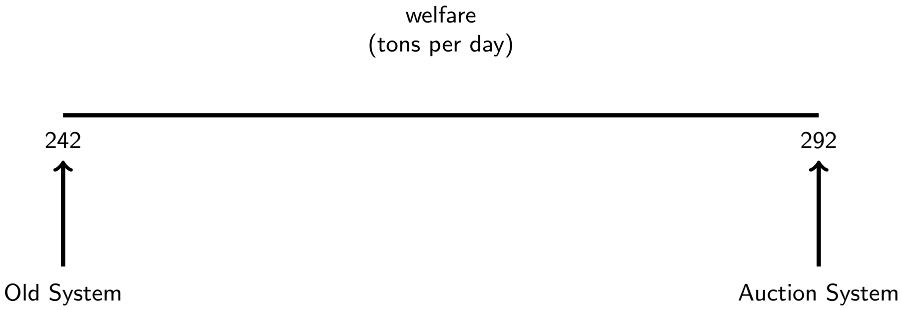

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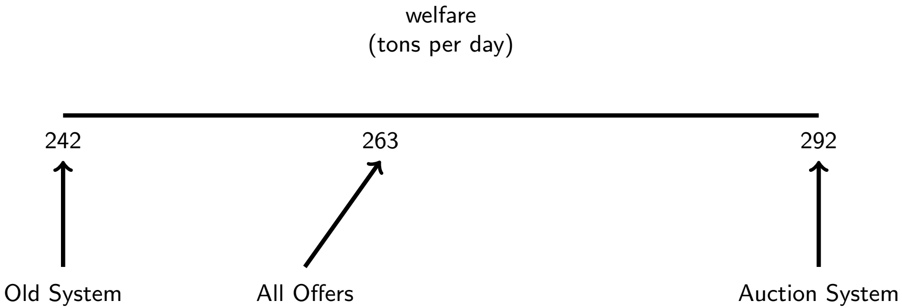

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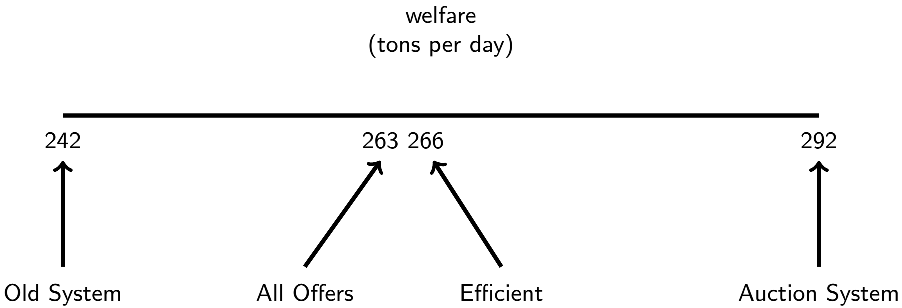

Summary

1. How important is it to give food banks Choice over the food they are allocated?
   - Applicable for numerous other food bank networks around the world

2. Developed a framework to estimate demand when stocks are unobserved
   - Found strong evidence of heterogeneity both across food banks and across time

3. Allowing Choice is extremely important
   - Increased welfare by an amount equivalent to increasing the food supply by 50 tons
   - This effect is driven by batching $\rightarrow$ larger choice sets $+$ better information

Summary

1. How important is it to give food banks Choice over the food they are allocated?
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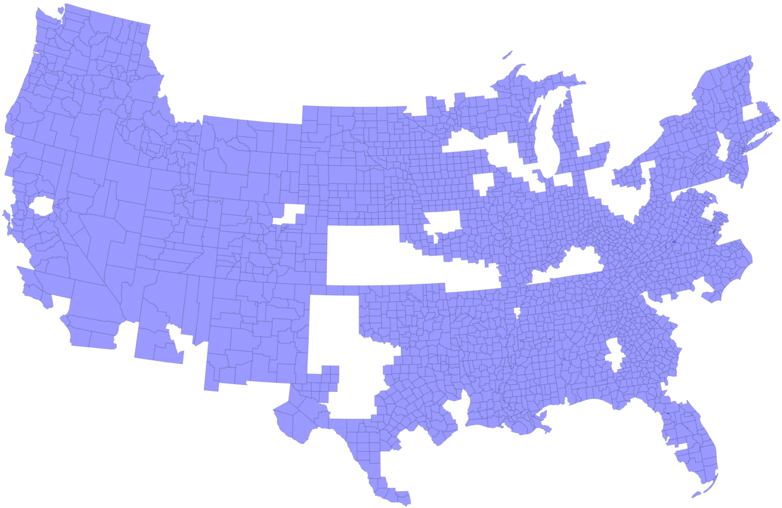
Future directions:

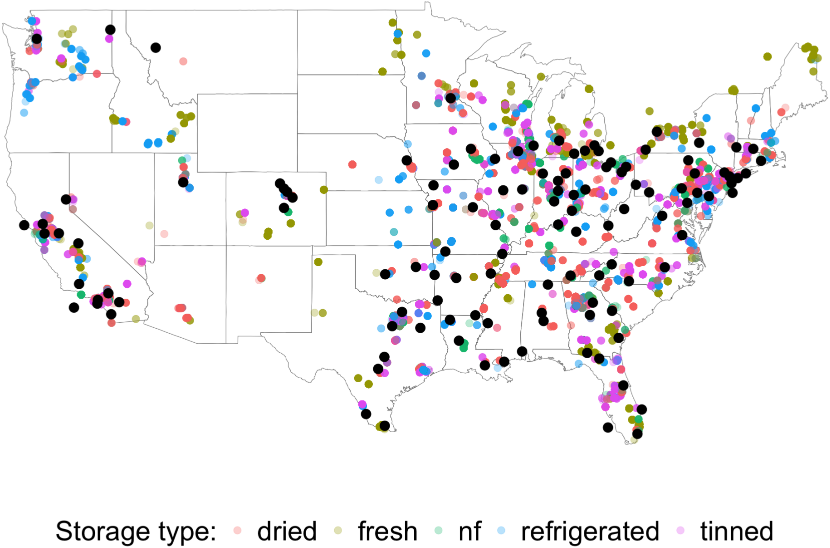
- Is there room for improvement?
- How do these results translate to other food bank networks?



Note: Map plots counties in the catchment areas of food banks who make regular use of the Choice System.

◂ return


crackers & cookies
snacks
candy
condiments
non-dairy milk
bars
coffee
dairy
lunch
flavoured milk
pop
crisps
towel
dressing
cabbage
nappy
jelly
cream
vegetables
soup
melon
corn flakes
oranges/lemons
squash
sugar
food
yoghurt
shake
milk
cookie
sauce
pasta
beans
peanut butter
detergent
meat
apple
onion
pizza
breakfast
slim jims
tomato
dessert
juice
water
potato
cheerio
carrot
cheese
meal
boxes
baked goods
Kellogg



return

Altmann (WP)

The Identification and Estimation of a Dynamic Multi-Object Auction Model

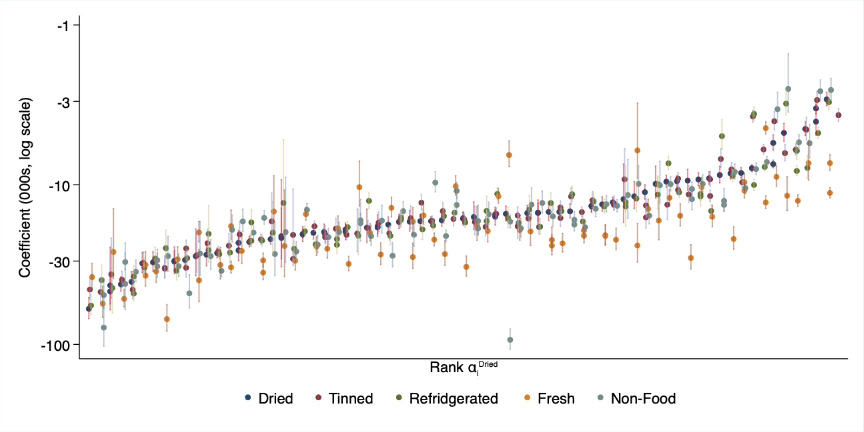
- Auctions rarely take place in isolation:
  - Many objects/contracts are often auctioned *simultaneously*
  - Auctions are *repeated* as new lots become available
  - Ignoring dynamics or complementarities will bias estimates

    $\rightarrow$ This is the first paper to unify the dynamic and multi-object setting

- I present a model of bidding in repeated rounds of simultaneous auctions
  - Identification / estimation is difficult because this is not a direct revelation mechanism
  - I show that primitives of the model are identified using observed variation in the state
  - I propose a computationally feasible estimation procedure (*more on this later!*)

- I apply the model to data from Michigan's Department of Transport procurement

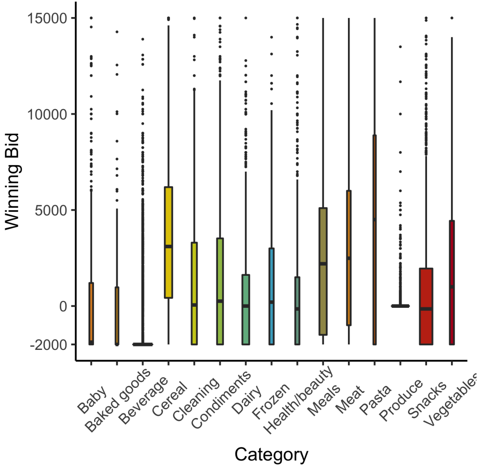
◂ literature ◂ estimation



Coefficient (000s, log scale)
-1
-3
-10
-30
-100
Rank α_i^{Dried}
Dried
Tinned
Refridgerated
Fresh
Non-Food

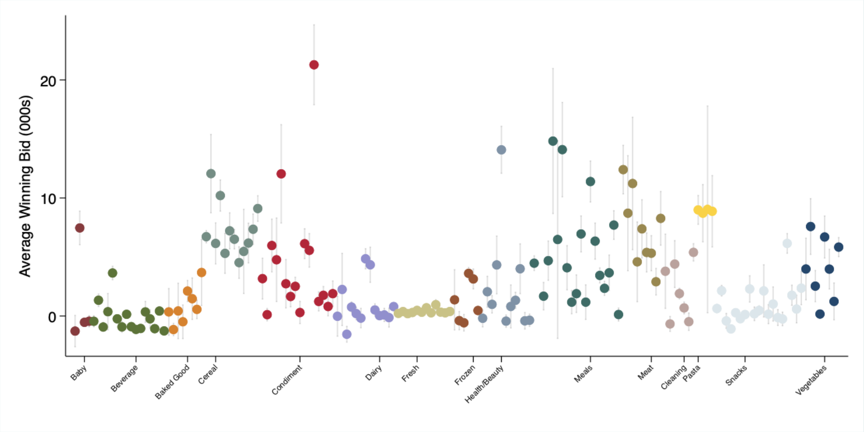
return

Heterogeneity in food



- Strong evidence that some goods are preferred to others
- But lots of variation within categories

return



Note: Plot shows average winning bids across 164 subcategories of food. Controlling for size, location, and composition of the lot. Subcategories are divided within the 15 categories shown.

return

Reduced Form exercise:

Consider a simple Tobit regression:

- Split food into 5 types, according to how the food is stored:
  - $\rightarrow$ Dried, Tinned / Bottled, Refrigerated, Fresh, and Non-food
  - $\rightarrow$ This helps me focus on storage costs, and how they vary with stocks, as a key margin
- Find each food bank's average bid for each type of food

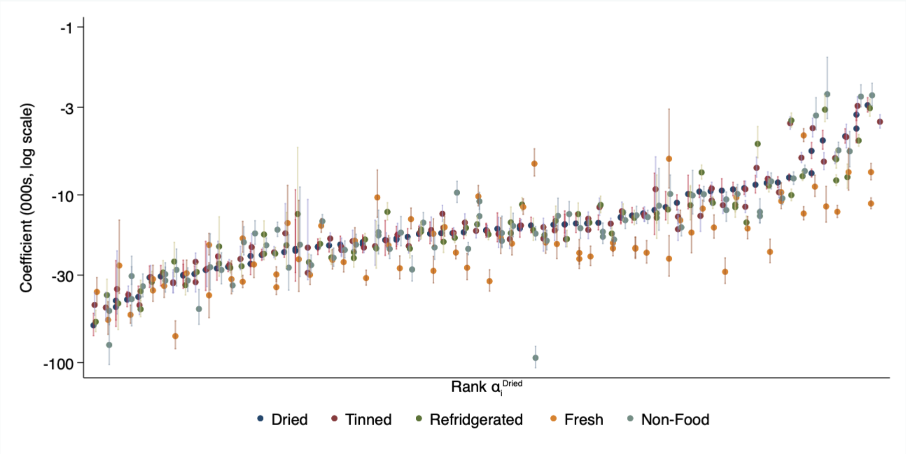
$$b_{itl} = \alpha_{ig} + \varepsilon_{itl} \qquad b^*_{itl} = \begin{cases} b_{itl} & \text{if} \quad b_{itl} \geq R_l \\ R_l & \text{if} \quad \text{Otheriwse} \end{cases}$$

$$\varepsilon_{itl} \sim N(0, \sigma_{il}) \tag{1}$$

- Where α_{ig} are food bank $\times$ type specific means

return

Heterogeneity Across Food Banks



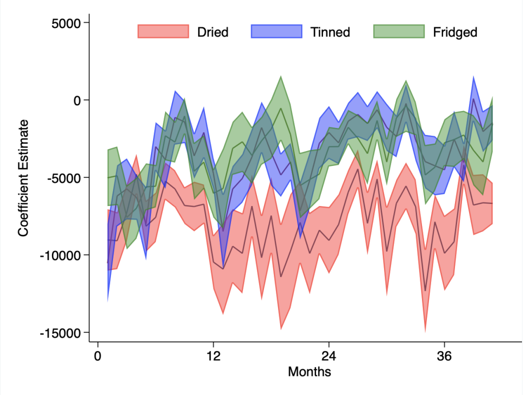
Note: Plot shows average bids across food banks × food types, controlling for available lots and endogenous entry. Estimates are sorted by average bid on dried food. 95% confidence intervals are shown.

return

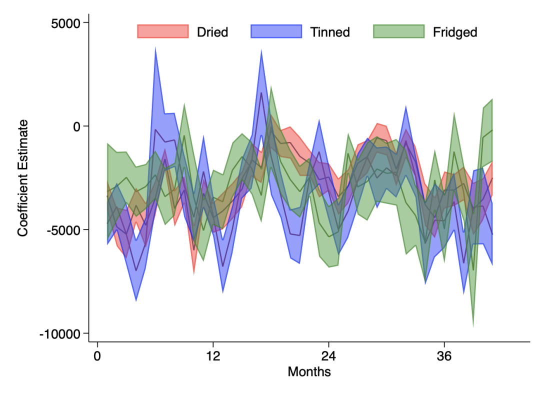
Instead, estimate α_{igm} = food bank $\times$ type $\times$ month specific means

return

Food bank (A)



Food bank (B)



Note: Plots show average bids across food types $\times$ months, controlling for available lots and endogenous entry. The two food banks shown are the two highest consumption food banks ($\approx$ 5% of total food each). Fresh / Non-food are excluded for graph-ability. The shaded area gives the 95% confidence intervals.

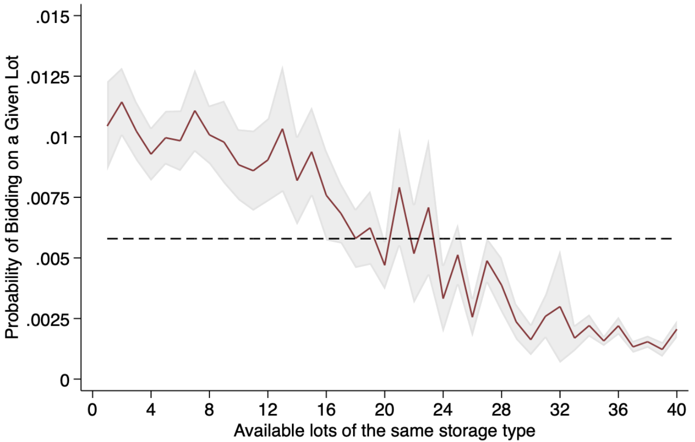
A Running Theme

A central theme will be this idea of heterogeneity:

1. Heterogeneity in food Graphs
   - Is Cereal qualitatively different from Frozen Dinners?
   - If food is all the same they will not care what they consume
2. Heterogeneity in needs across food banks Graphs
   - 5 food banks receive as much food as the 122 food banks that receive the least food
   - But, these 122 food banks spend 4 times as many shares
3. Heterogeneity in needs over time Graphs
   - Bidding behaviour within a food bank varies significantly over time

return

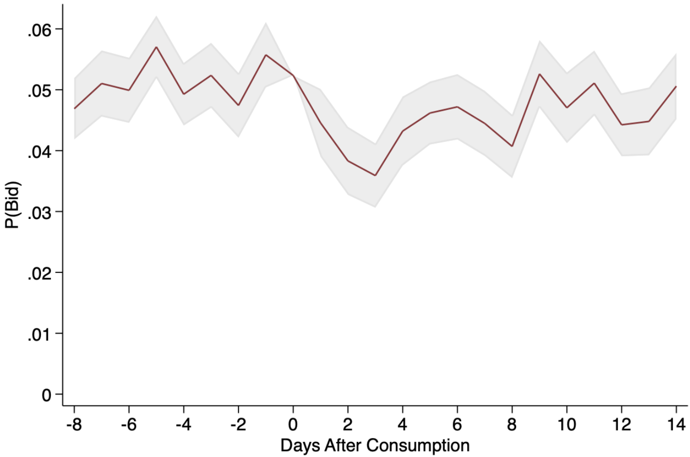
Static Substitution



Probability of bidding on a given lot, as a function of total available lots of the same storage type.
The dotted line gives the unconditional probability of bidding on any given lot.
Controlling for foodbank x storage method fixed effects, day of week, and good subcategories.

return

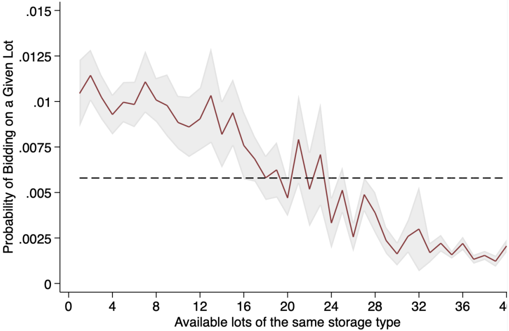
Dynamic Substitution



Controlling for foodbank x storage method fixed effects, conditional on goods being available.
P(Bid) at day 0 is normalised to the long-run average probability of bidding, to demonstrate scale.

return

Static Complementarities



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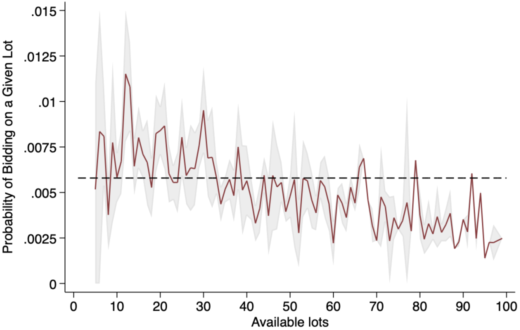

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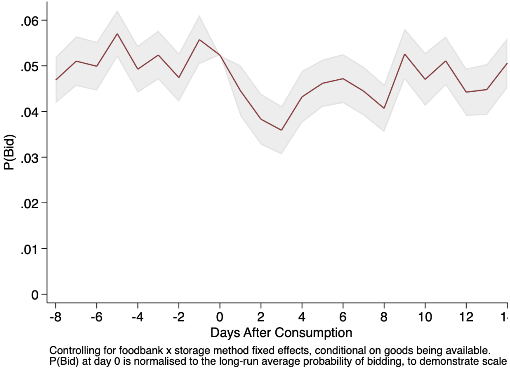
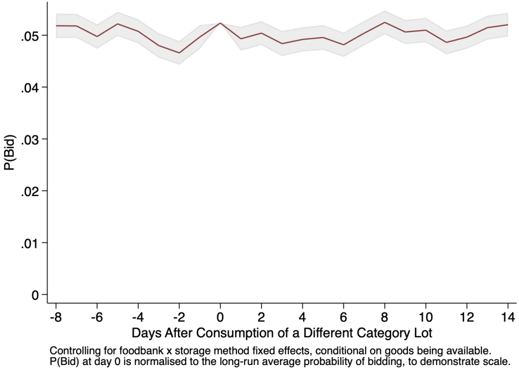
Dynamic Complementarities





◂ Stylised Facts ◂ Identification

Standard Approaches

The institutional setting is a challenge for **standard approaches**:

1. *Demand System Estimation* to find Compensating Variation
   - Accounting Period - Aggregate demand by month, or week?
   - Price Variation - Lack of within good type price variation
   - High Dimensional - A problem for Discrete Demand Estimation
   - Bid versus Win - Losing bids are not irrelevant
2. *Welfare Index Numbers* to find the Compensating Variation
   - Negative Prices/Satiation - Incompatible with most indices
   - Heterogeneity over time - Incompatible with most methods
3. *Sufficient Statistics* approach to estimating CV
   - Complexity - Only excessively simplistic models are tractable
   - Misses key variation - Difficult to introduce changes over time

return

Exogeneity of $\mathbf{x}$

- Essentially, I assume stocks *just happen* - $\mathbf{x}_{it}$ are an exogenous process then food banks respond by trying to win food on the Choice System

- This assumption likely biases my results **against** the value of choice
  - If there is reverse causality, can use winning to influence future net donations
  - Hence, additional benefits of allowing choice - more influence over net donations!
  - However, the effects on equity are more ambiguous $\rightarrow$ could be interesting to explore

- To an extent should be able to test this assumption using estimated donations

  $\rightarrow$ Look for correlation in net donations over time
  $\rightarrow$ Testing whether winnings Granger causes future net donations.

- I am also investigating whether I can do this as a robustness exercise
  - allow for reverse causation, or autocorrelation in net donations
  - This is possible in practice, but it is unclear whether any such process is identified

return

The Food Bank Model

- The set of food on offer
  - Pounds by storage method, $\mathbf{z}^g_{lt}$ and by Subcategory, $\mathbf{z}^h_{lt}$
  - $\mathbf{c}_{lt}$ - Other lot characteristics, e.g. location.

- States
  - Stock of each storage type $\mathbf{s}^g_i$

    $\rightarrow$ This helps me capture storage costs
  - Stock of each subcategory $\mathbf{s}^h_i$

    $\rightarrow$ But, assume $j(\mathbf{s}_i)$ is linear in $\mathbf{s}^h_i$, i.e. Constant Returns

    $\rightarrow$ Therefore the level of $\mathbf{s}^h_i$ doesn't matter, so I focus on changes through $\mathbf{z}^h_{lt}$
  - Aggregate supply $\mathbf{s}_0$: daily and previous 30 day supply, by storage type

    $\rightarrow$ This *might* impact $P(i \text{ wins } l|\mathbf{b})$

- Transition Function: $\mathbf{s}^g_{it} = \mathbf{s}^g_{it-1} + \mathbf{w}^T_{it-1}\mathbf{z}^g_{t-1} + \mathbf{x}_{it}$
  - This is **not** a random walk. It is closer to an error correction process

    $\rightarrow$ winnings $\mathbf{w}^T_{it-1}\mathbf{z}^g_{t-1}$ vary with $\mathbf{s}^g_{it-1}$ to prevent stocks dropping too low
  - I assume the process is stationary

    $\rightarrow$ This is an assumption about the competitive equilibrium

    $\rightarrow$ If $\mathbf{s}^g_{it}$ ends up as an $AR(1)$ process, I can actually test stationarity

return

Primitives (1)

return

- **Setup**
  - *Rules:* Player i wins lot l in period t if $b_{itl} \geq \max_{j \neq i} b_{jtl}$
  - *Reservation Prices* R_{tl} on each lot
  - *Entry* is costless - valuations are known before entering
  - *Ties* occur with zero probability*

Example: Two lots $\{apples, carrots\}$

Primitives (1)

return

- **Setup**
  - *Rules:* Player i wins lot l in period t if $b_{itl} \geq \max_{j \neq i} b_{jtl}$
  - *Reservation Prices* R_{tl} on each lot
  - *Entry* is costless - valuations are known before entering
  - *Ties* occur with zero probability*
- **States:**
  - Player i begins period t in state $\mathbf{s}_{it}$
  - Player i ends period t in state $\mathbf{s}_{it}^{a}$
  - superscript a refers to which combination of lots they ended up winning

Example:

- $\mathbf{s}_{it} = (stock_{it}^{apples}, stock_{it}^{carrots})$
- $\mathbf{s}_{it}^{a} = (stock_{it}^{apples} + winnings_{it}^{apples}, stock_{it}^{carrots} + winnings_{it}^{carrots})$

Primitives (1)

return

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  - superscript a refers to which combination of lots they ended up winning

- **Lots**
  - $\mathbb{L}_t$ gives the set of lots players may bid on, with $max|\mathbb{L}| = L$
  - Lot l is described by a vector of characteristics $\mathbf{c}_{tl}$.

Example:

- $\mathbb{L}_t \in \{\{\emptyset\}, \{apples\}, \{carrots\}, \{apples,\ carrots\}\}$
- $\mathbf{c}$ = (type of apples, location of apples)

return

- **Setup**
  - *Rules:* Player i wins lot l in period t if $b_{itl} \geq \max_{j \neq i} b_{jtl}$
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- **Lots**
  - $\mathbb{L}_t$ gives the set of lots players may bid on, with $max|\mathbb{L}| = L$
  - Lot l is described by a vector of characteristics $\mathbf{c}_{tl}$.
- Denote the *Overall* state $\mathbf{s}_t = (\{\mathbf{s}_{it}\}_{i \in \mathbb{N}}, \mathbb{L}_t, \mathbf{C}_t)$

Primitives (2)

return

- **Valuations:**
  - *Lot specific:* $\boldsymbol{\upsilon}_{it} \sim F(.|\mathbf{s}_t)$, an L dimensional vector
  - *Combination Value:* $J_i(\mathbf{s}_{it})$, a 2^L dimensional vector
    Element a corresponds to ending period t in state $\mathbf{s}^a_{it}$: $j_i(\mathbf{s}^a_{it})$

Example:

- $\boldsymbol{\upsilon}_{it} = \begin{pmatrix} \upsilon_{it\ apples} \\ \upsilon_{it\ carrots} \end{pmatrix}$
- Or, if carrots are not available at t: $\boldsymbol{\upsilon}_{it} = \begin{pmatrix} \upsilon_{it\ apples} \\ . \end{pmatrix}$
- $J_i = \begin{pmatrix} J_{win\ nothing} \\ J_{win\ apples} \\ J_{win\ carrots} \\ J_{win\ apples\ \&\ carrots} \end{pmatrix}$

Where $J_{win\ apples\ \&\ carrots} \neq J_{win\ apples} + J_{win\ carrots}$

Primitives (2)

return

- **Valuations:**
  - *Lot specific:* $\boldsymbol{v}_{it} \sim F(.|\mathbf{s}_t)$, an L dimensional vector
  - *Combination Value:* $J_i(\mathbf{s}_{it})$, a 2^L dimensional vector
    Element a corresponds to ending period t in state $\mathbf{s}_{it}^a$: $j_i(\mathbf{s}_{it}^a)$

- **Actions:**
  - Player i chooses a subset of auctions to enter; $\mathbf{d}_{it}$
  - They then choose their bids conditional on entry; $\mathbf{b}_{it}$
  - *Strategies* conditional on primitives are given by σ_i

Example:

- If they only bid on apples: $\mathbf{d}_{it} = \begin{pmatrix} 1 \\ 0 \end{pmatrix}$
- If they only bid on apples: $\mathbf{b}_{it} = \begin{pmatrix} b_{it\ apples} \\ . \end{pmatrix}$

Primitives (2)

return

- **Valuations:**
  - *Lot specific:* $\upsilon_{it} \sim F(.|\mathbf{s}_t)$, an L dimensional vector
  - *Combination Value:* $J_i(\mathbf{s}_{it})$, a 2^L dimensional vector
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  - Player i chooses a subset of auctions to enter; $\mathbf{d}_{it}$
  - They then choose their bids conditional on entry; $\mathbf{b}_{it}$
  - *Strategies* conditional on primitives are given by σ_i
- **Equilibrium Win Probabilities:**
  - Player i wins lot l with probability $\Gamma_{il}(b_{itl}, d_{itl}; \sigma_{-i})$
  - $P_{ia}(\mathbf{b}_{it}, \mathbf{d}_{it}; \sigma_{-i})$ gives the probability of combination outcome a

Example:

$$P(\mathbf{b}_{it}, \mathbf{d}_{it}) = \begin{pmatrix} P(\text{win nothing}|\mathbf{b}_{it}, \mathbf{d}_{it}) \\ P(\text{win apples only}|\mathbf{b}_{it}, \mathbf{d}_{it}) \\ P(\text{win carrots only}|\mathbf{b}_{it}, \mathbf{d}_{it}) \\ P(\text{win both}|\mathbf{b}_{it}, \mathbf{d}_{it}) \end{pmatrix} = \begin{pmatrix} [1-\Gamma_{apples}(b_a)][1-\Gamma_{carrots}(b_c)] \\ \Gamma_{apples}(b_a)[1-\Gamma_{carrots}(b_c)] \\ [1-\Gamma_{apples}(b_a)]\Gamma_{carrots}(b_c) \\ \Gamma_{apples}(b_{apples})\Gamma_{carrots}(b_{carrots}) \end{pmatrix}$$

Primitives (2)

return

- **Valuations:**
  - *Lot specific:* $\boldsymbol{\upsilon}_{it} \sim F(.|\mathbf{s}_t)$, an L dimensional vector
  - *Combination Value:* $J_i(\mathbf{s}_{it})$, a 2^L dimensional vector
    Element a corresponds to ending period t in state $\mathbf{s}_{it}^a$: $j_i(\mathbf{s}_{it}^a)$
- **Actions:**
  - Player i chooses a subset of auctions to enter; $\mathbf{d}_{it}$
  - They then choose their bids conditional on entry; $\mathbf{b}_{it}$
  - *Strategies* conditional on primitives are given by σ_i
- **Expected Payoffs:** $EU(\mathbf{b}, \mathbf{d}|\boldsymbol{\upsilon}_i, \mathbf{s}; \sigma_{-i}) =$

$$\Gamma_i(\mathbf{b}, \mathbf{d}; \sigma_{-i})^T(\boldsymbol{\upsilon}_i - \mathbf{b}) + P_i(\mathbf{b}, \mathbf{d}; \sigma_{-i})^T[J_i(\mathbf{s}) + \beta V_i(\mathbf{s}; \sigma_{-i})]$$

Example: $EU(\mathbf{b}, \mathbf{d}|\boldsymbol{\upsilon}_i, \mathbf{s}; \sigma_{-i}) =$

$$\begin{pmatrix} \Gamma_a(b_a) \\ \Gamma_c(b_c) \end{pmatrix}^T \begin{pmatrix} \upsilon_{it\ apples} - b_a \\ \upsilon_{it\ carrots} - b_c \end{pmatrix} + \begin{pmatrix} P(\text{nothing}|\mathbf{b}_{it}, \mathbf{d}_{it}) \\ P(\text{apples}|\mathbf{b}_{it}, \mathbf{d}_{it}) \\ P(\text{carrots}|\mathbf{b}_{it}, \mathbf{d}_{it}) \\ P(\text{both}|\mathbf{b}_{it}, \mathbf{d}_{it}) \end{pmatrix}^T \begin{pmatrix} J_{win\ nothing} + \beta V_{win\ nothing} \\ J_{win\ apples} + \beta V_{win\ apples} \\ J_{win\ carrots} + \beta V_{win\ carrots} \\ J_{win\ both} + \beta V_{win\ both} \end{pmatrix}$$

Bellman equation (Mulit-Object, endogenous entry, reservation prices)

$$W(\boldsymbol{\upsilon}, \mathbf{s}; \sigma_{-i}) = \max_{\mathbf{b},\mathbf{d}} \left\{ \begin{array}{l} \sum_{l \in \mathbb{L}(\mathbf{s})} \Gamma_l(\mathbf{b}, \mathbf{d}|\mathbf{s})(\upsilon_l - b_l) + \sum_{\mathbf{w}^a \in \mathbb{W}(\mathbf{s})} P_a(\mathbf{b}, \mathbf{d}|\mathbf{s}) j(\mathbf{s}^a) \\ \\ +\beta \sum_{\mathbf{w}^a} P_a(\mathbf{b}, \mathbf{d}|\mathbf{s}) \int_{\tilde{\mathbf{s}}} \int_{\tilde{\boldsymbol{\upsilon}}} W(\tilde{\boldsymbol{\upsilon}}, \tilde{\mathbf{s}}); \sigma_{-i}) dF(\tilde{\boldsymbol{\upsilon}}|\tilde{\mathbf{s}}) dT(\tilde{\mathbf{s}}|\mathbf{s}^a) \\ \qquad\qquad\qquad\qquad\qquad\qquad\qquad\qquad\qquad\qquad\qquad s.t. \quad b_l \geq R_l \ \ \forall l \end{array} \right\}$$

Where:

- $\Gamma_l(\mathbf{b}, \mathbf{d}|\mathbf{s}) = P(\text{win lot } l|\mathbf{b}, \mathbf{d}; \mathbf{s})$
- $P_a(\mathbf{b}, \mathbf{d}|\mathbf{s}) = P(\text{the combination outcome is } a|\mathbf{b}, \mathbf{d}; \mathbf{s})$
- $\mathbf{s}^a$ gives the ex-post state from combination outcome a

return

Equilibrium

- Focus on *Markov Perfect Equilibria* in Symmetric Markovian Strategies
  1. Agent's maximise the NPV of payoffs, given beliefs
  2. Beliefs are consistent with observed play

  $\rightarrow \sigma_i$ depends only on $\mathbf{s}_t$, not on t itself

- *Equilibrium Existence*
  - Conditional on the existence of a Bayesian Nash Equilibrium in the Stage Game, taking entry as given, a Markov Perfect Equilibrium exists.

    (For the quasi-linear utility case)
    For the proof, see my first chapter
  - However, equilibrium in the Stage Game has yet to be proven

    Except for specific cases of preferences
  - But this is not a practical problem
    - In practice, I assume food banks have beliefs consistent with observed behaviour
    - This is consistent with a number of non-standard equilibrium models
      e.g. Backus & Lewis (2016)

return

Proposition (*Semi-Parametric Point Identification*)

Assuming that:

1. $\mathbf{x}_{it}$ *and* $\boldsymbol{\upsilon}_{it}$ *are weakly exogenous w.r.t stocks and the set of lots on offer*
2. *Demand curves are linear in* $\mathbf{s}$ $\quad$ *(*$\equiv j(\mathbf{s}) + \beta V(\mathbf{s})$ *is quadratic)*

Then $j_i(\mathbf{s}), F_i^x$, *and* F_i^υ *are point identified*

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Assuming that:

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Then $j_i(\mathbf{s}), F_i^x$, *and* F_i^{υ} *are point identified*

Proof Outline:

1. Linear demand ensures FOCs/Inverse Bid Function are affine in $\mathbf{s}$
2. First differencing then differences out the unobserved stocks
3. Correct for endogeneity due to:
   - Correlation between $\boldsymbol{\upsilon}_{it-1}$ and $\mathbf{w}_{it-1}$
     $\rightarrow$ Instrument using lagged lot specific characteristics, e.g. distance
   - Endogeneity from the multi-object environment (correlation between υ_{itl} and b_{itm})
     $\rightarrow$ Instrument using Altmann (WP)'s instruments (e.g. *non-lagged* lot characteristics)

◂ Identification

This estimation procedure is unusual, but used for tractability

- In the Auction literature: Assume a bid distribution then back out j & V
  - This is not possible on account of the unobserved state / Multi-object environment
  - We cannot write V as a distribution of bids **only**

- In the Dynamic Discrete Choice literature: Given functional form for j, solve for V
  - Assume a form for J, solve for V in each likelihood evaluation
  - Solving for V given j requires numerically finding optimal $\mathbf{b}^*$, which is slow

- CCP methods: Given observed actions (bids, entry) solve for V
  - We cannot write V as a distribution of bids **only**
  - But in a discrete choice context, fitting a parametric functional form to CCPs is numerically equivalent to this 3 step method.

return

Estimation Step 1

Estimate $P(i \text{ wins } l|\mathbf{b}) = \Gamma_l(b_{il})$:

- For lot l with characteristics $\mathbf{c}_{lt}$

$$\Gamma_{il}(x|\mathbf{c}_{lt}, \mathbf{s}_t) = GEV(x; \xi_c, \zeta_c, \nu_h + \vartheta_g \mathbf{s}_0) \quad (2)$$

- Shape and Scale parameters ξ_c and ζ_c, category specific
- Subcategory specific mean parameter ν_{ch}
- Storage type specific linear 'demand' parameters ν_g
- The distribution is 'censored' at the reservation price

GEV assumption is motivated by extreme value theory

- $P(i \quad wins|b_i)$ is equivalent to b_i is the highest bid
- i.e. The extreme value

return

Estimation Step 2 (a)

- Assume parametric form $k_i(\mathbf{s}_i) = \Phi \mathbf{s}_i^h + \mathbf{s}_i^{gT} \Psi_i \mathbf{s}_i^g$
  - Φ are assumed common across i - food banks have the same 'utility'
  - Ψ_i vary across i and negative definite, similar to quadratic storage costs.

    $\rightarrow$ More like 'opportunity cost' in this dynamic context

    $\rightarrow$ Different food banks likely have different storage costs, but very different opportunity costs

- I make the following distributional assumptions:
  - $\upsilon_{ilt} \sim N(\alpha_i \text{distance}_{ilt}, \sigma_c^2)$
  - $\mathbf{x}_{it} \sim N(\boldsymbol{\mu}_i, \Sigma_i)$

- The bidder's maximisation problem yields the optimality condition:

$$\lambda_i\left(b_{ilt} + \frac{\Gamma_l(b_{ilt})}{\nabla\Gamma_l(b_{ilt})}\right) \geq \upsilon_{ilt} + \Phi \mathbf{z}_{lt}^h + \mathbf{z}_{lt}^{gT} \Psi_i \left(\mathbf{z}_{lt}^g + 2\mathbf{s}_{it}^g + 2\sum_{m \neq l} \Gamma_m(b_{imt}) \mathbf{z}_{mt}^g\right) \tag{3}$$

Which holds with equality when $b_{ilt} > R_l$

$\rightarrow$ If I observed $\mathbf{s}_{it}^g$ this would just be a censored regression equation!

return

Estimation Step 2 (b)

I have a three equation (censored) Linear Gaussian State Space model:

$$\mathbf{s}^{g}_{it} = \mathbf{s}^{g}_{it-1} + \mathbf{w}^{T}_{it-1}\mathbf{z}^{g}_{t-1} + \mathbf{x}_{it} \qquad \rightarrow \text{ Transition Eq.}$$

$$\lambda_i y_{ilt} = \upsilon_{ilt} + \Phi\mathbf{z}^{h}_{lt} + \mathbf{z}^{gT}_{lt}\Psi_i(\mathbf{z}^{g}_{lt} + 2\mathbf{s}^{g}_{it} + 2\sum_{m\neq l}\Gamma_m(b_{imt})\mathbf{z}^{g}_{mt}) \qquad \rightarrow \text{ Observation Eq.}$$

$$y_{ilt} = \begin{cases} b_{ilt} + \frac{\Gamma_l(b_{ilt})}{\nabla\Gamma_l(b_{ilt})} & \text{if } b_{ilt} > R_l \\ R_l & \text{otherwise} \end{cases} \qquad \rightarrow \text{ Censoring Eq.} \quad (4)$$

Estimation is done using a Gibbs Sampler:

- We want to draw samples of (θ_1, θ_2) from its posterior; $f(\theta_1, \theta_2|data)$
  $\rightarrow$ but sampling from this distribution is hard.
- Instead, we can iteratively draw samples from $f(\theta_1|\theta_2, data)$ and $f(\theta_2|\theta_1, data)$
  $\rightarrow$ these conditional samples approximate the posterior distribution

return

Estimation Step 2 (b)

I have a three equation (censored) Linear Gaussian State Space model:

$$\mathbf{s}_{it}^{g} = \mathbf{s}_{it-1}^{g} + \mathbf{w}_{it-1}^{T}\mathbf{z}_{t-1}^{g} + \mathbf{x}_{it} \qquad \rightarrow \text{ Transition Eq.}$$

$$\lambda_i y_{ilt} = \upsilon_{ilt} + \Phi \mathbf{z}_{lt}^{h} + \mathbf{z}_{lt}^{gT}\Psi_i(\mathbf{z}_{lt}^{g} + 2\mathbf{s}_{it}^{g} + 2\sum_{m \neq l} \Gamma_m(b_{imt})\mathbf{z}_{mt}^{g}) \qquad \rightarrow \text{ Observation Eq.}$$

$$y_{ilt} = \begin{cases} b_{ilt} + \frac{\Gamma_l(b_{ilt})}{\nabla \Gamma_l(b_{ilt})} & \text{if } b_{ilt} > R_l \\ R_l & \text{otherwise} \end{cases} \qquad \rightarrow \text{ Censoring Eq.} \quad (4)$$

Estimation is done using a Gibbs Sampler:

1. Given beliefs Γ, parameters of the pseudo-static model $\{k_i, F_i^{\upsilon}, F_i^{\mathbf{x}}\}$, and states $\{\mathbf{s}_{it}^{g}\}$:
   $\rightarrow$ draw censored values of $\{y_{ilt}\}$ using the Censoring Equation
2. Given Beliefs Γ, $\{k_i, F_i^{\upsilon}, F_i^{\mathbf{x}}\}$, and censored observations $\{y_{ilt}\}$:
   $\rightarrow$ draw $\{\mathbf{s}_{it}^{g}\}$ using the Transition / Observation equations (Carter-Kohn)
3. Given beliefs Γ, censored observations $\{y_{ilt}\}$, and states $\{\mathbf{s}_{it}^{g}\}$:
   $\rightarrow$ draw $\{k_i, F_i^{\upsilon}, F_i^{\mathbf{x}}\}$ from their posterior using the Observation Equation.
4. Repeat

return

Estimation Step 3

Write the continuation value $V(\mathbf{s})$ as a function of Γ, F^{υ}, F^{x} and k:

Proposition

The ex-ante Value Function can be expressed as:

$$E[W(\upsilon, \mathbf{s}_i^g)|\mathbf{s}_i^g] = \frac{E[q_t(\mathbf{s}_i^g)\pi(\mathbf{b}_{it}|\mathbf{s}_i^g)]}{E[q_t(\mathbf{s}_i^g)]}$$

Where $q_t(\mathbf{s}_i^g)$ gives the posterior probability that $\mathbf{s}_{it}^g = \mathbf{s}_i^g$ and

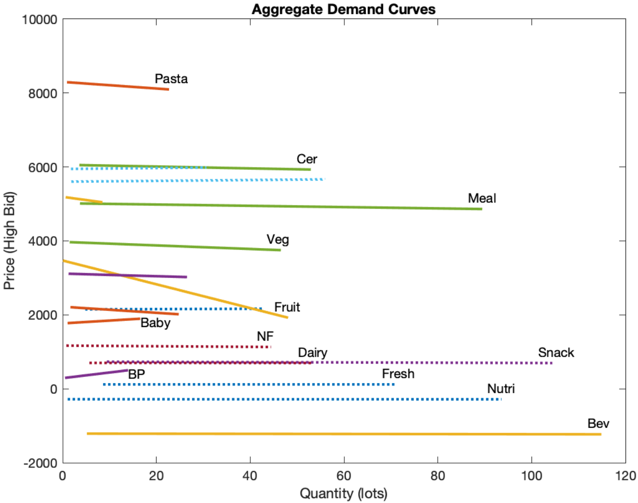
$$\pi(\mathbf{b}|\mathbf{s}_i^g) = \sum_l \lambda_i \frac{\Gamma_l(b_{il})^2}{\nabla_b \Gamma_l(b_{il})} - \sum_{m \neq l} \Gamma_l(b_{il}) \mathbf{z}_l^{g\,T} \Psi_i \mathbf{z}_m^g \Gamma_m(b_{im}) + \mathbf{s}_i^{g\,T} \Psi_i \mathbf{s}_i^g$$

$\rightarrow$ This is essentially just an extension of Arcidiacono & Miller (2011)

- The continuation value is given by $V(\mathbf{s}_i^g) = \int E[W(\upsilon, \mathbf{s}_i^g + \mathbf{x})|\mathbf{s}_i^g + \mathbf{x}]dF^{x}(\mathbf{x})$
  and, finally, $j(\mathbf{s}_i^g) = k(\mathbf{s}_i^g) - \beta V(\mathbf{s}_i^g)$
- Evaluate these expressions for a sample of parameters, drawn from their posterior

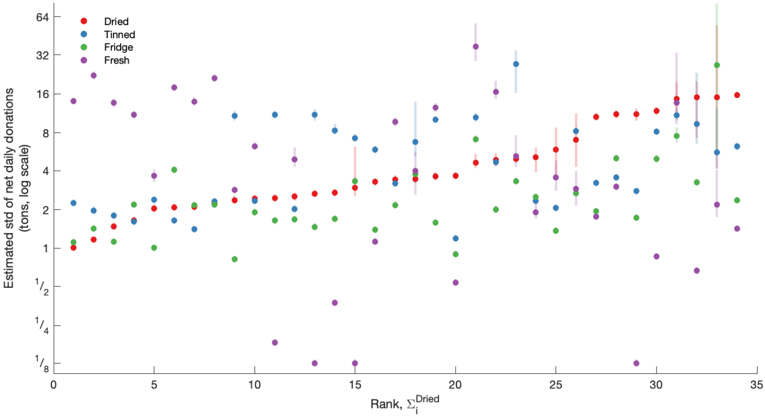
return

First Stage Demand results



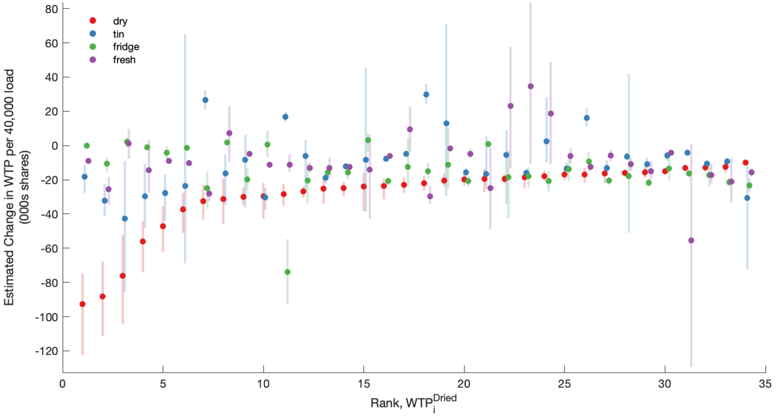
return

Estimated Standard Deviation of Net Donations ($\sqrt{\boldsymbol{\Sigma}_i} = \sqrt{\hat{Var}[\mathbf{x}_{it}]}$)

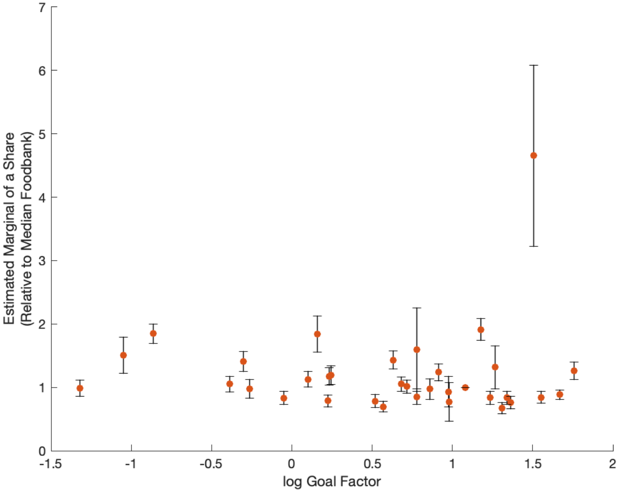


Note: Plot shows estimated standard deviation of net donations by food bank × food type, sorted across food banks by estimate for Dried food (red). Error bars give 95% credible intervals. return

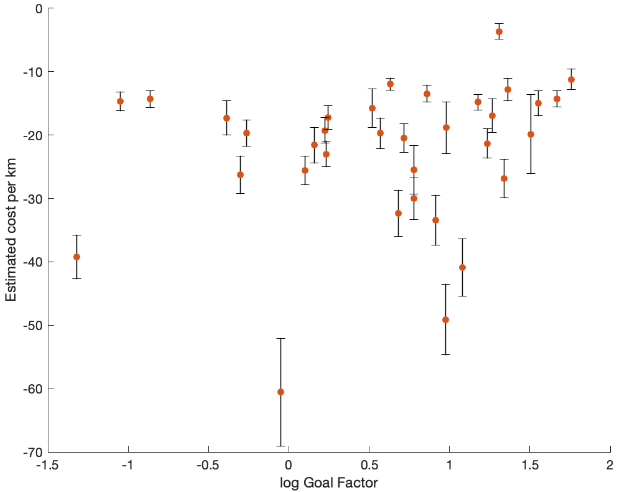
Estimated Marginal Pseudo-Static Payoff $\nabla k_i(\mathbf{s}_i)$



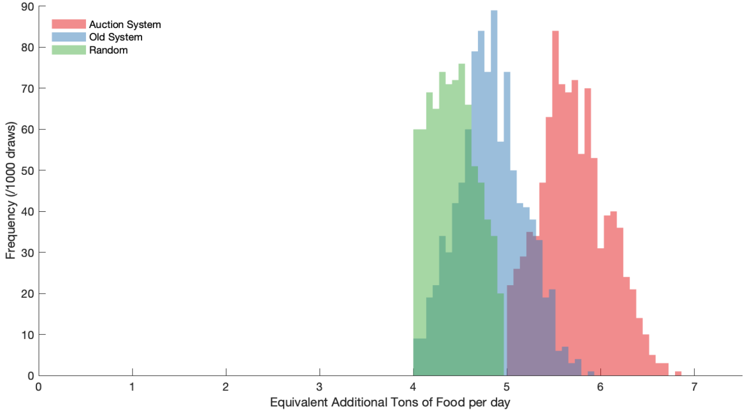
Note: Note: Plot shows estimated marginal pseudo-static pay-off from receiving an average lot by food bank × food type, evaluated when stocks are empty. Estimates are sorted across food banks by estimate for Dried food. 95% credible intervals are plotted. return


Estimated Marginal of a Share
(Relative to Median Foodbank)
log Goal Factor
0
1
2
3
4
5
6
7
-1.5
-1
-0.5
0
0.5
1
1.5
2

return

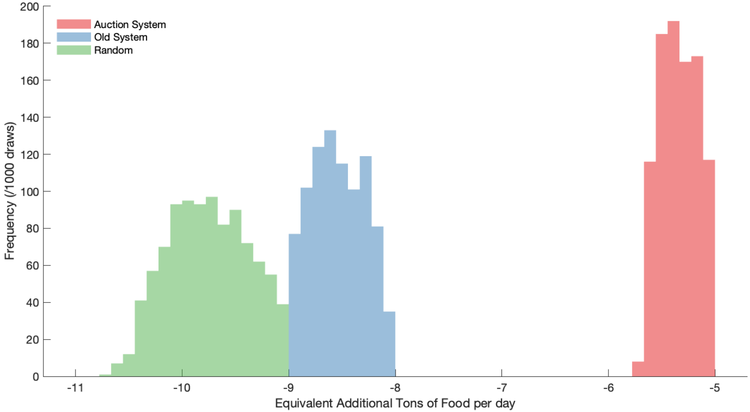

0
-10
-20
-30
-40
-50
-60
-70
Estimated cost per km
-1.5
-1
-0.5
0
0.5
1
1.5
2
log Goal Factor

return



Note: Figure shows the distribution of the quantity of food allocated, weighted by estimated preference weights, measured in equivalent increase in the food supply. Using 1000 draws from the posterior distribution of parameters. On average, the increase allocated food is worth around 38 additional tons of food each day.

return



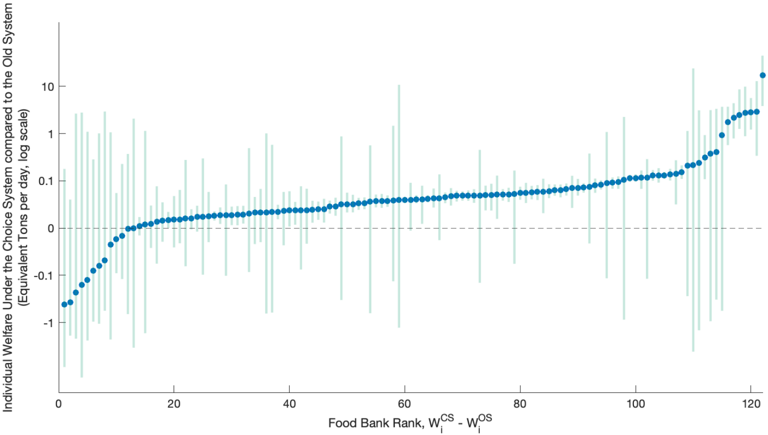
Note: Figure shows the distribution of transportation costs under each of the mechanisms, measured in equivalent increase in the food supply. Using 1000 draws from the posterior distribution of parameters. On average, the reduction in transportation costs is worth around 43 additional tons of food each day.

return

Equity

Welfare by food bank

return

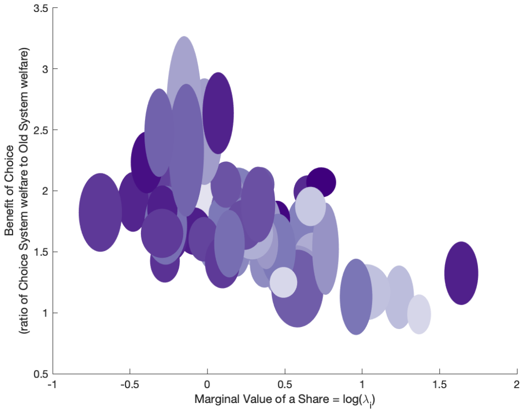


Note: Plot shows estimated welfare by food bank, ordered by posterior mean. 95% credible intervals are plotted.

Equity

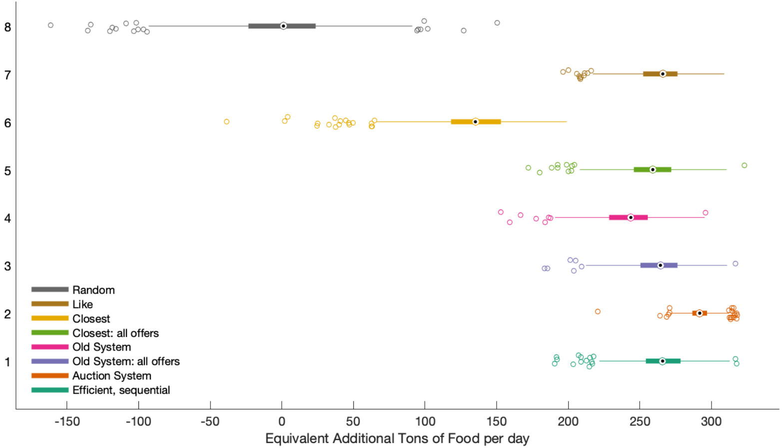
return

Gains from Choice vs Marginal Value of Wealth $\hat{\lambda}_i$



Note: Plot shows relative welfare against opportunity cost of spending a share. y-axis gives welfare under the Auction System divided by welfare under the Old System. x-axis gives estimated opportunity cost. Colour indicates local poverty rate, with darker oval = more poverty. Size of oval indicates 95% credible intervals.

Additional Mechanisms



return

References