The Allocation of Food to Food Banks

Canice Prendergast

University of Chicago

Feeding America allocates donated food to over 200 food banks. In 2005, it transitioned from a queueing mechanism to one where food banks use a specialized currency to bid for food. Food banks chose very different food than they received before. Small food banks acquired 72% more pounds per client than large food banks at little nutritional cost. This reallocation of food is estimated to have increased its value by 21%, or $115 million per annum. Food banks also sourced food much closer, saving an additional $16 million per annum. Finally, donations of food rose by over 100 million pounds.

I. Introduction

Feeding America distributes food to over 200 food banks across the United States. In the early 2000s, it used a queueing mechanism to allocate 200 million pounds of food donated by distributors, retailers, and manufacturers. In 2004, a group that included the author replaced it with a market-based mechanism called the Choice System.[1] This involves a

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[1] Nine members of the committee were directors of regional Food Banks, three were senior staff at Feeding America, and four were academics at the University of Chicago. The members are named in the online appendix. At the time, the organization was called America's Second Harvest, but throughout this essay, we will refer to the organization as Feeding America.

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specialized currency called *shares*, which are used to bid on truckloads of food. We outline the market design and evaluate its implications.

The old assignment algorithm gave each food bank an equal number of (random) pounds of food per needy client. This was problematic for a variety of reasons, despite its perceived fairness. First, food banks differ in their needs. The Choice System allocated an average of 10% of food distributed to food banks, but Feeding America knew little about the other food. This was further complicated by food richness, where some food banks had better access to outside food donations and had different residual needs. Second, food was randomly assigned on the basis of geography, leading to high transportation costs. Third, the allocation system was slow and deterred some donations.

Instead of equal pounds per client, the Choice System gives food banks an equal number of shares per client. These are used to bid in first-price sealed bid auctions, run twice a day. Shares can be saved and borrowed, and any shares spent on a given day are recirculated back to food banks that night. Bids can be negative, a feature used to ease donor relations. Through this mechanism, shares allow a food bank to match its purchases to both its permanent and transitory needs and to the geographic location of the donor.

Despite the benefits that choice allows, many of the practitioners involved in the redesign were initially skeptical of a market-based system. Their concerns were primarily focused on the fear that smaller or less sophisticated food banks would suffer. To ensure equity across food banks, a series of safeguards outlined below were used, among them access to credit and the ability to bid jointly with other food banks.

The Choice System went live on July 1, 2005. We consider a variety of outcomes from 2002 to 2011. A feature of the design is that any food bank can purchase its old allocation, assuming that food banks face common prices. As a result, all food banks are at least as well off as before. This assumes that transactions costs are low enough that all food banks engaged with Choice, and a concern raised was that smaller food banks may not do so. We show that food banks quickly engaged, bidding over 200 times a year and winning more than 70 times. Furthermore, small food banks bid more per client than do large ones. We also show that the safeguards implemented to encourage the participation of small food banks were used as intended.

We then quantify how different outcomes were under Choice. We begin by documenting how different the typical client's (2-month) consumption bundle was compared with that under the old algorithm. Using a percent absolute error measure, we document that the consumption of the average pound of food by the average client differed from the old allocation system by over 100%. This dispersion was in both the amount of food consumed and its composition. Furthermore, two-thirds of that variation is differences in the average food bundle consumed, with the remaining third temporal variation around that permanent bundle.

The old system treated all pounds of food as equal. By contrast, auction outcomes show a huge premium on quality. A share bought 4 pounds of food on average. Yet for a quarter of auctions, it yielded more than 100 pounds. Most of this is variation across food type: a pound of cereal traded for almost 80 pounds of produce or 8 pounds of dairy products. We show that much of the dispersion across food banks is generated by preferences for such quality, with food banks permanently sorting in extreme ways on the trade-off between quality and quantity.

Food banks vary by a measure called goal factor, which reflects the number of needy clients in a food bank's area. It primarily reflects the size of the food bank. Larger food banks tend to be the food rich, with better access to outside donations, while small food banks are typically food poor. We show that small food banks, the food poor, responded to Choice by buying 72% more pounds of food per client than did the large food banks. More generally, under the old regime, a food bank with a 1% higher goal factor got 1% more food. After 2005, that food bank got only 0.43% more pounds. This derived from two sources. First, they bought more desirable food: a 1% increase in goal factor increased the average price paid per pound by 0.4%. We additionally show that a fifth of the extra food obtained by smaller food banks was caused by their greater likelihood of winning negative price auctions. We interpret this as a response to food richness, where the food poor value quantity over quality at market price ratios, and vice versa for the food rich. Second, some food banks did not spend all their shares, deciding that the additional food was not worth paying transportation costs. This was mostly done by large food banks, resulting in yet more food for the poorest food banks.

The extra food obtained by small food banks did not come at the cost of significantly worse nutrition. Using a points system devised by Weight Watchers, we show that the average bundle bought by small food banks had a nutritional value only 1.8% lower than that of the larger food banks. As the smaller food banks are getting 72% more pounds, nutritional concerns seem of limited importance.

Food banks pay for transportation costs, and donated food is geographically dispersed throughout the country. As food was randomly assigned under the old algorithm, another concern was that food banks traveled farther than was necessary. Using ArcGIS software, we show that food banks traveled an average of 1,030 kilometers (one way) to collect food. We simulate the old algorithm with observed donations and estimate that distance traveled would have been 1,720 kilometers. Using estimates on average trucking costs, this generated annual savings of $15.7 million.

A primary objective of this market design was to increase supply of donated food.[2] First, the old algorithm was illiquid and slow, as loads were offered sequentially to food banks. This limited donations that Feeding America could accept. The Choice System allows all food banks to bid simultaneously and speeds up distribution, encouraging donations. Second, the Choice System allows food banks to sell food sourced elsewhere, called *maroon pounds*. The total supply of food rose from an average of 210 million pounds of food per annum to over 330 million pounds soon after the changeover. Maroon Pounds averaged 15 million per annum, with maroon pounds selling for 30% more than the average pound.

It is often hard to interpret magnitudes denominated in artificial currency. To allow us to measure outcomes in dollars, we compute the dollar value of a share by estimating the revealed preference relationship between distance traveled and shares bid. Using auction outcomes for a set of homogeneous foods, we show that food banks bid one share less for each nine extra kilometers. This allows us to estimate a share to be valued at $5.97. This implies that the average pound of food allocated was valued at $1.67, though produce valued at only $0.12.

Our final exercise is to use a model to estimate welfare gains that accrued just from the redistribution of food across food banks. The key assumptions are (1) linear demand curves and (2) that the first-best outcome is achieved. We use estimates of elasticities of food demand from two recent metastudies (Andreyeva et al. 2010; Cornelsen et al. 2015) to compute diminishing returns. We estimate annual welfare gains of 19.28 million shares, or 68.9 million pounds of food. This is equivalent to 21% of the food in the Choice System. Using the estimated dollar value of a share, we find that this implies a welfare gain of $115.1 million per annum. Adding reduced transportation costs increases this to $130.8 million per annum. The value of increased food donations should be appended to this.

II. The Transition

A. *Context*

Feeding America receives food donated from many sources and allocates it to a regional network of over 200 food banks. Some donations are targeted, such as when a donor specifies that the local food bank must receive it. It can allocate other donations as it sees fit. We address the allocation of these *yellow pounds*.

[2] Much of the market design literature in economics addresses how to better assign items to a fixed supply of slots: children to schools, courses to students, kidneys to patients, and so on (for a survey, see Roth 2008). See Roth and Peranson (1999), Abdulkadiroglu, Pathak, and Roth (2005), Pathak and Sonmez (2008), Roth (2008), Budish and Cantillon (2012), and Delacretaz, Kominers, and Teytelboym (2020).

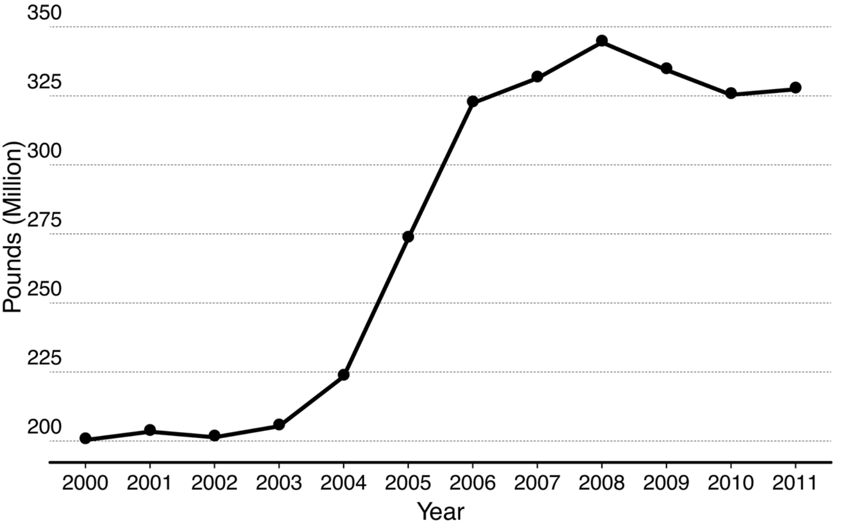

FIG. 1.—Supply of pounds (2000–2011).

Before July 2005, these were allocated using a queueing system based on a food bank's *goal factor*. This is a weighted measure of (1) the relative poverty of a food bank's service area compared with the nation and (2) the relative population of the service area. This measure generated goal pounds, the total number of pounds to be allocated to the food bank. To implement this, on any given day there was a ranking of food banks of the ratio of goal pounds to pounds received. Food was then offered on the basis of a food bank's position in the queue. This mechanism was used since the late 1980s and allocated 200–220 million pounds of food from 2000 to 2004 (see fig. 1).

At a concrete level, a food bank would receive a call or email from Feeding America letting them know that they had been assigned a load in a particular location. The load almost always had a required pickup time. Food banks were (and remain) liable for transportation costs from the donor's location. The food bank had a number of hours to accept or reject the offer. Even if a food bank refused the lot, the ranking algorithm was recomputed as if it had been accepted. This penalty on refusals was used to encourage food banks to take undesirable lots and was imposed to maintain donor relationships.[3]

[3] Donors typically want excess food removed from their warehouses for a variety for reasons—to free up storage space, for tax reasons, and so on. As such, there are pressures on Feeding America to remove food quickly, and that pressure was sometimes felt by the food banks.

This queueing system was widely seen as representing Feeding America's commitment to fairness, allied to a desire to assign based on need. Despite this, it could not be tailored to idiosyncratic food bank need. A primary reason for this was that yellow pounds constituted only 10% of total food distributed, and Feeding America knew little about the other food. Some variation in external supply was transitory, where, for example, a food bank may already have received milk from another source. The more important source of variation was permanent, known as food richness. Some food banks have close ties with local manufacturers or distributors—these are called food rich—whereas others have little access to other food—these are the food poor. Smaller food banks were more often the food poor.

Inefficiencies arose on both the demand and the supply side. First, food banks sometimes received food they did not need or could not distribute. This is exacerbated by capacity constraints on storage, particularly for foods that require refrigeration. Take dairy products, for example: sending eggs or cheese to a food bank whose fridges are full likely results in those products being wasted. Second, the allocation system took considerable time, with food banks being offered loads sequentially. Donors became unhappy if loads remained in their warehouses for a long time. As a result, Feeding America would turns down donations if it believed that it could not place them quickly. Finally, food banks were often offered food thousands of kilometers away. It is in this context that the Choice System arose.

B. *The Choice System*

The broad objective of the Choice System was to implement a competitive equilibrium with equal per capita incomes. Its starting point was the creation of a currency called shares. Shares were initially allocated to a food bank in proportion to its goal factor.[4] Share balances do not depreciate, cannot be traded for real money, and cannot be used for anything other than the items on the choice system.

Auction mechanism.—Food banks use their balance of shares to bid on (typically) truckloads of food, which are usually between 20,000 and 40,000 pounds of food. Bidding occurs twice a day, at noon and 4 p.m. central time. Food for each bidding cycle is posted at least 2 hours beforehand but usually the night before.

Bidding.—First-price sealed bid auctions are used (see the online appendix for a discussion of why this was chosen). Outcomes are revealed immediately by email after bidding closes. Any items that do not sell on a given day are carried over to the following day's auction.

[4] The Choice System also implemented a small change in the definition of goal factor (see online appendix).

Hard-to-move product and negative prices.—Many donors who are highly valued at times offer loads that are undesirable. Under the old assignment method, food banks were pressurized to accept these. Under Choice, food banks can make negative bids up to a limit of −2,000 shares per load.

Joint bidding.—Small food banks may only be able to effectively distribute less than a full truckload of food. Food banks can split a truckload by coordinating to bid jointly.[5]

Credit.—To overcome possible liquidity constraints, small food banks can access short-term credit. Credit limits are set at the estimated cost of the most desired type of food. Food banks pay off debts with a minimum of half of their daily allocation of additional shares (see below for the money supply rule) until the debt is paid off. There is no interest rate on debt. Credit is available only to food banks below median goal factor, as larger food banks typically hold large enough balances to afford expensive loads.

Maroon pounds.—Food banks can sell food through the Choice System. These are called maroon pounds. These are treated similarly to other pounds except that the winning bid is transferred to the account of the seller. They cannot sell for negative prices. Maroon pounds proceeds are taxed at a rate of 10%, with revenues redistributed to all food banks.

Share money supply.—The Choice System is infinitely repeated and requires a rule for replenishing shares. This is done daily. On any given day, spent shares are recirculated on the basis of relative need at midnight, where food bank f with goal factor G_f receives a share $s_f = G_f / \Sigma_j G_j$.[6] The money supply rule was chosen to maintain constant average prices if fundamentals were unchanged. More shares can be printed as circumstances change.

The online appendix shows the platform used by participants. Before the platform went live, food banks played a demonstration version for over 3 months and were familiar with its operation.

III. Supply and Prices

We now turn to considering outcomes. To do so, proprietary data were provided by Feeding America. Data are offered both before the change (2000–2004) and after. Only aggregate data on the total number of pounds received by each food bank are available before 2005. After July 1, 2005, auction data are provided, outlining individual loads of food, the winning bidder(s), whether it is purchased with credit, and the location

[5] Some food banks always bid together. These are known as clusters. They also received food jointly under the old system.

[6] There is one exception: if a food bank reaches a cap of 200,000 shares, no more shares are given to that food bank.

of the food. The number of losing bidders is known, but Feeding America did not retain the losing bids themselves. We consider outcomes until the end of 2011. There are a total of 75,183 auctions.

Our objective is to observe food bank behavior before and after the change. To do so, we use food banks that we can match before and after 2005. We additionally exclude auctions for two reasons. First, because of a merger, Feeding America acquired additional food charities called Food Rescue Organizations. They were not offered food through the old allocation system, but they were successfully added as part of this process. We exclude these. These account for 10% of pounds.[7] Second, some food banks have no coded goal factor, and we exclude their 10,920 auctions.[8] Excluding these two cases, we typically use 54,058 auctions. This results in 107 bidding entities for most of the analysis below. This includes clusters, where a number of food banks always bid together. Unless otherwise stated, this is the data used in the analysis below.

We begin by highlighting the variety of food offered and the prices generated by winning bids. Table 1 shows the distribution of supply from 2005–11. A wide variety of products can be readily seen, including nonfood items. Yet almost 50% of pounds (40% of auctions) were produce, snacks, or beverages. These tend to be among the least desired foods. By contrast, many of the most desired items are not abundant, with, for example, meat and cereal jointly accounting for only 6% of loads.

Markets mediate choice through prices. Figure 2 shows the distribution of price paid per pound generated by winning bids. We typically describe outcomes below as pounds per share. However, here we use shares per pound, as some prices are negative. The average price was 0.28 shares. Yet for 25% of auctions, the buyer paid less than 0.01 shares per pound. At the more expensive end, 3% of loads resulted in a single pound costing 1.5 shares or more. Negative prices arose in 7.8% of auctions (table 2).

Most of this variation is across food type. Figure 3 shows the price of each food, estimated from a regression using food type and year × month dummies. Throughout our analysis, standard errors are clustered at the food bank level. The price of the most desired food, cereal, is normalized to 1 in figure 3. Prices show enormous variation. Foods banks got 2 pounds of meat, 5 pounds of dairy, 40 pounds of beverages, or 80 pounds of produce for a pound of cereal. Another measure of a food's desirability is the average number of bidders that it attracted. This is shown in table 1. This

[7] Geographic data also illustrated one data error where a number of food banks were combined as one observation, food bank 222, and given a goal factor of zero. This is excluded from our analysis. The data have also excluded a single food bank, number 262, whose goal factor was clearly miscoded one year, increasing by a factor of 10 one year, and declining by a factor of 10 the following year.

[8] Repeated attempts to get more data from Feeding America to clarify these cases were unsuccessful.

TABLE 1
SUPPLY (POUNDS) AND BIDDERS (2005–11)

	% of Total Supply	Number of Bidders
Produce	31.75	1.2
Beverage	13.94	1.6
Other	10.28	3.3
Snack	6.63	3.6
Juice	4.92	2.4
Cleaning Supplies	4.37	6.3
Cereal	3.84	8.9
Dairy	3.67	2.0
Prepared meals	3.34	6.8
Vegetable (processed)	3.29	3.1
Condiments	2.44	3.7
Drug store items	2.33	2.3
Rice	2.31	6.9
Meat	2.15	3.4
Health drinks	1.85	2.6
Bread	1.44	5.5
Baby products	.82	1.9
Cutlery/plates	.81	4.9
Protein	.71	4.9
Pasta	.47	8.3
Diapers	.4	5.5
Fruit (processed)	.39	4.2

aligns with the price data. The average auction received 3.7 bids, cereal had 8.9, and pasta had 8.3, but produce received only 1.2 bids. (Examination of rare subcategories also illustrates some particularly appealing loads, as laundry detergent had an average of 17 bidders.) It is in the backdrop of these extreme preferences for food type that we address benefits to food banks.

IV. Weak Benefits and Engagement

We now turn to the objective of showing welfare gains. We begin by providing a simple theoretical implication of the market design, namely, that food banks can buy their old allocation if they wish, assuming that all food banks face common prices.

Assume that food bank $f = 1, 2, \ldots, F$ derives welfare from its clients each consuming c_{ift} pounds of food type $i = 1, 2, \ldots, K$ in a time period $t = 1, 2, \ldots, T$, where T is large. We typically use 2 months as the interval over which food banks balance their food portfolio. Discounting plays no role in our analysis and is ignored. Food bank f has Y_f clients (proportional to its goal factor), and its utility is $\Sigma_{i=1}^{K}\Sigma_{t=1}^{T} Y_f U(c_{1ft}, c_{2ft}, \ldots c_{Kft})$, where U is per capita utility, with $U_i \geq 0$, and $U_{ij} \leq 0$.[9] We

[9] Our setting also has little need for contingent bidding, as there are relatively few cases where demands are linked either as complements (Budish 2011) or substitutes (Ausubel and Cramton 2004).

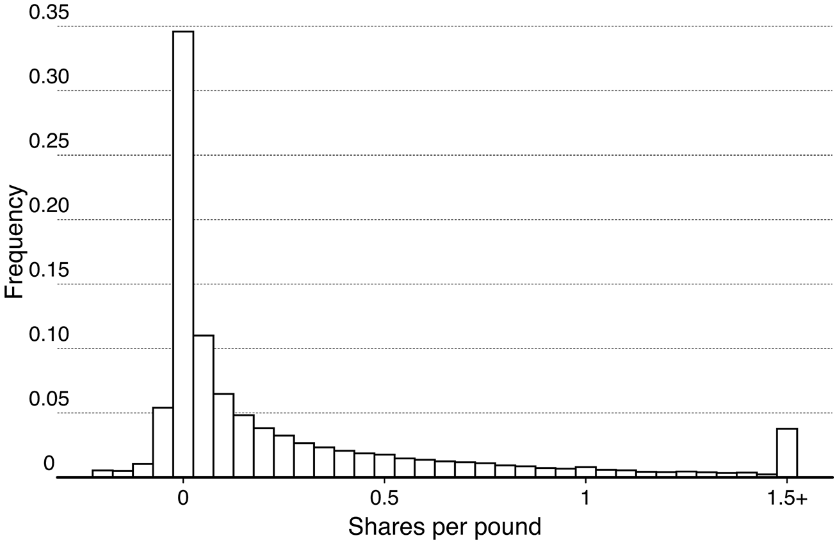

FIG. 2.—Distribution of price per pound (2005–11).

assume that food comes from two sources: from Feeding America (indexed by q) and from other sources (indexed by d) via $c_{ift} = q_{ift} + d_{ift}$, where q_{ift} is the per capita number of pounds of good i in period t that food bank f receives from Feeding America and d_{ift} is its endowment from other sources. Under the old assignment method, $q_{ift} = \bar{q}_{it} = Q_{it}/\Sigma_f Y_f$, where Q_{it} is the total supply of food i in period t assigned by Feeding America. Food banks have a normalized budget of 1 share per client per period. Let the outcome of the Choice System be a set of prices p_{it}. Food bank f chooses q_{ift} to maximize its utility subject to the intertemporal budget constraint, $\Sigma_{i=1}^{K}\Sigma_{t=1}^{T} p_{1t}q_{1ft} + p_{2t}q_{2ft} + \cdots + p_{Kt}q_{Kft} \leq T$. Then the observation below (shown in the appendix) follows:

TABLE 2
AUCTION OUTCOMES (2005–11)

Year	Average Number of Bids	Credit (%)	Joint Bids (%)	Negative Price (%)	Maroon Pounds (millions)
2005	4.32	2.62	1.58	8.77	8.9
2006	3.60	6.22	1.62	13.65	17.3
2007	3.55	9.80	2.20	9.02	18.3
2008	3.95	12.27	1.92	7.83	15.9
2009	3.63	11.96	1.82	7.78	14.0
2010	3.64	12.47	1.44	5.00	16.5
2011	3.28	10.92	1.19	3.08	8.8
Average	3.66	9.99	1.69	7.8	14.7

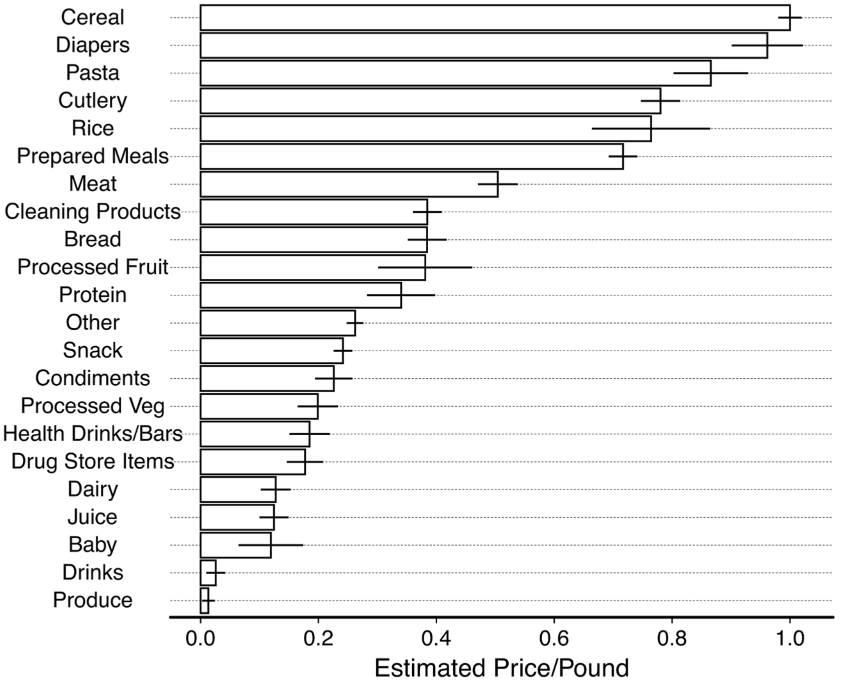

FIG. 3.—Price of different foods (cereal = 1).

OBSERVATION. For any fixed average donation $\bar{q}_{it}$, all food banks are weakly better off from the ability to choose than under the old allocation system.

This arises because food banks can choose to buy their old allocation. Despite its simplicity, this argument was unpersuasive to some involved in the redesign process. Their concern was that small food banks could face sufficient transactions costs to deter them from effectively engaging with Choice. To address this, we show that food banks were active bidders and that smaller food banks were not disadvantaged. First, the average food bank bids 238 times a year and wins 77 auctions.[10] There were an average of 3.66 bidders, which varied annually from 3.3 to 4.3 (table 2). Furthermore, small food banks bid more per client: the online appendix shows regression results illustrating that a 1% reduction in goal factor increases bids per client by 0.66%. We also show there that conditional on bidding, small food banks won less often, but the differences were small. As a result, we conclude that the Choice System at least offered weak benefits to all its participants.

[10] Including the Food Rescue Organizations changes these to 194 and 66, respectively.

Many design choices were made to facilitate small food banks. Table 2 shows the frequency of two primary ones, credit facilities and joint bidding. First, in the early stages, the use of credit was limited, but from 2008 to 2011, 12% of winning bids used credit. As only half of food banks qualify for credit, almost a quarter of all winning bids used it. Credit was intended to allow smaller food banks to afford expensive food. We show in the online appendix that credit was used in this way. Second, table 2 shows that 1.7% of auctions had joint bid winners. On average, three food banks bid jointly so that 5% of auction winners were joint bidders. Joint bidding was concentrated among a small set of food banks but intensively used among those who did. More generally, the features designed to allow food banks to engage and equalize opportunity fulfilled these objectives.

V. Dispersion in Outcomes

If food consumption under Choice differed little from that observed before, we might conclude small welfare gains. We show on a series of dimensions that this is not so. Food banks choose a portfolio of food choices over a period of time. We choose 2 months, as this reflects that many foods are durable and can have a shelf life of up to a few months. We show robustness to other choices below.

We begin by documenting dispersion. To do so, we compute a measure that captures the change in the allocation of the average pound of food to the average client. Specifically, we estimate how different q_{ift} is from random assignment using an absolute difference measure. Food bank f received Q_{ift} pounds of food type i in (2-month) period t from Feeding America. The old assignment rule was designed to give an equal number of pounds per client, $s_f Q_{it}$. Then the percent absolute difference per client for food i at food bank f in period t is $|(Q_{ift} - s_f Q_{it})/s_f Q_{it}|$. We then need to aggregate across food banks and food type. We aggregate across f by weighting by goal factor, $\Sigma_f |(Q_{ift} - s_f Q_{it})/s_f Q_{it}| s_f$. Then to get average dispersion across foods, we weight by each food's share in total pounds s_i from 2005 to 2011. This yields an absolute percentage change in per client allocation in period t of

$$A_t = \sum_{i=1}^{K}\sum_{f=1}^{F} \left| \frac{Q_{ift} - s_f Q_{it}}{s_f Q_{it}} \right| s_i s_f. \tag{1}$$

This measure represents how different is the allocation of the average good to the average client. It averaged 1.26 from 2005 to 2011: the average pound of food is allocated to a client whose consumption of that good was 126% different than random assignment. As shown below, this is a combination of changes both in total food consumption and in the food bundle. (In the online appendix, we also use ex post weights that result in yet greater dispersion but are more sensitive to outlier food banks.)

Food banks used bidding to change both the average bundle they consumed and temporal variation around that bundle. To measure permanent choices, let the average share of all pounds of good i received by food bank f from 2005 to 2011 be $s_{if} = \Sigma_t Q_{ift}/\Sigma_t Q_{it}$. Aggregating this shows dispersion in permanent choices $A_p = \Sigma_{f=1}^{F}\Sigma_{j=1}^{K}[|Q_{it}(s_{if} - s_f)|/Q_{it}s_f]s_i s_f = \Sigma_{f=1}^{F}\Sigma_{j=1}^{K}|s_{if} - s_f|s_i$. This is given by 0.87, or 69% of total dispersion. Temporal variation around that bundle was the remaining 31%.

These results show that Choice led to very different outcomes. Yet without more structure, they alone cannot show welfare implications. For instance, if food banks value each pound of food at its price, $U_i = p_{it}$, all bundles yield identical welfare (ignoring geography). To address this, we now turn to illustrating systematic variation in two ways: by showing sorting (1) based on food bank size and (2) based on geography.

VI. Systematic Responses

Here we show evidence on vertical sorting, by which we mean that food banks choose different locations on a quality-quantity trade-off. To begin, figure 4 plots the distribution of the average purchase (pounds per share) made by each food bank from 2005 to 2011. Moving to the right of this figure represents sorting on cheaper foods. Under the old algorithm, every

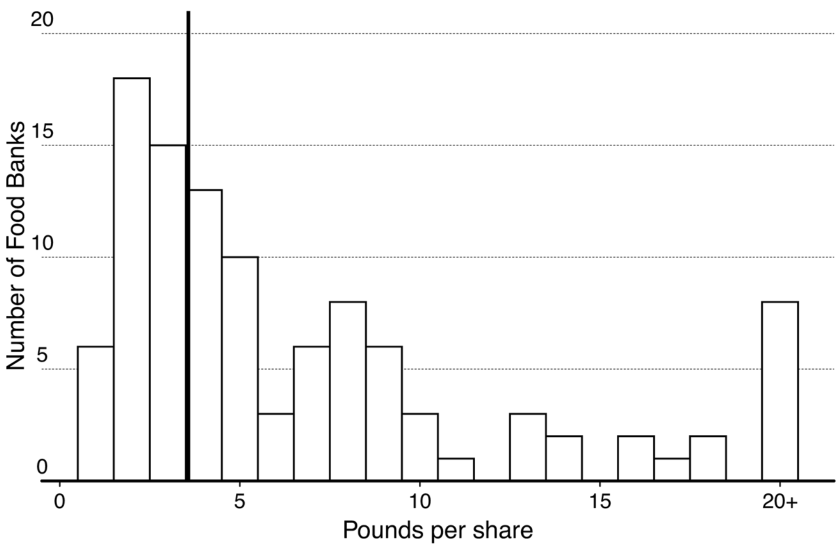

FIG. 4.—Distribution of average price per pound for each food bank (2005–11).

food bank would have received between 3 and 4 pounds per share (vertical line). By contrast, a quarter of food banks choose less than half the number of pounds per share than under the old system. On the other hand, almost 30% of all food banks received twice as many pounds per share, while 10% got at least three times as many.

A primary source of this sorting is food bank size, measured by goal factor.[11] As preliminary evidence, we compare the average choice made by above-median goal factor (large food banks) and below-median goal factor food banks (small food banks).[12] Small food banks responded to Choice by buying 72% more food per capita than their large counterparts (shown in more detail in the online appendix). Regression results reinforce this conclusion. Figure 5 plots the annual coefficient of a regression of log(total pounds) on log(goal factor). Before 2005, a 1% increase in goal factor was intended to result in a 1% increase in pounds, and it did so. For all years after 2005, this falls below 0.5%, averaging 0.43% from 2005 to 2011. This clearly shows how large food banks responded by getting less food than before compared with their smaller counterparts.

The main reason for this is that large food banks bought more expensive food. Table 3 shows regression results predicting the average annual price per pound paid by a food bank. Prices rose 0.396% per percentage point increase in goal factor, which remains constant for each year. This likely reflect income effects generated by food richness. Food banks care about both ensuring that clients have enough to eat and finding an optimal mix of food. The former is the primary objective. However, once a food bank has enough food, the composition of the bundle becomes more important. Specifically, they shift consumption toward luxuries. As food richness is located mostly among the large food banks, they buy more expensive food.

A second reason for larger consumption by small food banks per capita is greater share expenditure per capita. First, some food banks do not spend all their shares, even over the long run (see the online appendix for the data). This arises as some food banks decide that the cost of transportation exceeds the value of marginal food. Table 3 shows regression results predicting total annual share expenditures per capita by goal factor. This relationship is more fragile than for either total pounds received

[11] Goal factor comprises both population and a measure of poverty. We have data on the two ingredients of a food bank's goal factor for a single year (2015). In that data, 83% of goal factor in 2015 is predicted by population size. While this is later than our sample period, poverty rates and relative populations change slowly.

[12] This is measured at the level of the client, as we care about client outcomes rather than food bank outcomes here. Food banks are grouped by whether goal factor for a food bank is above or below the cutoff j, where $\Sigma_{i=1}^{j} G_i / \Sigma_{i=1}^{N} G_i = 0.5$ and i indexes food banks' goal factors ordered from smallest to largest.

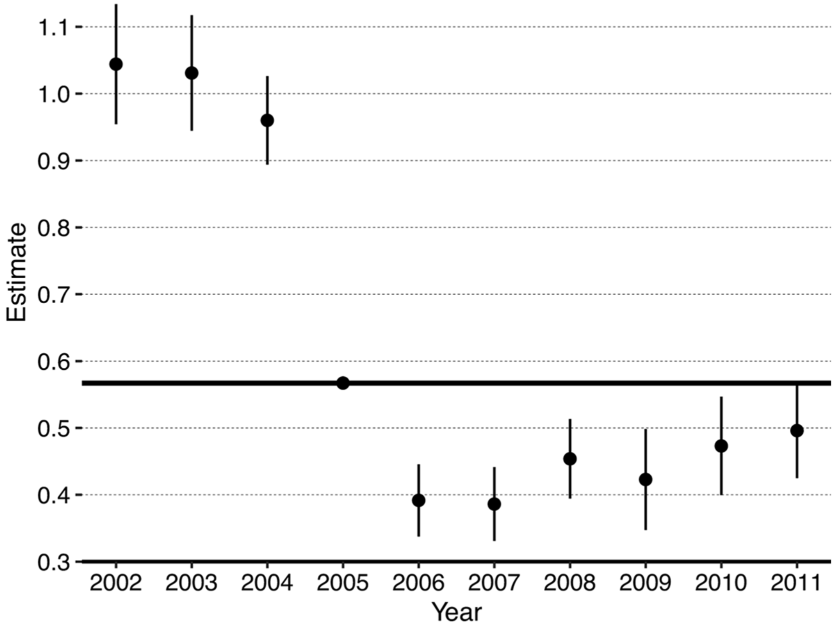

FIG. 5.—Coefficient of log(goal factor) on log(pounds of food).

or price paid. Over the entire 2005–11 time period, this coefficient is mildly negative and insignificant. However, this masks time variation. For the first 6 months after Choice was implemented, smaller food banks did not initially spend their shares, perhaps as they were still learning how to bid. However, from that initial 2005 benchmark, there was a consistently negative relationship between goal factor and propensity to consume, where a 1% increase in goal factor reduced the marginal propensity to consume by 0.2%.

The second source of share expenditure differences arises from negative priced auctions. This has also redistributed food to small food banks. We show in the online appendix that from 2005 to 2011, small food banks received 466 million more pounds of food than did the big food banks; 96 million of that was generated by negative priced food, both the food received (84 million pounds), and the extra food they buy from shares received from doing so (12 million pounds). In this way, negative priced auctions both served to alleviate donor tensions and redistributed food to the smallest, most needy food banks.

This section raises one important issue. These results clearly show that food bank needs differed radically. Why then did Feeding America ignore these under the old queueing mechanism? Feeding America knew that the food poor wanted more food and the food rich wanted better food. However, a paramount component of its mission was (and is) the

TABLE 3
AVERAGE PRICE PAID AND PROPENSITY TO CONSUME (2005–11)

	DEPENDENT VARIABLE			
	log(Average Annual Price per Pound)		log(Annual Shares Spent/ Goal Factor)	
	(1)	(2)	(3)	(4)
log(goal factor)	.396***	.390***	−.014	.159***
	(.101)	(.079)	(.033)	(.021)
log(goal factor) × 2006		.045		−.203***
		(.038)		(.030)
log(goal factor) × 2007		.098**		−.166***
		(.048)		(.030)
log(goal factor) × 2008		−.016		−.115***
		(.072)		(.036)
log(goal factor) × 2009		−.015		−.205***
		(.073)		(.029)
log(goal factor) × 2010		−.032		−.232***
		(.066)		(.044)
log(goal factor) × 2011		−.053		−.236***
		(.071)		(.049)
Observations	771	771	770	770
Adjusted R^2	.257	.254	.173	.185

** $p < .05$.
*** $p < .01$.

need for procedural fairness. Despite its warts, the old system was seen as fair. While Feeding America knew a better allocation might entail trading quantity for quality, it could not ensure fairness in that process. For instance, what rates of exchange should be used? A key benefit of the Choice System is that by giving all food banks equal shares per client, they could maintain procedural fairness, even though food consumption differed greatly across food banks.

Nutrition.—A concern about the outcome above could be that small food banks are sacrificing nutrition for extra pounds. This is not the case. We noted above that small food banks received 72% more pounds of food than their larger counterparts. The online appendix shows that they got more of every kind of food. As a result, smaller food banks are not trading extra pounds for total nutrition. Yet a concern may remain that perhaps the bundle received by a client of a smaller food bank became significantly less nutritious. To address this, we use a points system offered by Weight Watchers measuring the nutritional value of thousands of food products (see https://OneMorePound.com). We weight the average basket purchased by large and small food banks using that index. The nutrition index for the bundle consumed by the small food banks was only 1.8% lower than that of the large food banks. Given that smaller food banks got 72% more food per client, concerns about nutritional problems seem out of place.

VII. Geography

The old allocation system paid little attention to geography, often requiring food banks to travel long distances. Here we address transportation cost savings. We use the ArcGIS mapping platform to compute the distance a truck must travel from the warehouse housing the food donation to the location of the winning bidder. Under the Choice System, the mean one-way distance traveled was 1,034 kilometers. Mean distance for losing bids was 998 kilometers. Almost all food banks travel long distances: only 25% of food banks sourced food less than 380 kilometers away.

To compute the geographic impact of the Choice System, we simulate outcomes using the old algorithm and observed donations. We begin on July 1, 2005, by randomly assigning food banks to a queue position. Loads arrive on that day and are assigned to the food banks at the top of that (random) queue, with the first load being given to the food bank that is first in the queue. The queue is then recomputed using the old algorithm, and we proceed to the next day. We carry on each day in this way until December 31, 2011, and estimate the average distance traveled.

This simulation computes an average one-way distance of 1,921 kilometers. This is not the right benchmark, as food banks turned down offers. This was rare—less than 10%—but if food banks are more likely to turn down loads far away, 1,921 kilometers is an overestimate. We amend the simulations by imposing that food banks turn down all loads beyond a certain percentile of distances offered to them. If turned down, that load is then offered to the next person in the queue, and so on. In order to deal with undesirable loads, we assume that if a load is turned down three times, it is discarded. The online appendix shows distance traveled for different turn down rates. We use a conservative estimate by assuming that each food bank rejects the farthest 10% of offers. On the basis of this, we compute that food banks would have traveled 1,720 kilometers (one way) to collect the average load.

This allows us to carry out two exercises. First, Choice reduced average round trip travel by 1,373 kilometers. We use data provided by the American Transportation Research Institute (2017) to estimate average trucking costs per kilometer for this time period at $0.99. For all food banks, there are 11,555 auctions per year, which offers a welfare gain from the geographic component of the Choice System of $15.7 million per annum.

Second, these data imply that food banks must care about the composition of their food bundles, because they could have sourced food far closer. The average food bank won 13 truckloads in a 2-month period. We show in the online appendix that there were an average of 32 truckloads within 160 kilometers of a food bank and 91 loads within 320 kilometers. That they choose not to do so illustrates preferences over food type, as they could reduce one-way travel by an average of at least 1,500 kilometers. This would have reduced transportation costs by \$34.3 million per annum. As such, \$34.3 million should be seen as a lower bound on the value of food choice and further shows that the dispersion outcomes in section V represent welfare gains.

VIII. Supply of Food

One objective of the Choice System was to generate more food supply. First, the old assignment system was illiquid, as offers were made sequentially, where each food bank had 4–6 hours to respond. Here all food banks can bid on any load. This increased liquidity may induce more donations, as food spends less time in the donor's warehouse. Second, prices from the Choice System credibly reveal information on the most desired foods, which could be used to solicit valuable donations. Finally, the fact that food may be used more efficiently may itself be an inducement for donors to give more.

Total donations (to all food banks) are given in figure 1 and show donations rising from 200–225 million pounds before 2005 to 320–350 million pounds immediately after introduction of the Choice System. The increase in food supply of 100 million pounds offers total daily nutrition to an additional 55,000 people every day. Note that this is time series variation, so some caution should be applied to inferring causality.[13] However, qualitative evidence suggests that considerable gain was generated by greater liquidity for donors, where the Choice System facilitated faster pickup by offering donations to all food banks simultaneously.

Another source of increased supply was maroon pounds. Table 2 shows that maroon pounds added an average of 14.7 million pounds to the system. Furthermore, this is better than average food, as it traded for a 30.5% premium over the average pound.

IX. Translating Shares into Dollars

It can be hard to interpret magnitudes denominated in an artificial currency. Here we translate outcomes to dollars. Transport costs are paid in dollars, while food is paid in shares. The relationship between distance traveled and winning bids allows us to identify the dollar value of a share. Let κ be marginal transportation cost per kilometer in dollars and λ be the dollar value of a share. Then a food bank is indifferent between paying p shares at one location and $p - (\kappa/\lambda)m$ for an identical load m kilometers

[13] We use yellow pounds data for the 2000–2004 period and auction data for the post-2005 period. If we restrict attention to the 107 food banks on which we have data before and after the change, yellow pounds food received increased from an average of 126 million (from 2000 to 2004) to 183 million pounds (from 2006 to 2011).

further away. Then if γ is the observed change in winning bid per additional kilometer on otherwise identical loads, $\lambda = -(\kappa/\gamma)$.[14]

This requires empirical measures of κ and γ. For κ, many transportation costs are fixed, in particular, labor costs. Barnes and Langworthy (2003) estimate variable costs at 33% of total per kilometer trucking cost. Previously we showed that average costs were \$0.99 per kilometer, so we use $\$0.99 \times 0.33 = \$0.33$ as our estimate of κ. Then $\lambda = -(\$0.66/\gamma)$, as kilometers must be traveled round trip.

We estimate γ by regressing winning bids on distance for identical loads. To illustrate the idea with a single food, column 1 of table 4 regresses the winning bid for loads of a single homogeneous good (apples) on kilometers traveled (with a set of controls described below). Each additional kilometer reduces the winning bid by 0.34 shares. If we used only apples, then $\lambda = -\$0.66/-0.34 = \$1.94$.

To estimate γ more broadly, it must be that the winning bid varies with distance only because of transportation costs. However, when a load is preferred on unobserved dimensions, food banks will both bid more and travel farther, yielding a positive relationship between them. Unobserved differences occur either because loads vary in their characteristics (such as the sugar content of cereals) or because a desirable food is sold rarely, in which case a food bank that does not want to wait will bid more and travel farther. This is particularly important as transportation costs are low: the average round trip costs \$904 in marginal transportation costs, or 3*c* per pound of food (0.0014*c* per pound per kilometer) for an average truckload of 30,000 pounds. To address this, we need to eliminate heterogeneity on both the food and the food bank sides.

We do this in two ways. First, we consider finer definitions of foods than used above. For example, we identify individual vegetables and fruits and distinguish drinks by type (water, sports drinks, and other). Furthermore, we choose foods as homogeneous by low standard deviations in winning bids (see the online appendix). This rules out very desirable goods, such as rice and pasta, which are not common and have high dispersion in winning bids. All individual vegetables and fruit exhibit low price dispersion. On the basis of this, we use 28 foods for our analysis: 13 vegetables, 11 fruits, water, sports drinks, yogurt, and milk. There are 15,899 auctions for these 28 goods.

To further control for heterogeneity across food banks, our regressions employ a three-way interaction between food bank, disaggregated food type, and time. We use two time intervals. First, food banks balance their food over roughly 2 months, so we use bimonthly intervals. This

[14] A potential concern is that food banks mark down their bids in this first-price auction setting. However, this would be a concern here only if the extent to which they do so depends on distance.

TABLE 4
PRICE AS FUNCTION OF DISTANCE

	DEPENDENT VARIABLE: TOTAL WINNING BID				
	(1)	(2)	(3)	(4)	(5)
Distance	−.342**	−.111***	−.093*	.728***	.549**
	(.144)	(.039)	(.053)	(.226)	(.229)
Distance × homogeneous				−.840***	−.624***
				(.229)	(.231)
Food bank × food type × bimonthly	Yes	No	Yes	No	Yes
Food bank × food type × year	No	Yes	No	Yes	No
Estimated distance coefficient				−.112***	−.075
				(.041)	(.054)
Sample	Apples	Homogenous goods	Homogenous goods	All	All
Observations	1,030	15,899	15,899	54,058	54,058
Adjusted R^2	.63	.74	.78	.74	.89

NOTE.—Sample is all auctions won by one of the 107 food banks, given the restriction given in the table on type of food. Regressions include total pounds, subsidies, and number of losing bids as additional controls.
* $p < .10$.
** $p < .05$.
*** $p < .01$.

allows us to identify outcomes from, for example, the Chicago Food Depository buying multiple truckloads of corn in a particular 2-month interval at different distances. Two-month fixed effects may lack power if few food banks win two truckloads of the same homogeneous good in a 2-month period. As a result, we also interact food bank, disaggregated food type, and year. We additionally control for the size of the load, the number of other bidders, and any transportation subsidies (full details are in the online appendix). With these controls, our interest is in the marginal impact of distance for our 28 homogeneous foods.

Results are given in table 4. Column 1 is for apples, while columns 2 and 3 show outcomes using data for just the homogeneous goods. The coefficient on distance with three-way annual fixed effects is −0.111 (significant at the 1% level) and −0.093 using bimonthly fixed effects (significant at the 10% level). The online appendix offers regressions using two-way interactions that offer quantitatively very similar outcomes. Columns 4 and 5 offer regression results using our entire sample of foods, where the homogeneous foods are captured by an interaction term. This uses more data to estimate the additional X variables. The distance coefficient overall is positive, reflecting the positive selection issues described above, but the marginal impact of homogeneous foods is negative. The imputed impact of distance for the homogeneous foods is the sum of the two and offers very similar results. For the annual three-way interaction, the homogeneous goods regression offers −0.112 in column 4 compared with −0.111 in column 2. Put more simply, our results consistently show that an extra 9 or 10 kilometers traveled reduced bids by one share.

Using −0.111 in column 2 as our preferred estimate, a share was valued at \$5.97 ($\lambda = -\$0.66/-0.111 = \$5.97$). Then the average pound of food was valued at 0.28 shares × \$5.97 = \$1.67 per pound and ranges from \$0.12 per pound for fresh vegetables to \$6.45 for a pound of cereal.

It is worth noting that this estimate derives from a period when demand for food banks was abnormally high during the financial crisis. As such, food banks may have been especially reluctant to give up shares, as that was their mechanism for getting food to the poor in a particularly needy period. As a result, our estimate of \$5.97 may be higher than normal.

X. Estimating Welfare Gains

Our final objective is to use a simple model to estimate the welfare gains that arose from just the reallocation of a fixed supply of food across food banks. The objective of the Choice System was to implement a competitive equilibrium with equal incomes. Here we assume such an outcome and use a model to compute welfare gains, holding total supply fixed. To do so, we assume that transportation costs are linear and so returns from geography are separable from these gains. Our analysis uses four assumptions.

1. Feeding America's objective is to maximize average per period equal weighted food bank utilities, $\Sigma_{t=1}^{T}[\Sigma_{f=1}^{F} Y_f U(c_{1ft}, \dots c_{Kft})]/T$.
2. Per capita consumption is $c_{ift} = d_{ift} + q_{ift}$. We assume that $d_{ift} = \mu_f d_{it} + \epsilon_{ift}$, where μ_f measures food bank f's food richness, $E\mu_f = 1$, and d_{it} is the average endowment from other sources. ϵ_{ift} is a mean 0 transitory shock for all i, f, and t; is independent of q_{it}; and is uncorrelated across time. d_{ift} is exogenous and unobserved by Feeding America.
3. Utility, denominated in shares, is quadratic in c_{ift}: $U(c_{1ft}, c_{2ft}, \dots c_{Kft}) = \Sigma_{i=1}^{K}(\tau_i c_{ift} - \gamma_i c_{ift}^2)$, $\gamma_i \geq 0$. Note that all food banks have a common utility function.
4. Food banks achieve the first best, where $U_j(c_{1ft}, c_{2ft}, \dots c_{Kft}) = U_j(c_{1f't}, c_{2f't}, \dots c_{Kf't})$ for all j, f, and f'. This implies that with Choice, $c_{ift} = d_{it} + \bar{q}_{it}$, whereas under the old algorithm, $c_{ift} = \mu_f d_{it} + \epsilon_{ift} + \bar{q}_{it}$.

Because the food banks have a common utility function, τ_i has no impact on welfare changes. Instead, in the appendix we show that with these assumptions, the change in expected welfare from reallocated food in period t depends only on γ_i and is given by $\Delta_t^* = \Sigma_{f=1}^F \Sigma_{i=1}^K Y_f \gamma_i (q_{ift} - \bar{q}_{it})^2 = \Sigma_{f=1}^F \Sigma_{i=1}^K (\gamma_i / Y_f)(Q_{ift} - Q_{it})^2$, where $Q_{it} = Y_f \bar{q}_{it}$.

To measure γ_i, we use existing studies on the elasticity of food demand.[15] Let e_i be the own price elasticity of demand for food i. A food bank facing a price p_{it} chooses consumption by the first-order condition $U_i = p_{it}$. This implies that $dp_{it}/dc_i = U_{ii} = -2\gamma_i$. Estimated at appropriate consumption $\tilde{c}_{ift}$ and price levels $\tilde{p}_{it}$, we use elasticity estimates $e_i = (dc_{ift}/dp_{it})(\tilde{p}_{it}/\tilde{c}_{ift}) = -(\tilde{p}_{it}/2\tilde{c}_{ift}\gamma_i)$ to recover γ_i. We evaluate the elasticity at a food bank's average consumption level $\tilde{c}_{ift} = s_{if} C_{it}/Y_f$, where C_{it} is total consumption of good i in period t. Feeding America allocates 10% of total food through the Choice System, so we let $C_{it} = 10Q_{it}$ and hence $\tilde{c}_{ift} = 10 s_{if} Q_{it}/Y_f$. Second, we evaluate e_i at the average price for good i, $\tilde{p} = \bar{p}_i$ from 2005 to 2011. Hence, $\gamma_i = -(\bar{p}_i Y_f / 20 s_{if} Q_{it} e_i)$. Substituting for γ_i in Δ_t^* above then yields

$$\Delta_t^* = -\sum_{f=1}^{F}\sum_{i=1}^{K} \frac{\bar{p}_i (Q_{ift} - Q_{it})^2}{20 s_{if} Q_{it} e_i}. \tag{2}$$

Δ_t^* can be estimated with observed data and is denominated in shares (as $\bar{p}_i$ is in shares).

We use e_i estimates from two recent metastudies (Andreyeva et al. 2010; Cornelsen et al. 2015). In instances where they do not provide estimates for the categories used here (as arises for nonfood items, like diapers), we use the mean estimate for all food from that study (see details in the online appendix). Using the Andreyeva estimates, the average annual welfare gain from food reallocation was 19.28 million shares. As the average pound of food sold for 0.28 shares, this is equivalent to a gain of 68.9 million pounds of food.

The Choice System allocated an average of 330 million pounds of food per annum. Our benchmark welfare gain of 68.9 million pounds estimates that Choice increased the value of that food by 20.8%. It may be more appropriate to see this in the context of the entirety of the food banking sector. The Choice System allows food banks to reallocate 10% of their food to rebalance inefficiencies in the other 90%. From that perspective, Choice allows them to achieve benefits of roughly 2% on their entire stock of food.

Using our imputed value of a share of $5.97, we find that the welfare gain of 19.28 million shares translates to $115.1 million per annum. Adding the transportation cost savings above increases this to $130.8 million.

[15] One possible approach to this would be to search for exogenous supply-side shifters to plot demand curves. However, there are no such immediate candidates.

These gains do not include the value of increased donations described in section VIII.

Note three issues. First, we have assumed that food banks rebalance their consumption over a 2-month interval. As many foods have a much shorter time before expiration, a 1-month interval may be more appropriate. We have also computed outcomes for 1 month. One-month benefits are considerably higher: \$161 million. Three-month intervals yield a gain of \$98 million. Second, the results do not change significantly using the Cornelsen et al. (2015) elasticity estimates (\$130 million rather than \$115 million), nor do they vary significantly by year (see the online appendix for details). Finally, welfare gains arise from both permanent differences in food purchases and temporal smoothing. The welfare gain from the permanent choices is

$$\Delta^*_{pt} = -\sum_{f=1}^{F}\sum_{i=1}^{K}\frac{\bar{p}_i(Q_{it}(s_{if} - s_f))^2}{20 s_{if} Q_{it} e_i} = -\sum_{f=1}^{F}\sum_{i=1}^{K}\frac{\bar{p}_i Q_{it}(s_{if} - s_f)^2}{20 s_{if} e_i}.$$

This yields permanent benefits of 9.79 million shares (\$58.4 million), or 51% of all benefits. Temporal consumption smoothing accounts for the remainder.

XI. Conclusion

Other economic systems have used specialized currency. Timberlake (1987) and Gatch (2008) describe examples of scrip in company towns in the United States at the turn of the twentieth century, while Radford (1945) famously illustrates the use of cigarettes as currency in prisoner of war camps in World War II. Finally, bidding systems for university courses are common, as studied by Budish (2011) and Budish and Cantillon (2012). Our contribution should be seen in the context of these previous successes.[16]

To conclude, the idea that a specialized currency could be used to allocate donated food more efficiently may seem straightforward. Yet it is rare to observe these kinds of monopoly money solutions being used in real-world settings. First, it is critically important that it is infinitely repeated. Second, the flow of offerings is high: the average food bank that turns down an offering today does not have to wait long to get something that it wants. In addition, there is wide variation in valuations across goods, which helps induce agents to be patient. These issues help to avoid the kind of unraveling that arose in Sweeney and Sweeney (1977) and Sonmez and Unver

[16] A number of recent contributions (e.g., Friedman et al. 2006; Budish 2011; Kash et al. 2012, 2015) illustrate how efficiency can be attained in settings using scrip currencies such as ours. Agarwal et al. (2019) also outline how such a mechanism may be valuable in the context of kidney exchange.

(2010). Finally, there are a large number of players, which likely mitigates strategic concerns. For all these reasons, this is likely terrain that lends itself to the use of a specialized currency.

Appendix

A1. Observation: Weak Benefits from the Choice System

Under the old regime, consumption in period t is $d_{ift} + \bar{q}_{it}$, where $\bar{q}_{it} = s_f Q_{it}$ and $s_f = Y_f / \Sigma_{i=1}^{F} Y_i$ is food bank f share of total clients. Let the budget be normalized to 1 per capita per period, and let the price of good i in period t be p_{it}. A food bank chooses quantities q_{ift}^{*} to maximize its utility subject to the intertemporal budget constraint $\Sigma_{i=1}^{K} \Sigma_{t=1}^{T} (p_{1t} q_{1ft}^{*} + p_{2t} q_{2ft}^{*} + \cdots + p_{Kt} q_{Kft}^{*}) / T \leq 1$. To show that the bundle under the old regime is feasible, we need to show that $\Sigma_{i=1}^{K} \Sigma_{t=1}^{T} (p_{1t} \bar{q}_{1t} + p_{2t} \bar{q}_{2t} + \cdots + p_{Kt} \bar{q}_{Kt}) / T \leq 1$. Summing the budget constraint over all food banks, each of which has Y_f clients, yields $\Sigma_{f=1}^{F} Y_f \Sigma_{i=1}^{K} \Sigma_{t=1}^{T} (p_{1t} q_{1ft}^{*} + p_{2t} q_{2ft}^{*} + \cdots + p_{Kt} q_{Kft}^{*}) / T \leq \Sigma_{f=1}^{F} Y_f$. Then as $\Sigma_{f=1}^{F} Y_f q_{ift}^{*} = \bar{q}_{it} \Sigma_{f=1}^{F} Y_f$, it follows that $\Sigma_{i=1}^{K} \Sigma_{t=1}^{T} (p_{1t} \bar{q}_{1t} + p_{2t} \bar{q}_{2t} + \cdots + p_{Kt} \bar{q}_{Kt}) / T \leq 1$, as required.

A2. Computing Welfare Gains

Under the old algorithm, food bank f consumes $d_{ift} + \bar{q}_{it}$ in period t. The total utility from that consumption in period t is $\Sigma_{f=1}^{F} \Sigma_{i=1}^{K} Y_f (\tau_i (d_{ift} + \bar{q}_{it}) - \gamma_i (d_{ift} + \bar{q}_{it})^2)$. Under the Choice System, food bank f consumes $d_{ift} + \epsilon_{ift} + q_{ift}$, with total utility $\Sigma_{f=1}^{F} \Sigma_{i=1}^{K} Y_f (\tau_i (d_{ift} + \epsilon_{ift} + q_{ift}) - \gamma_i (d_{ift} + \epsilon_{ift} + q_{ift})^2)$. As a result, welfare change in period t is $\Delta_t = \Sigma_{f=1}^{F} \Sigma_{i=1}^{K} Y_f (\tau_i (d_{ift} + \epsilon_{ift} + q_{ift}) - \gamma_i (d_{ift} + \epsilon_{ift} + q_{ift})^2) - \Sigma_{f=1}^{F} \Sigma_{i=1}^{K} Y_f (\tau_i (d_{ift} + \bar{q}_{it}) - \gamma_i (d_{ift} + \bar{q}_{it})^2)$. As total supply of food is unchanged, $\Delta_t = \Sigma_{f=1}^{F} \Sigma_{j=1}^{K} \gamma_i Y_f [(d_{ift} + \bar{q}_{it})^2 - (d_{ift} + \epsilon_{ift} + q_{ift})^2] = \Sigma_{f=1}^{F} \Sigma_{j=1}^{K} \gamma_i Y_f [(\mu_f d_{it} + \epsilon_{ift} + \bar{q}_{it})^2 - (\mu_f d_{it} + \epsilon_{ift} + q_{ift})^2]$. At the first best, $\mu_f d_{it} + \epsilon_{ift} + q_{ift} = d_{it} + \bar{q}_{it}$. Then as $\Sigma_{f=1}^{F} \epsilon_{ift} = 0$ from the definition of d_{ift} and is uncorrelated with q_{it}, $\Delta^* = \Sigma_{f=1}^{F} \Sigma_{j=1}^{K} \gamma_i Y_f E[(\mu_f^2 - 1) d_{it}^2 + \epsilon_{ift}^2] = \Sigma_{f=1}^{F} \Sigma_{j=1}^{K} \gamma_i Y_f E[((1 - \mu_f) d_{it} + \epsilon_{ift})^2]$, as $E\mu_f = 1$. But $q_{ift} - \bar{q}_{it} = (1 - \mu_f) d_{it} - \epsilon_{ift}$ at the first best, so $\Delta^* = \Sigma_{f=1}^{F} \Sigma_{j=1}^{K} \gamma_i Y_f (q_{ift} - \bar{q}_{it})^2 = \Sigma_{f=1}^{F} \Sigma_{j=1}^{K} \gamma_i Y_f [(Q_{ift} / Y_f) - (Q_{it} / Y_f)]^2 = \Sigma_{f=1}^{F} \Sigma_{j=1}^{K} (\gamma_i / Y_f)(Q_{ift} - Q_{it})^2$.

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