Neighbor Helping Neighbor: Local Giving and the Geography of Charity*

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Abstract

In this paper, I ask if donor preferences for giving to local charities create a gap between where high-capacity food pantries are located and where food pantry customers live, indicating under-provision of charitable resources where charities are in highest demand. I find that food pantry customers living in high-income, rural neighborhoods live within 20 miles of 40 more food pantries than customers in low-income neighborhoods. Customers in low-income neighborhoods also face more restrictions, such as limits on the number of visits allowed per month. I estimate the value of each food pantry visit based on characteristics such as flexible distribution times and availability of food. I then show that customers in high-income neighborhoods receive higher per-visit benefits than those in low-income neighborhoods, driven by greater access to well-resourced and flexible pantries. In a counterfactual simulation, I show that redistributing funding to improve pantries in low-income areas increases consumer surplus by 3.3% overall, with welfare gains of 4-5% for customers in the lowest-income neighborhoods, equivalent to nearly one additional meal per visit.

JEL Codes: D64; H23; I32; L31; Q18
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1 Introduction

In 1981, the Reagan Administration passed the Economic Recovery Tax Act, which substantially cut federal funding for social programs. These cuts left a hole in the social safety net and low-income households turned to charitable organizations, like nonprofits and religious groups, for support. In a speech to religious leaders, Reagan said he believed it was a "good thing for the soul of the country to encourage people to get involved and accept more direct responsibility for one another's health, happiness, and well-being, rather than leaving it to the bureaucracy" (Reagan 1982). However, a charity's ability to respond to an increase in demand depends on decisions of private individuals, like donors and volunteers, who often prefer to support their local community.

This paper explores how local giving impacts the quality of nonprofit service offered in different areas. Researchers show that donors prefer to support organizations in their local community (Card, Hallock, and Moretti 2010; DellaVigna, List, and Malmendier 2012; List 2011, Blackwell and McKee 2003). Charitable organizations rely on support from donors and volunteers to operate, and therefore the level of service that a charity can provide and the number of customers it can serve will vary based on the local support of donors and volunteers. If higher-income individuals primarily invest in their own community, how does this affect the geographic distribution of high-capacity, charitable services, and would social welfare improve if donations were redistributed?

While this paper focuses on food pantries, the question applies broadly to other charitable organizations—including low-cost childcare services, affordable housing, community meals, public radio, and healthcare—where the capacity to provide services depends on donors and volunteers. Food pantries are particularly equipped to answer this question because they are small, locally operated, and some pantries rely entirely on community support. Unlike national charities that support research or advocacy, food pantries provide resources to their local community, and some pantries restrict their customers' eligibility by geographic location, like zip code or school district. This location dependence creates a mismatch between where resources are available and where they are most needed.

Food pantries are also ubiquitous and heavily utilized, providing a service to many households annually. There are more than 60,000 food pantries affiliated with Feeding America serving communities across the United States and Feeding America (2024) estimates that over 50 million people—nearly 15% of the US population—used a food pantry in 2023. In contrast, the Supplemental Nutrition Assistance Program (SNAP), which provides federal nutrition benefits for low-income families, served 12.6% of the population in 2023 (U.S. Department of Agriculture, Economic Research Service 2024). This is partially because food pantries are open to a larger share of the population than SNAP; depending on the state, food pantries provide food for households with incomes up to 300% of the federal poverty line, while households up to 130% of the federal poverty line are eligible for SNAP benefits.

To understand the relationship between community support for charities and community need for charitable services, I use a novel data set from the Mid-Ohio Food Collective (MOFC), a large food bank in central Ohio that provides food to pantries in 20 counties. These data include household-level details on food pantry utilization for over 100,000 food pantry customers, including the date and time the customer visited a pantry and the distance between the customer's home and the food pantry.

Using these data, I document spatial differences in food pantry locations. While fewer food pantry customers live in high-income neighborhoods,[1] these customers have over 40 more food pantries within 20 miles of their residence when compared to customers living in low-income neighborhoods. The characteristics of the food pantries near high- versus low-income neighborhoods also vary; a larger share of households in low-income neighborhoods do not live near any pantry that allows flexible access. For example, though all pantries in the MOFC network must provide at least three-days' worth of food each month, many pantries limit the number of times a customer can visit within a month. Other pantries allow their customers to visit as frequently as necessary. 72% of customers in low-income neighborhoods live near at least one pantry without restrictions on visit frequency compared to 96% of customers in high-income neighborhoods.

To determine if differential access leads to disparities in the value that customers derive from visiting a food pantry, I use a random utility model allowing for heterogeneous preferences. In the model, customers either choose to source their meals from any of the food pantries within 20 miles of their home or from a grocery retailer. The costs that customers face when visiting the pantry are travel costs. They choose the pantry that provides the greatest benefit, such as more food or flexible distribution times, given the distance they must travel.

I find that food pantries in high-income areas offer characteristics that customers prefer, such as better distribution times, leading to more value per visit for customers in high-income areas. Next, I find that households in the highest-income neighborhoods are more sensitive to travel costs, yet these households are willing to travel farther than households in low-income neighborhoods to access their preferred pantry. This result suggests that households in high-income neighborhoods visit food pantries that provide a greater per-visit benefit than households in low-income neighborhoods.

Given that high-capacity pantries tend to be concentrated in high-income areas, I investigate whether redistributing funding would improve welfare for low-income customers. Using the preferences derived from the random utility model, I estimate the counterfactual change in consumer welfare if a portion of funds supporting pantries in high-income neighborhoods were redistributed to pantries in low-income neighborhoods. Under the counterfactual funding distribution, I find that customer welfare increases in low-income areas by 4-5% and decreases in high-income areas by 1-2.5%, re-

[1] All food pantry customers in the data used for this project are self-reported to be below 200% of the federal poverty line. Therefore, a food pantry customer living in a high-income neighborhood is not a high-income individual.

sulting in overall customer welfare increases of 3.3% over the donor-generated funding structure. My findings suggest that consumer welfare could improve by redistributing food pantry funding, which implies that allocations based on donor and volunteer preferences result in a distribution of resources that is misaligned with customer needs. While redistributing funding across independent organizations is not feasible, charitable foundations or government organizations, could target under-resourced organizations to help close the gap.

This work lies at the intersection of literature on spatial inequities, charitable giving, and social service provision. Research on spatial inequities demonstrates how neighborhood characteristics shape access to resources. Early literature focused on the effects of segregation on amenities, housing, and access to labor markets (Cutler, Glaeser, and Vigdor 1999; Brueckner, Thisse, and Zenou 1999; Gobillon, Selod, and Zenou 2007; Waldfogel 2008). More recent work finds that low-income and predominantly Black neighborhoods face higher costs and reduced access to infrastructure and markets. For example, these neighborhoods experience rougher roads (Currier, Glaeser, and Kreindler 2023) and have more limited access to rooftop solar photovoltaic markets (Dorsey and Wolfson 2024). This literature highlights how residents of low-income neighborhoods, who are less likely to have expendable income, often are faced with higher costs in terms of local infrastructure and accessing other amenities. My work adds to this literature by demonstrating that individuals living in low-income, rural neighborhoods are also less likely to have access to well-resourced charitable organizations.

This work also contributes to literature on charitable giving, highlighting how donor preferences shape the level of resources available to organizations.[2] In addition to research showing that donors and volunteers prefer to support local organizations, List (2011) finds that higher-income households not only give more to charity, but are more likely to give to charity than lower-income households. This finding suggests that charities in areas with fewer high-income households may find it more difficult to attract donors and may receive less money per donation. Structural models further suggest that nonprofits are only economically viable in markets with a threshold number of potential donors, which varies by sector (Gayle, Harrison, and Thornton 2017). These findings motivate my analysis of how the distribution of donor support shapes access to charitable services across neighborhoods.

Other nonprofit characteristics influence a charitable organization's ability to attract donors. A salient increase in need, like natural disasters, can lead to increases in giving (Deryugina and Marx 2021) while subtler changes, such as rising food insecurity, are less responsive (Karol 2023). Donor behavior is also influenced by group identity. Using a public goods experiment that varies the benefit of contributing to a good that is exclusive to one's own group versus a non-excludable, global public

[2]In addition to research on donor preferences, there is extensive literature on the fundraising efforts of charitable organizations. For example, see Name-Correa and Yildirim (2013); Andreoni and Payne (2003); and Andreoni and Payne (2011) .

good, Blackwell and McKee (2003) find that participants seem to have a bias to support the group good, meant to represent local, public goods. The authors find that this bias can be overcome if the global public good's benefit to society is sufficiently high. Along the same lines, Andreoni et al. (2016) find that charitable contributions decrease as racial, ethnic, and religious diversity increases. Together, these patterns suggest that donor preferences are partially driven by local ties and demographic characteristics, which can create gaps between charitable resources and community needs.

Finally, this paper contributes to the limited literature on the role of food pantries in the larger food assistance system. Food banks and food pantries are a part of the nationwide response to food insufficiency, but the role of these organizations is understudied due to a lack of data. Byrne and Just (2022) offers a review of the publications focusing on private food assistance, which includes food pantries, but also includes community meals and programs like Meals on Wheels. Existing research on food pantry utilization focuses on topics like customer characteristics, barriers to access, use patterns and the relationship between food pantry use and food security (Byrne and Just 2022). Most of the available research relies on either qualitative data or local or national surveys such as the US Current Population Survey (CPS) Food Security Supplement (FSS), which asks households if they have ever used a food pantry. However, survey data, and particularly survey data related to food assistance, is subject to nonclassical measurement error due to misreporting or poor recall (Brzozowski, Crossley, and Winter 2017; Gundersen and Kreider 2008; Heflin and Price 2019). Additional research on food pantry management uses data from surveys of food pantries, and focuses mainly on the nutritional value of food provided and the size and scope of food pantries (Byrne and Just 2022).

Research using administrative data from food banks and food pantries is rare. Work by Byrne and Just begins to scratch the surface on understanding food banks and food pantries, using administrative data from a large food bank in urban Colorado. Their first paper documents cyclical food pantry utilization that corresponds to when SNAP benefits run out toward the end of the month (Byrne and Just 2021). Next, the authors use a travel costs approach to estimate that each food pantry visit is worth between \$40 and \$60 (Byrne and Just 2023). They also examine stigma in private food assistance, showing that negative perceptions of pantry food can be mitigated with visual cues (Byrne, Just, and Barrett 2023). More recently, Ruffini, Öztürk, and Pekgün (2025) uses data on Feeding America contributions to food banks and finds that counties with school districts participating in the Community Eligibility Provision (CEP), which allows schools to serve breakfast and lunch at no cost to students, see a reduction in the amount of food that food banks distribute. Their work suggests that government-provided services decrease the need for charitable services. To my knowledge, my work is the first, large-scale study of cross-county food pantry utilization and demand, and the first focusing on rural food pantry access.

The remainder of this paper is structured as follows: Section 2, explains the charitable food sector in the United States and in the focal region in rural Ohio. Section 3 describes the data and Section 4 explains the conceptual framework motivating this research. Section 5 provides a descriptive analysis of food pantry access among households in high- and low-income neighborhoods. Section 6 details the demand estimation model used to quantify customer preferences. Section 7 describes the results and counterfactual analysis. Section 8 concludes.

2 Background and Environment

2.1 Food Banks and Food Pantries

Private, charitable food assistance likely pre-dates public assistance of all types. For instance, the Salvation Army adopted the emblematic red kettles to collect their Christmas donations as a nod to Count Rumford, who is credited with establishing the first soup kitchen in the late 1700s (Bramen 2010). The term ‘breadline’ was coined in the late 1800s by Louis Fleischmann, a baker who offered to feed hungry people who came to his bakery in New York City. The modern US food banking was established much later in 1967 in Arizona by John van Hengel, who founded the St. Mary’s Food Bank (Byrne and Just 2022; Mook, Murdock, and Gundersen 2020). In this model of food banking, food is donated to or purchased by food banks and then distributed to food pantries.

In many ways, food banks and their network of food pantries operate like food distributors and grocery retailers, where independently owned retailers purchase food from a distributor. The food bank stores the food in a large-scale warehouse and food pantries, which are independent organizations, receive food from the food bank to distribute to the public, free of charge. The pantries receive some food, such as fresh produce, either free of charge or for a small fee to cover storage and delivery. Pantries purchase other products at-cost, allowing the food bank to pass on savings from high-volume purchases.

Charitable food programs grew in the 1980s due to a combination of factors (Poppendieck 1999). Economic stagnation in the 1970s led to high poverty rates that continued to climb into the 1980s. At the same time, the Reagan Administration implemented cuts to social programs, which led many families to turn to charitable assistance to make ends meet. Finally, reports of a government-owned stock of dairy surplus in the face of widespread hunger led to the federal institutionalization of commodities distribution through the Temporary Emergency Food Assistance Program in 1981.

The initial intention of the program was to be a temporary method of distributing government agricultural surpluses, but in 1990, Congress removed ‘Temporary’ from the name of the program, renaming it The Emergency Food Assistance Program (TEFAP). Since then, Congress appropriates funds to purchase just under $500 million in USDA foods annually to be distributed through TEFAP, along with limited funding for storage and distribution.[3] TEFAP also acquires surplus food from agricultural markets to distribute throughout the year including $955 million in agricultural surpluses in fiscal year 2023 (U.S. Department of Agriculture, Food and Nutrition Service 2024). Foods available through TEFAP include products like fresh and canned fruits and vegetables (apples, peaches, potatoes, peas), milk, eggs, pasta, cereal, dry and canned beans, rice, peanut butter, nuts, and cheese (U.S. Department of Agriculture, Food and Nutrition Service 2025b).

State governing agencies, such as Job and Family Services in Ohio, distribute TEFAP products to eligible food banks. State-level funds also support food banks through their own programs. In Ohio, the Ohio Community+Agriculture+Nutrition, or Ohio CAN,[4] provides funding for food banks to purchase food from local farmers. Ohio also has several programs similar to TEFAP including the Ohio Food Program, which uses state funds to provide shelf-stable products to food banks, and the Ohio Agricultural Clearance Program, which makes agricultural surplus from Ohio farmers available to food banks. The food banks distribute this food to their food pantry network either free of charge or at a steep discount.

In addition to government funding, private financial contributions from individuals, corporations, and private foundations subsidize the operating costs of food banks, including staff, food storage and distribution, and food purchases. Donations from private sources can make up a substantial portion of the food bank's budget. For instance, the Mid-Ohio Food Collective (MOFC) brought in $19.3 million in donations from individuals and corporations in 2023, nearly 60% of the non-food budget.[5]

Unlike food banks, which receive some federal and state support, food pantries rely almost entirely on private funding, which directly determines their size and scope. Some food pantries are like grocery stores, managing a facility open regular hours with shelves stocked with a wide variety of products. Others are smaller in scale and may distribute food to the community weekly or monthly out of borrowed space, like a church fellowship hall or school gymnasium. Some food pantries are independent, while others are a program within a larger organization, such as a community development organization. Pantries also differ in their methods of distribution; some pantries offer boxes of food packed by volunteers and staff, others allow customers to walk through the pantry to choose a limited number of items, and others combine both strategies, such as offering a pre-packed box of produce, meat, and dairy, and allowing customers to choose snacks and packaged foods.

The variation in the size of food pantries is a function of funding and staff, as well as organizational type. Typically, food pantries operate as a part of a local nonprofit organization, a church, or a branch

[3]Funding for administrative costs from TEFAP totaled $80 million in fiscal year 2024 (U.S. Department of Agriculture, Food and Nutrition Service 2024).

[4]Though Ohio CAN was active during the time period studied in this paper, it has since been discontinued due to funding cuts.

[5]For context, Food Bank News (2023), a publication that ranks US food banks by revenue, ranked MOFC 40th of the 300 US food banks studied, the second-largest by revenue in Ohio behind the Greater Cleveland Food Bank.

of a larger nonprofit organization. Anecdotally, food pantries would like to offer their customers more food, variety, and flexibility in pickup times, but can only expand their services with an increase in volunteer labor or funding. Many food pantries are all-volunteer organizations, and therefore can only offer food if enough volunteers are available to assist with distribution. These organizations also need devoted volunteers willing to manage the logistical needs of the pantry, such as ordering food, coordinating pick-up and delivery, marketing the services, and fundraising. Larger organizations with full-time staff still rely on volunteer labor to operate. For instance, full-time staff may coordinate a group of volunteers who then pack and distribute the food to the community. In 2022, food pantries in the MOFC network that were large enough to file a Form 990 reported a median of 10 staff members and 192 volunteers.

Funding limitations also determine how frequently a pantry is open, along with the variety of food available. For example, some pantries have limited or no refrigeration or freezer space. Without refrigeration, organizations must either distribute refrigerated food within a few hours of delivery to avoid spoilage, or avoid offering refrigerated products altogether. Similarly, organizations that do not have space to store leftover items must give away everything they purchase for distribution during their distribution hours. Often this means that these pantries order less food than they actually need in order to ensure all food is taken at the end of their distribution hours.

One way of addressing storage issues is offering pop-up distribution sites, known as "mobile food pantries" or "produce markets," in areas known to face food access challenges. Such pop-up distribution sites may be situated in low-income housing communities, community centers, library parking lots, or other centralized locations. Many food pantries coordinate mobile distribution, and the food bank studied in this paper also intentionally organizes several produce markets throughout the region to target underserved areas. A food bank employee trucks in food and stays until the end of the distribution to return undistributed food to the food bank, which circumvents the issue of storage.

Finally, although the food pantries purchase food from the food bank at a lower cost than they could from retailers, the food is still costly. MOFC offers some products free of charge, but pantries pay for other items. In 2022, for example, the pantries paid an average of $10,562 for an average of 236,781 pounds of food purchased from the food bank within the year.

2.2 The Mid-Ohio Food Collective

MOFC is a large nonprofit organization that operates the Mid-Ohio Food Bank. Each food bank within the state serves a different geographic region and MOFC provides food to over 700 agencies in 20 of the 88 counties in Ohio. Most of these agencies are food pantries, but some are senior centers, community meal sites, daycares, and other organizations.

This paper specifically looks at the 19 rural counties served by MOFC and the over 200 pantries that serve rural customers, as shown in Figure 1. I exclude customers living in Franklin County, which is mostly urban and home to Columbus. I focus on rural counties because, in general, rural counties face higher poverty and food insecurity rates than their urban counterparts (Haynes-Maslow et al. 2020), and yet rural areas are largely understudied. Feeding America (2025b) finds that 86% of counties with high food insecurity are rural. MOFC calculates a 'Missing Meal Index' using data from the American Community Survey and the Bureau of Labor Statistics to quantify the number of meals that members of the MOFC service area skip due to economic hardship.[6] They estimate that individuals below 200% of the federal poverty line skip 3.56 meals per week on average in the 20 county footprint. In Franklin County, the Missing Meal Index is among the lowest at 3.21 meals per week, while the index is above four meals per week in almost all rural counties. In addition, urban and rural areas in Ohio face different challenges in supporting low-income households, such as variation in access to public transportation, employment opportunities, and public services, making it difficult to compare access in urban and rural areas. I therefore leave research on urban food pantry access to future work.

In spite of the variation between pantries, all pantries within the MOFC network receive training and support and meet requirements set forth by MOFC, the USDA, and JFS. JFS requires households to earn less than 200% of the federal poverty line to be eligible for food pantry services, meaning that resources from food pantries in Ohio are available to a larger share of the population than SNAP benefits. Additionally, while SNAP benefits involve a long application process, work and asset requirements, and potentially long wait times (Herd and Moynihan 2019), food pantry customers can come to the food pantry and take food home in the same day. Many states allow individual organizations to determine if they would like to request proof of income, but Ohio is among the few states that are "self-declaration states," which means that food pantries and other agencies are forbidden from asking their customers to show proof of income in exchange for food (Feeding America Action 2020).

In addition to enforcing government guidelines, MOFC ensures that the pantries within the network adhere to additional requirements, including food safety training, food storage guidelines, civil rights training, and data and reporting requirements. MOFC imposes a minimum service requirement of three-days' worth of groceries at least once per calendar month, and strongly encourages pantries to provide five-days' worth of groceries if possible. Although food pantries can set geographic service area restrictions, they cannot require that their customers participate in activities unrelated to

[6]To arrive at this figure, MOFC calculates the total number of meals that families under 200% of the federal poverty line need, assuming three meals per person, and the cost of those meals using Feeding America's Average Meal cost, which is adjusted for county-level food prices and taxes. They then subtract out meals purchased by the individuals using the Bureau of Labor Statistics Consumer Expenditure Survey, meals provided by the government (SNAP, WIC, NSLP, etc.) using average expenditure and utilization rates, and food provided by charitable resources using their own data. The number of missing meals is the number of meals not covered by the individual, government, or charitable programs.

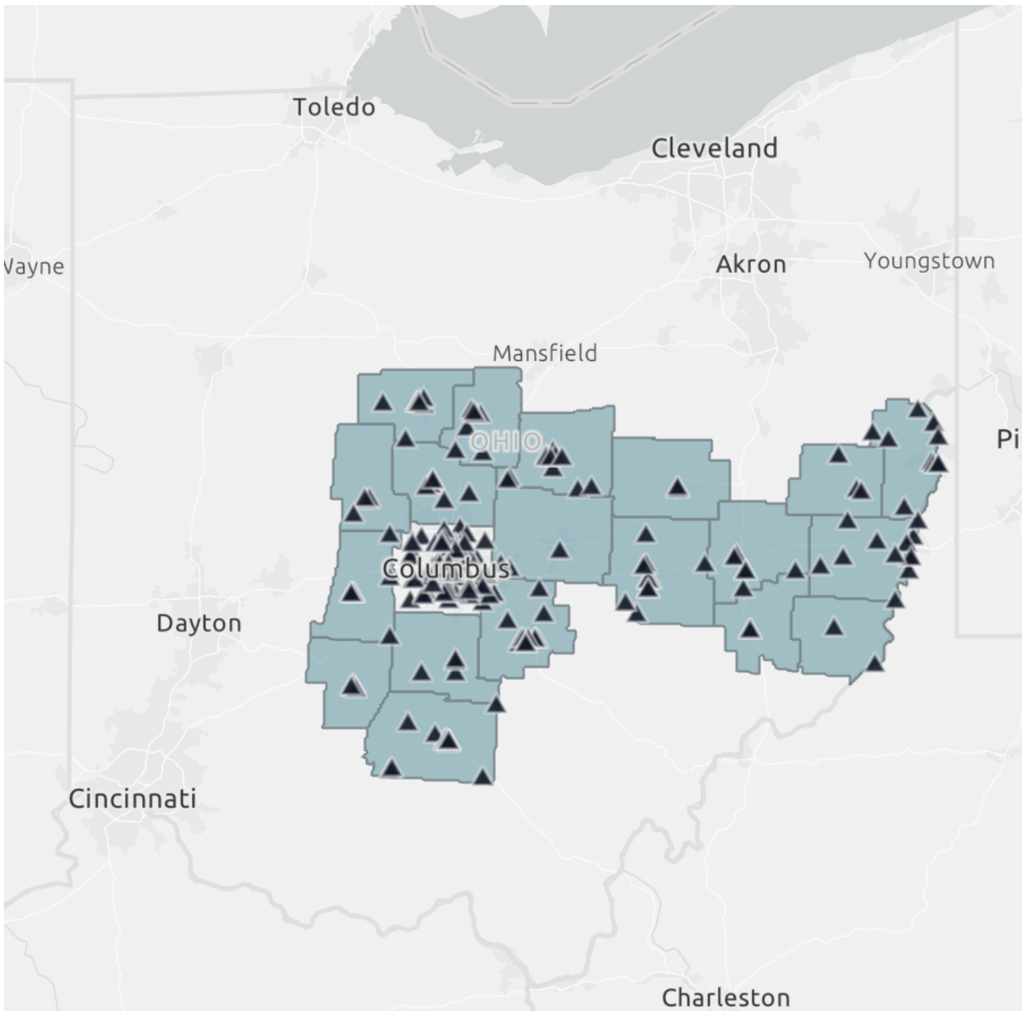

Figure 1: Map of MOFC Rural Counties & Pantry Locations

Notes: The map displays the rural counties served by MOFC and marks the locations of the over 200 food pantries accessible to rural households.

food service provision to receive food. In other words, pantries cannot require that their customer participate in religious services, sign petitions, or donate to a cause in exchange for food from MOFC. To enforce these policies, MOFC randomly audits the food pantries within the network and evaluates customer complaints.

Food pantries offer food in-kind, and users are limited by the food available at each pantry, as well as any restrictions imposed at the pantry-level, such as the hours the pantry is open, geographic service area restrictions, or limits on the amount of food each household can take. Staff at MOFC and the food pantries report that these restrictions are typically a result of insufficient resources to meet demand. For example, pantries in high-demand areas may restrict their service areas to better meet the need of individuals living closest to the pantry. However, customers can visit multiple pantries within the MOFC network, and therefore if they are unable to meet their needs by visiting one pantry, they can use another within the same day if necessary.

3 Data

3.1 Pantry Utilization and Order Data

The primary data come from the MOFC client-management system. When a customer first visits a pantry, they fill out an intake form, required by JFS for charitable food program eligibility. The form includes a section where households agree that their household income falls below 200% of the federal poverty line, along with the individual's address, household size and the number of children (birth to 17), adults, and adults over 60. Upon first visiting a food pantry in the MOFC network, the pantry captures this information through the digital client-management system and assigns each household a unique household identifier. On subsequent visits, customers check in to the pantry and verify their information is up-to-date, or update their profile if necessary. Their visit date is recorded and linked to all additional visits within the network.

The data include the recorded household demographics extracted from the intake forms along with the dates the customer visited a pantry. MOFC also generates geocoded household locations,[7] allowing me to match households with census tract data from the American Community Survey, which I use to define a neighborhood. I take the median income of each census tract in the 19 rural counties served by MOFC, and I divide the tracts into income quintiles. While I conduct my primary analysis at the individual-level, I assign each individual in the sample a neighborhood income quintile that matches the income quintile of the tract where they live. Because all food pantry customers are below 200% of the federal poverty line, the income quintile represents the income of the neighborhood where the customer lives, rather than the customer's own income. Identifying the neighborhood

[7] Exact household locations are masked to prevent individual identification.

income quintile allows me to compare how the income of potential donors and volunteers to the local food pantry impacts the food pantry's capacity and resources.

I also obtain detailed data about each food pantry from MOFC, including the pantry's geocoded location, allowing me to calculate the Euclidean distance between a food pantry customer's home location and all food pantries. To indicate organization type and structure, MOFC provided the Employer Identification Numbers (EIN) for most organizations. I fill in missing EINs by hand by searching for the organization using the ProPublica EIN lookup, a search engine that scrapes data from the available tax filings from the Internal Revenue Service (IRS). I then use the EINs to match agencies with their publicly-available tax records. Nonprofit organizations file a Form-990 tax document, and the IRS requires a different version of the form based on the organizations gross receipts and total assets. Organizations with gross receipts over \$200,000 or total assets over \$500,000 file a Form-990, while organizations under these thresholds file a shorter, Form-990-EZ. The smallest organizations, with gross receipts under \$50,000, file a Form-990-N, known as a 'postcard,' which essentially confirms that the nonprofit is still actively conducting business under their EIN.

Prior literature, such as Ruffini, Öztürk, and Pekgün (2025) or Heflin and Harrington Meyer (2025), rely on the National Center for Charitable Statistics (NCCS) to count the number of organizations that provide charitable food. However, NCCS only compiles data extracted from the 990 and 990-EZ tax forms, along with a list of 990-N filers. I match the NCCS data to the MOFC data and find that the NCCS data significantly under counts the total number of organizations providing charitable food. First, NCCS only considers organizations who submitted their tax form online. Because e-filing was not mandatory until 2022, several organizations are missing tax filing data from earlier years, meaning that studies using only NCCS data may not account for these organizations. I generate the missing data for these organizations by scraping handwritten, digital files from the IRS website. Next, relying on NCCS data overlooks small organizations or churches that do not file a 990. Comparing the NCCS data to the MOFC data, I find that the NCCS data only accounts for just over 35% of all of the organizations providing charitable food in the MOFC region, highlighting the importance of using local, administrative data when studying the efforts of small, community-facing charitable organizations.

In my work, using the NCCS data allows me to identify the organization type, particularly whether they are a church-based pantry, an independent nonprofit, or a branch of a larger nonprofit. Church-based organizations are not required to file a tax form.[8] Branches, which include smaller chapters of local or national organizations, use the larger organization's EIN for tax filing purposes. In addition to details on organization type, 990 and 990-EZ documents provide operational details, including

[8]If the organization does not have an EIN number, I look up their website to identify the type of organization. If I am unable to find the organization, I use details from the organization's name, such as "Methodist Church Pantry" to identify the organization.

the number of employees and volunteers, revenue (grants and dontation) and expenditures (employee compensation, advertising, and rent).

Finally, I observe the types of food the pantries order from MOFC through their online ordering system. The online system includes the full inventory of food available for purchase, including the name of the food product (i.e., 'Red Pepper Hummus') and several categories to describe the food (i.e. fresh, junk food, canned, etc.). I access the invoices for all pantry orders within the MOFC ordering systems, including the quantity (in pounds) and description of food ordered, including the name of the product and related food categories. I also obtain the date and time of the order. I aggregate the total number of pounds of food each pantry ordered per year, which I then divide by the number of visits to each pantry to proxy for the amount of food visitors could expect to receive at each visit.[9]

3.2 Summary Statistics

I focus on food pantry utilization between 2018 and 2023, when all pantries in the MOFC network used the client-management system. I also only include households with complete home location data.[10] Table 1 reports summary statistics about the sample of food pantry customers used for analysis, offering insights into the customer base. Overall, there are 102,403 unique households in rural counties that used a food pantry between 2018 and 2023. A majority of customers who visit the pantry are female, and the average household size is just under three individuals. Customers travel a one-way, Euclidean distance of 4.9 miles on average per visit.

To better understand pantry access, I define each customer's choice set, or the pantries the customer could realistically visit, as all food pantries within 20 miles of the customer's home, a distance that captures 90 percent of observed pantry trips. If a customer visits a pantry beyond this radius, I include the selected pantry in the choice set, which extends the maximum distance to about 23 miles in practice. Because many pantries create geographic restrictions to limit their service area, I exclude pantries that are not available to a customer, such as pantries with zip code restrictions that would make the customer ineligible. Based on this definition of choice set, I find that households choose from just over 25 food pantries on average.

Table 2 presents descriptive statistics on each of the census-tract neighborhoods that food pantry customers live in by income quintile. Panel A includes the total number of customers living in a neighborhood that matches each income quintile and the total number of census tracts that fall into

[9] Although pantries can acquire food through donations from local retailers, MOFC manages the relationship between pantries and most large chain retailers. This means that retailers can donate food to the MOFC and then deliver it directly to the local food pantry that needs it instead of transporting it to MOFC for redistribution. In recent surveys, pantries estimated that over 75% of their food stock came from MOFC. MOFC suspects that many pantries do not realize that food from chain retailers is also distributed through the food bank, and therefore the estimate of 75% likely underestimates the total amount of food supplied by MOFC.

[10] Because home location data define the choice set and demand for food pantries, individuals experiencing homelessness are not included in this analysis.

Table 1: Customer Summary Statistics

	Mean	Standard deviation
	Panel A. Overview	
Average age at first visit	45.1	16.6
Total pantry options	26.5	30.7
Average distance to chosen pantry	4.8	4.9
	Panel B. Gender	
% Male	30.5	
% Female	59.7	
	Panel C. Household size	
Total	2.8	1.9
Children	0.9	1.3
Seniors	0.4	0.7
Adults	1.5	1.2
Observations	102,403	

Notes: This table reports summary statistics about the population that used a food pantry in rural, MOFC counties between 2018 and 2023. Note that Male and Female do not add up to 100 percent as some pantry customers either did not report a gender or reported 'Other.' Total pantry options includes the count of pantries within a 20-mile radius of the customer's home location. Average distance is the average, linear distance from customer's home location to the pantry they visited. (Source: author's calculations using MOFC food pantry utilization data.)

each income quintile. More than five times as many food pantry customers live in the lowest income neighborhoods compared to the number of customers living in the highest income neighborhoods. For the most part, the number of customers in each income quintile decreases with neighborhood income, suggesting a higher need in low-income neighborhoods.

Panel B of Table 2 gives demographic details of the neighborhoods in each income quintile where food pantry customers reside. The average, median income of the highest income neighborhoods is nearly $100,000 more per year than the lowest income neighborhoods. Discussions with fundraisers for food pantries suggest that typical donors have a household income of $75,000 or more, and so higher-income neighborhoods likely have more potential donors. Similarly, charitable giving and volunteerism increase with education level (Jones 2023). Table 2 shows that the fraction of households with a bachelor's degree increases with income quintile, again suggesting that there are more potential donors living in higher-income neighborhoods.

On the other hand, according to MOFC's eligibility forms, a family of three earning 200% of the federal poverty line would earn $53,300 annually. Therefore many households in the first and second

Table 2: Demographics by Income Quintile

	Income quintile of customer's census tract				
	1	2	3	4	5
	Panel A. Overall				
No. of customers	36,660	21,400	21,639	15,593	7,111
No. of census tracts	65	66	65	65	64
	Panel B. Per census tract				
Median income ($)	40,936	56,297	68,532	84,767	136,924
	(7,127)	(3,281)	(4,377)	(5,941)	(34,743)
Population	3,046	3,820	4,033	4,049	4,986
	(1,125)	(1,005)	(1,159)	(1,577)	(2,032)
% With public benefits	0.12	0.06	0.04	0.03	0.01
	(0.05)	(0.02)	(0.02)	(0.01)	(0.01)
% With bachelor's	0.06	0.08	0.10	0.13	0.22
	(0.03)	(0.04)	(0.04)	(0.05)	(0.05)
% White	0.92	0.95	0.96	0.93	0.87
	(0.37)	(0.04)	(0.16)	(0.18)	(0.13)

Notes: This table presents the count of food pantry customers in each income quintile as well as census-tract level descriptive statistics. Income quintiles are defined at the census tract level, relative to all census tracts within the 19 rural counties in the MOFC region. Row (1) of Panel A is the total of number of households living in each income quintile that visited a food pantry in the data, and Row (2) of Panel A is the total number of census tracts that fall into each income quintile. Panel B presents descriptive statistics at the census-tract level. Row (1) of Panel B gives the median income of the quintile at the census-tract level, not the income of the customer. Panel B also shows demographic details about the census tracts in each income quintile including the average population, the share of individuals on any form of public benefits, the share of individuals with a bachelor's degree, and the share of individuals who identify as white. (Source: author's calculations using MOFC and ACS data.)

income quintile neighborhoods are likely eligible for food pantry services, even if they are not visiting the pantry. Likewise, the fraction of households in each income quintile on public benefits, including SNAP or Temporary Assistance to Needy Families (TANF), decreases with neighborhood income quintile, again indicating that households in the lower income quintiles are more likely to be eligible for food pantry services in conjunction with other services.

While each census tract is similar in size, the lowest income quintiles are less populous, likely due to rurality. Figure 2 shows the MOFC territory divided into census tracts. The darker blue shaded areas represent the higher income quintile neighborhoods while the lighter blue represent lower income quintile neighborhoods. The map shows that the higher-income neighborhoods tend to be clustered around Franklin County, while the lower-income neighborhoods are farther away toward the West Virginia border in Appalachian Ohio. The concentration of food pantries, which are represented by triangles, is much higher in Franklin County than in the rural counties, and there are fewer food pantries in the Appalachian region than there are near Franklin County. Pantry concentration varies and some households live near as many as 130 pantries, while others only have two. This means that in these rural areas, the resources available to the few local pantries directly determine households' access to charitable food.

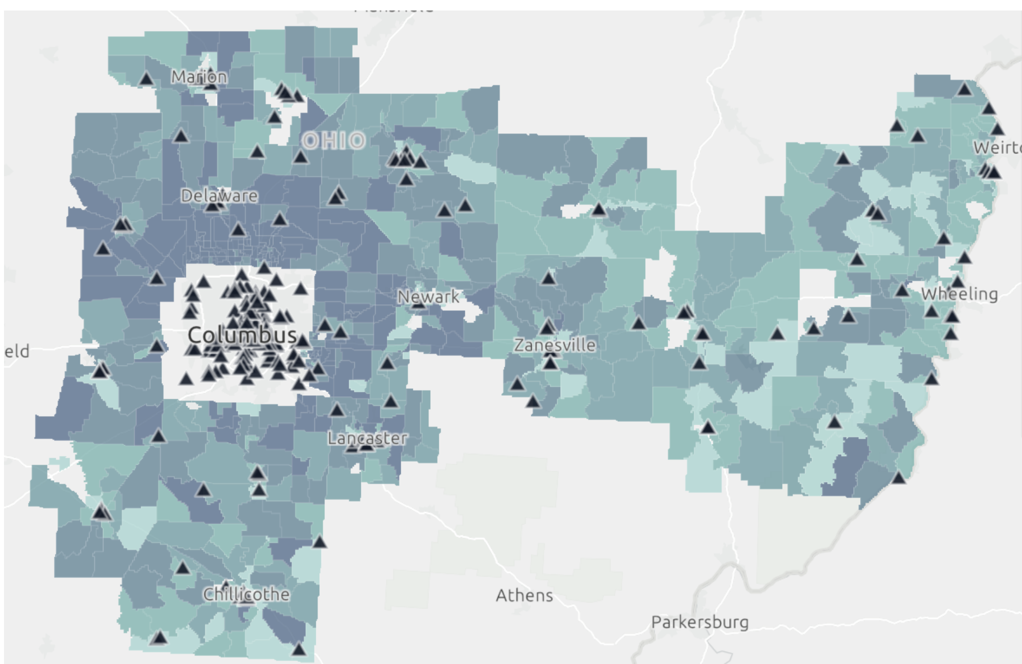

Figure 2: Map of Income Quintiles and Pantry Locations

Notes: Each polygon in the map represents a rural census tract. The darker colored polygons represent higher income quintiles, while the lighter colors represent lower income quintiles. The triangular points represent food pantry locations.

Next, Table 3 demonstrates the variation in the amount of food distributed by different types of food pantries by displaying the total amount of food ordered by each type of non-mobile pantry. Approximately half of the food pantries are churches, with over 100 church pantries available each year throughout the sample time frame. Nonprofits represent the next largest type of pantry, with nearly 80 nonprofits each year. Finally, branch organizations represent about 25 organizations in a given year. In total, there are over 200 food pantries each year, with some entry and exit, mostly around the COVID pandemic in 2020 and 2021. Over the six-year period from 2018 to 2023, 36 food pantries entered the sample. Of these, 22 entered during 2020 or 2021. A total of 19 pantries exited the sample, 12 of which were in 2021 or 2022. Appendix Figure 3 shows the total entry and exit by year.

While church food pantries are more common, they order less food, so households relying on them may receive less food than those with nearby nonprofits or branches. Nonprofits order 272,201 lbs (SD 448,499) of food per pantry on average compared to 88,910 lbs (SD 115,689) per pantry for churches. Branches also order even more, driven by two, large Mid-Ohio Markets that offer food multiple days per week for extended hours, and serve hundreds of customers daily. Excluding the Mid-Ohio Markets from the calculation reveals that branches order less food per year that nonprofits, for a total of 151,664 (SD 226,772) total pounds per year.[11] The share of different types of food ordered by different organizations is similar, though churches tend to order a larger share of canned goods and a smaller share of fresh products compared to other organization types.

Although nonprofits represent one type of food pantry, the amount of food they distribute varies dramatically based on the size of the nonprofit. I therefore break down the food orders of nonprofit pantries by filing type in Appendix Table 2, which includes the amount of food ordered by nonprofits that filed a Form-990, which I call 'large nonprofits,' and a Form-990-EZ, which I call 'mid-sized nonprofits.' I also show the amount of food ordered by nonprofits that file a 990-N and nonprofits that did not file.[12] Because non-filers tend to order about the same amount of food as 990-N filers and spend about the same amount, I refer to both 990-N and non-filers as 'small nonprofits.' Appendix Table 2 illustrates the variation in resources within nonprofit food pantries; large nonprofits order more than twice as much food as both mid-sized and small nonprofits. The large nonprofits also spend three times as much on food as small nonprofits. Small nonprofits still order more food and spend more than churches, on average. Perhaps surprisingly, the amount of food ordered by non-filers is comparable to the amount of food ordered by branch organizations excluding the large MOFC locations, but branches spend almost as much on food as large nonprofits on average. Large nonprofits also order a larger share of fresh products than any other type of organization; 57.7% of the food ordered by large nonprofit pantries includes fresh produce, meat, or dairy. Fresh products make up a

[11] Appendix Table 1 includes the breakdown of food ordered by branches without MOFC.

[12] These could be organizations that missed a filing year, or organizations that claim to be nonprofits but have not registered with the IRS.

Table 3: Food Pantry Orders by Pantry Type

	Type of pantry			
	All	Church	Branch	Nonprofit
	Panel A. Total ordered			
Quantity (lbs)	200,518.3	88,910.0	492,183.9	272,201.2
	(676,717.9)	(115,688.9)	(1,711,087.0)	(448,498.5)
Price ($)	8,569.1	4,789.6	18,805.4	10,773.8
	(17,628.3)	(7,421.9)	(34,916.1)	(17,738.3)
	Panel B. Quantity per food category (%)			
Bread	3.6	2.5	3.6	5.3
	(6.0)	(4.5)	(5.8)	(7.6)
Shelf-stable	28.4	31.6	28.9	23.2
	(16.9)	(17.1)	(16.8)	(15.3)
Fresh foods	43.3	39.4	46.1	48.4
	(22.0)	(20.4)	(24.5)	(22.3)
Dairy	5.8	5.3	6.3	6.4
	(4.4)	(4.1)	(5.0)	(4.6)
Meat	13.3	13.6	12.1	13.2
	(8.4)	(8.5)	(8.4)	(5.1)
Snacks	11.6	13.0	9.9	10.1
	(6.7)	(6.5)	(6.8)	(6.5)
Non-dairy beverages	7.4	8.1	7.4	6.4
	(6.8)	(7.0)	(7.5)	(6.1)
Non-food necessities	4.5	4.1	4.1	5.1
	(5.9)	(5.5)	(4.7)	(6.8)
Observations	1,354	727	170	457

Notes: This table shows the total amount of food in pounds that each type of food pantry orders on average, the amount spent on food on average, and the percent of food that falls into each category. Although most categories are self-explanatory, 'Shelf-stable' represents canned, boxed, or frozen foods, and 'Non-Food Necessities' includes items like cleaning products, personal hygiene products, diapers, and vitamins. The total price is the average amount spent on food and food delivery during each year for the pantries that ordered food. Note: fresh foods include meat, dairy, and produce. The food bank offers fresh food for free to all pantries. (Source: author's calculations using MOFC data.)

smaller share of the average amount of food ordered at between 38.9% and 46.7%. On the other hand, smaller nonprofits order a larger share of shelf-stable products with an average of 26.4% to 28.3% of mid-sized and small nonprofits orders including shelf stable products, compared to 17.8% of large nonprofit orders.

Table 4: Finances of Nonprofit Pantries

	Nonprofit	990	990-EZ
Total Revenue ($1,000s)	1,941.9	2,541.5	85.6
	(3,742.1)	(4,131.9)	(49.6)
Government Grants ($1,000s)		1,598.1	
		(3,130.2)	
Total Contributions ($1,000s)	1,577.9	2,062.3	78.3
	(2,656.9)	(2,895.8)	(46.7)
Program Revenue ($1,000s)	370.5	429.4	5.8
	(1,897.3)	(2,039.5)	(17.9)
Total Expenditures ($1,000s)	1,838.1	2,406.0	79.9
	(3,556.5)	(3,928.1)	(48.5)
Rent & Utilities ($1,000s)	17.3	20.7	6.8
	(61.6)	(70.2)	(12.9)
Total Salary Expenditure ($1,000s)	667.7	880.3	9.4
	(1,667.1)	(1,869.8)	(15.4)
Employees		33.9	
		(64.8)	
Volunteers		634.1	
		(1,383.2)	
Observations	213	161	52

Notes: This table presents summary statistics about the nonprofit organizations that file a tax document, therefore excluding 990-N and nonfilers. All nonprofit filers in the sample are in the first column, nonprofits that file a Form-990 in the second column, and nonprofits that file a Form-990-EZ in the third. The Form-990-EZ does not contain information on government grants, employees, or volunteers, so these variables are omitted in the first and third columns. Government Grants is conditional on receiving a government grant, for a total of 79 pantry-year observations. (Source: author's calculations using NCCS and IRS data.)

Though Form-990 filers are considered 'large' in the data, compared to national organizations, all nonprofit food pantries are small, with annual total revenue of just under $2 million,[13] as shown in Table 4. The table breaks down information from the nonprofit tax records for all Form-990 and Form-990-EZ filers, and then separately by filing type. The table only compares the largest types of nonprofit organizations, and still show considerable differences in the amount of funding each organization receives. A majority of the annual revenue for food pantries comes from contributions

[13]For comparison, the American Red Cross earned over $3 billion in total revenue in 2022, according to their Form-990 tax document.

from donors, corporations, and private foundations. Large nonprofits receive over two million dollars in contributions, while mid-sized nonprofits bring in closer to $80,000. Government grants are only reported for large nonprofits and the average grant amount was nearly $1.6 million.[14] A much smaller portion of an organization's budget comes from program revenue, which includes the sale of goods or services related to the nonprofit organization's mission. For example, an organization focused on community health may offer cooking classes for a fee, or may provide a box of community supported agriculture (CSA) from a farm operated by the nonprofit. The total revenue from programs for mid-sized nonprofits is $5,600, while program revenue for large nonprofits is $429,400, larger than the total revenue earned by mid-sized nonprofits.

I also include details on salary expenditure and rent and utilities. Larger organizations spend more on these expenses, likely because they have more staff and operate more programs than the mid-sized nonprofits. Mid-sized nonprofits spent some funds on rent and utilities in 18 pantry-year observations, and spent some funds on rent and utilities in 15 pantry-year observations. Organizations who do not use funding for staff rely entirely on volunteers, while organizations that do not spend on rent and utilities could be relying on donated space.

4 Conceptual Framework

My primary objective is to estimate how giving locally leads to disparities in the level of service that food pantries can provide in different geographic areas and, in turn, how variation in the quality of food pantry service contribute to disparities in consumer welfare. Food pantries share a common goal of reducing hunger and each food pantry focuses on fighting hunger in their own community subject to their own funding constraints. This system results in fewer individuals facing hunger in communities with food pantries, but does the community-centered approach lead to the greatest aggregate benefit for food pantry customers?

In this section, I consider how pantries determine their service design and food distribution levels based on the amount of funding and community support they receive. Formally, I indicate the amount of funding as $f(d, v)$, representing the total amount of pantry resources available to alleviate hunger for a pantry in the community. Community members contribute money (d) and volunteer time (v) to support the pantry's mission.

Each customer i derives utility, $u_i(b, \mathbf{x})$, from visiting a pantry. Utility depends not only on the amount of food received from the pantry, b, but also on the pantry's service design, represented by the vector $\boldsymbol{x}$. Service design includes the total hours of operation in a month, the specific days (e.g.

[14] The total revenue from contributions is only broken into 'Government Grants' and 'Total Contributions' on the Form-990 and not on the Form-990-EZ. However, as shown in the Table 4, government grants tend to be large, meaning that organizations that receive them likely do not fall under the threshold to file a Form-990-EZ. Large nonprofits received a government grant in 79 of the 161 pantry-year observations.

Monday, Sunday) and times (e.g. mornings, evenings) the pantry is open, limits on the number of visits allowed per month, and pantry type (e.g. church, nonprofit). For example, a customer may need to take off work to visit a pantry that is only open on Monday mornings, and may find visiting a pantry open on Friday evenings more convenient. Service design also includes the types of food that the pantry offers. A customer may value a bundle of products that includes dairy, meat, and produce offered at one pantry more than a bundle of products that includes canned vegetables, rice, and juice offered at another pantry, even if the total amount of food is the same.

Although the food a customer receives from the pantry is free to the customer, the customer does incur some cost with each visit, $c_i(a_i)$. The cost is a function of the distance that customer i travels to the pantry, a_i, and a customer's sensitivity to travel costs vary with the customer's characteristics, like household size and neighborhood income.

Distributing food is costly to the food pantries, and the amount of funding received by each pantry serves as a budget constraint. A pantry's cost is a function of the total amount of food purchased to distribute, $B = \sum_i b_i$, as well as the service design they choose, $\boldsymbol{x}$. Each pantry will choose a combination of food to distribute and service design characteristics in order to maximize the benefit that the customers who visit the pantry gain from each visit constrained by f, such that $f(d, v) = c(B, \boldsymbol{x})$. The subset of customers who visit a given pantry j is represented by $\mathcal{I}(b_j, \boldsymbol{x_j})$ and is a function of the food pantry's service design and level of food distributed.

Formally, pantries solve the following problem:

$$\begin{aligned} &\max_{b_j, \boldsymbol{x}_j} \sum_{i \in \mathcal{I}(b_j, \boldsymbol{x}_j)} u_{ij}(b_j, \boldsymbol{x}_j) - \sum_{i \in \mathcal{I}(b_j, \boldsymbol{x}_j)} c_i(a_{ij}) - c_j(B_j, \boldsymbol{x}_j) \\ &\text{s.t.} \quad c_j(B_j, \boldsymbol{x}_j) = f_j(d_j, v_j) \end{aligned} \tag{1}$$

Food pantries each face an individual budget constraint based on the support from their own donors and volunteers, where donors and volunteers give to pantries according to their own preferences. Volunteers, for instance, may choose to work at a pantry that is easy for them to drive to and is located in a neighborhood where they are comfortable. Donors may give to a pantry that they are familiar with, perhaps because they see it on their way to work or because it is promoted at their place of worship. In other words, it is likely that the amount of funding each pantry receives is not solely driven by demand for the food pantry's services, rather by donor and volunteer preferences. This means that aggregate welfare could possibly be improved by redistributing the total amount of funding received by food pantries according to *customer* demand, rather than donor preferences. In other words, there may be alternative distributions of the total amount of funding received by pantries, $(f_1^*, f_2^*, ..., f_J^*)$, that improves aggregate welfare.[15]

[15]Improving aggregate welfare also assumes that the utility of donors and volunteers increases if aggregate customer utility is maximized. However, if supporters prefer to increase utility only for customers within a certain region, for

While mission-driven pantries try to maximize the benefits their customers receive, they are not able to easily change their service design. Therefore, these characteristics can be taken as given when considering customer welfare. In practice, pantries can rapidly change their supply of food, given additional funding. Increasing or even changing hours of operation requires an additional supply of food, and therefore the primary constraint that pantries face is funding for food. In other words, conditional on funding, pantry characteristics are plausibly exogenous to the unobservable preferences of the customers who visit them.

To understand how local giving may result in a distribution of funding that restricts access in areas that need the most support, consider two food pantries. The first pantry is in a low-income area with many potential customers and few donors and volunteers, and therefore the pantry is resource-constrained. This restrictive budget and high demand means that the pantry will choose limit the amount of food they give away so that they are able to meet their budget restriction.[16] In this stylized example, customers who visit the pantry will receive less utility per visit than they would have if the pantry received more funding. Because of the restrictions in the distribution times, some customers may not be able to visit the pantry at all and may choose to source all of their meals from grocery stores. If these households are particularly income-constrained, this may mean they are unable to adequately meet their food needs.

The other pantry is in a higher-income area and not only receives significant contributions from donors and volunteers, but also has very few customers. This means that the customers that visit the pantry in the high-income area receive a lot of utility from each visit. Additionally, because the pantry in the high-income area has more resources, customers from the low-income area may travel farther to access the higher-capacity pantry. This would suggest that the high-capacity pantry provides so much utility that visiting the pantry is worth the additional travel costs for customers in low-income areas. It is possible, however, that taking some funding from the pantry in the high-income area and giving it to the pantry in the low-income area could significantly increase utility for the customers in the low-income area without significantly decreasing utility for the customers in the high-income area. Customers in the low-income area may not need to travel as far to receive high-quality pantry service, for example, or they may be able to visit the pantry more frequently because the pantry can now offer more frequent distribution.

In the next sections, I analyze the geographic distribution of food pantry characteristics to determine if pantries in low-income areas, which may have fewer donors and volunteers, impose more restrictions

instance, if they prefer to support their neighbors, it is possible that donor and volunteer utility would decrease if funding were reallocated.

[16]In practice, meeting the lower budget constraint may involve limiting the number of visits each customer is allowed in a given month. Alternatively, some pantries are open for just a few hours in a month, restricting their service to only the customers who are able to visit the pantry during those hours. This often means that pantries are open during inconvenient hours, such as during the workday. Some pantries will offer food distribution on just a few days a month, and will distribute food until it is all gone, meaning that individuals run the risk of waiting for food that they ultimately will not receive.

on their customers. I then estimate a demand model to quantify how variation in food pantry access impacts the value derived from each food pantry visit. Using the parameters from the demand model, I propose an alternative funding distribution that improves aggregate consumer welfare by increasing the utility of customers in low-income areas without substantially decreasing the utility of customers in high-income areas.

5 Descriptive Analysis

In this section, I document differences in food pantry access by the income of a customer's neighborhood. If food pantry resources are determined by donors and volunteers, then households in higher-income areas will live near more, well-resourced food pantries compared to customers in lower-income areas. Because pantry resources determine both distribution hours and visit restrictions, pantries near customers in high-income neighborhoods may be open more often and impose fewer restrictive visit policies. Further, more resources in high-income areas may support a greater number of food pantries overall.

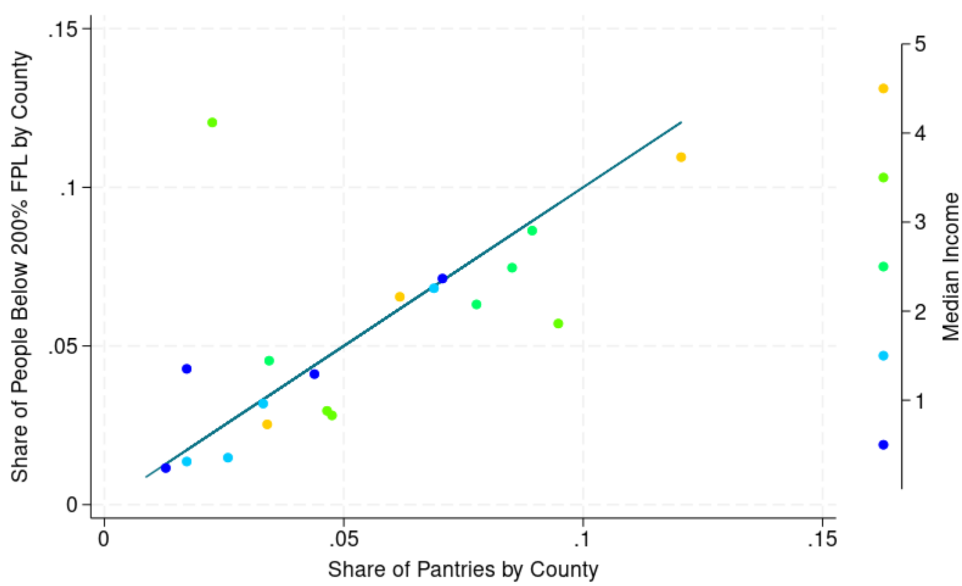

Figure 3: Share of Pantries vs. Share of Pantry-Eligible Individuals by County

Notes: The figure plots the share of households below the 200% of the federal poverty line in each county against the share of food pantries in each county, and a 45 degree line. Points above the line have a disproportionately high share of individuals below 200% of the federal poverty line relative to the share of food pantries, while points below the line have a disproportionately high share of pantries relative to the number of eligible individuals. Each point is colored according to the county income quintile with yellow points representing the highest income quintile counties and dark blue points representing the lowest income quintile counties.

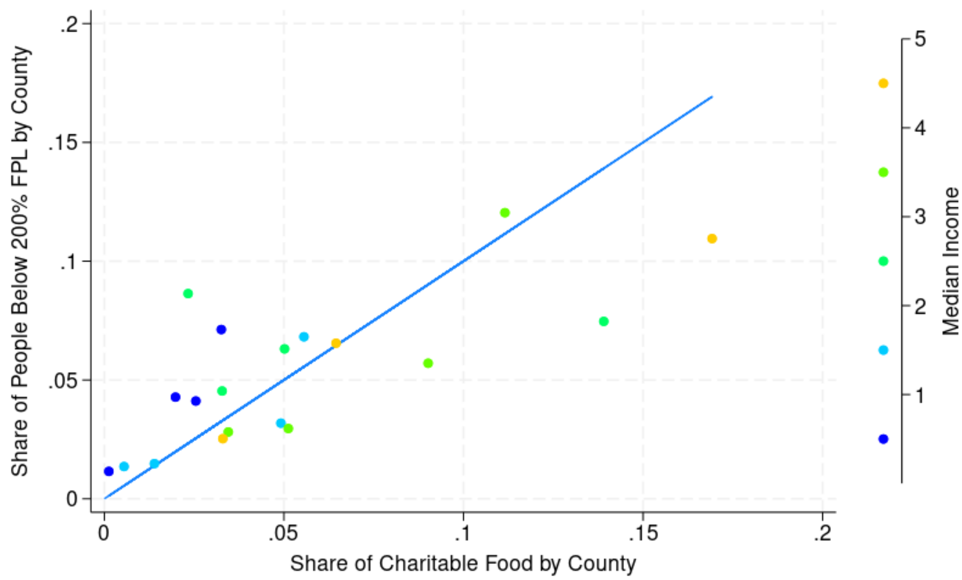

Figure 4: Share of Charitable Food vs. Share of Pantry-Eligible Individuals by County

Notes: This figure shows the share of food in pounds purchased from MOFC by food pantries in each county against the share of households below the 200% of the federal poverty line. Points above the line have more individuals below below 200% of the federal poverty line relative to the amount of food they purchase, while points below the line purchase more food relative to the number of households below 200% of the federal poverty line. The points are colored according to the income quintile of the county.

I begin by broadly considering the number of food pantries within a given county compared to the number of people eligible for services. If pantry locations were driven by customer demand, the distribution of pantries would align with the share of eligible customers living in each county; for example, if a county is home to 5% of the total number of individuals below 200% of the federal poverty line in the region, that county would have 5% of all food pantries in the region.

Figure 3 plots the share of food pantries in the MOFC region located in each county against the share of households below 200% of the federal poverty line in the region that reside in each county along with a 45-degree line. Counties above the 45-degree line contain a larger share of the region's eligible households than their share of food pantries, whereas counties below the line contain a larger share of pantries than eligible households. I also identify the income quintile of each county by marker color.

Most of the counties are clustered along the 45-degree line or just below, suggesting that the share of pantries and the share of eligible households is equal in these counties. A few counties have a higher share of eligible households than pantries, but most counties that deviate away from the 45-degree line have a disproportionately high share of pantries when compared to the share of eligible individuals.

Not all food pantries distribute the same amount of food, so it is possible that a county with a disproportionately high number of pantries may actually receive a smaller proportion of charitable food. Therefore, Figure 4 takes the share of all charitable food distributed in each county and compares it to the share of eligible households. Nearly all counties in the lowest two income quintiles are above the 45-degree line, meaning that the share of food distributed by pantries in these counties is less than the share of eligible food pantry customers. On the other hand, almost all higher-income counties are located below the line. Both Figure 3 and Figure 4 are consistent with a mismatch between where food pantries are located and where food pantry customers live.

Next, Table 5 shows how individual food pantry access varies for customers residing in different income quintiles, indicating that food pantry customers living in the highest income quintiles have access to more pantries of every type within their choice set. Panel A shows that there are nearly 80 food pantries within 20 miles of a customer living in the highest-income neighborhoods and only 17 pantries within 20 miles of a customer living in the lowest-income neighborhoods. Customers living in high-income neighborhoods also live near more pantries with more flexibility, as shown in Panels B-D. On average, customers in high-income areas live near 46 pantries that are open at least weekly, 52 pantries open on weekends, and eight pantries that do not restrict the number of visits a customer can make. Customers in the second-lowest income quintile neighborhoods live near fewer pantries than those in the lowest-income quintile neighborhoods, with only 14 food pantries and half as many open at least weekly.

The descriptive statistics in Table 5 support the theory that pantries in low-income areas are more restrictive than pantries in high-income areas on average. However, recall that the highest-income neighborhoods are more populous and tend to be clustered around Franklin County, suggesting that the apparent advantage in food pantry access may reflect easier access to urban spaces. To test whether the variation in pantry access reflects differential access to donors and volunteers, I look at how the number of nearby pantries varies with neighborhood income controlling for population and proximity to Franklin County using the following specification:

$$Y_i = \alpha_i + \sum_{q=2}^{5} \beta_1 \cdot [i \in IncomeQuintile = q] + \beta_2 Pop_i + \beta_3 \mathbf{1}[FC_i] + \varepsilon_i \tag{2}$$

Where Y_i is the number of pantries in individual i's choice set and β_1 represents the change in Y_i associated with a change in individual i's census-tract-level income quintile, relative to the lowest income quintile. Pop_i is a control for the population of individual i's census tract and $\mathbf{1}[FC_i]$ is an indicator equal to one if individual i lives in a county adjacent to Franklin County. β_1 captures the difference in the number of food pantries within the choice set of a household living in each income quintile, relative to income quintile one. I plot the β_1 coefficients and 95 percent confidence intervals in Figure 5 below.

Table 5: Pantry Access by Income Quintile of Customer's Census Tract

	Income quintile of customer's census tract				
	1	2	3	4	5
	Panel A. Number of nearby pantries				
Total	16.7	14.1	22.7	49.8	78.5
	(16.4)	(12.2)	(23.7)	(40.2)	(43.3)
Nonprofits	5.6	5.0	7.9	16.2	24.9
	(5.1)	(5.0)	(7.9)	(16.2)	(12.6)
990	1.5	1.3	2.6	6.3	9.9
	(2.6)	(2.2)	(3.9)	(6.6)	(8.0)
990-EZ	0.7	0.6	0.8	1.7	2.5
	(0.8)	(0.6)	(1.0)	(1.3)	(1.3)
Postcard	1.2	1.2	1.8	2.5	3.0
	(1.3)	(1.3)	(1.6)	(1.8)	(1.9)
Churches	9.2	7.5	11.8	26.6	43.1
	(9.4)	(7.1)	(13.4)	(22.8)	(25.3)
Branch	1.9	1.5	2.8	6.6	9.8
	(2.3)	(1.9)	(3.1)	(5.5)	(5.5)
	Panel B. Open frequency				
Open Weekly	14.1	7.3	12.5	29.2	45.9
	(14.2)	(8.0)	(14.1)	(24.0)	(25.3)
Open Semi-Monthly	3.4	3.2	4.7	10.0	16.9
	(3.6)	(2.4)	(5.3)	(9.2)	(10.7)
Open Monthly	3.2	2.7	3.9	7.2	10.2
	(2.7)	(2.2)	(3.3)	(4.7)	(5.1)
Infrequent	1.1	0.9	1.4	2.9	4.9
	(1.1)	(0.9)	(1.7)	(2.8)	(3.1)
	Panel C. Weekends				
Open on weekends	11.0	9.3	15.0	32.9	51.5
	(11.0)	(8.6)	(15.7)	(26.0)	(28.0)
	Panel D. Visit restrictions				
Weekly Cap	14.1	11.9	19.1	42.2	66.7
	(14.2)	(10.5)	(20.6)	(34.5)	(37.4)
Monthly Cap	1.2	0.9	1.2	2.0	2.8
	(1.1)	(0.9)	(1.0)	(1.5)	(1.5)
No Cap	1.5	1.4	2.4	5.2	8.4
	(1.9)	(1.8)	(2.7)	(4.9)	(5.4)
Observations	36,660	21,400	21,639	15,593	7,111

Notes: This table gives a count of the average number of food pantries within 20 miles of a customer living within each income quintile by pantry characteristics. Panel A breaks down the number of pantries by pantry type, including church, branch, and nonprofit. Panel B gives the average number of pantries that are open weekly, semi-monthly (2+ weeks per month), monthly, or less than monthly. Panel C gives the count of pantries open on Saturday or Sunday. Panel D presents the count of pantries that restrict the number of visits each customer is allowed to weekly or monthly, along with pantries that do not restrict visits. (Source: author's calculations using MOFC data.)

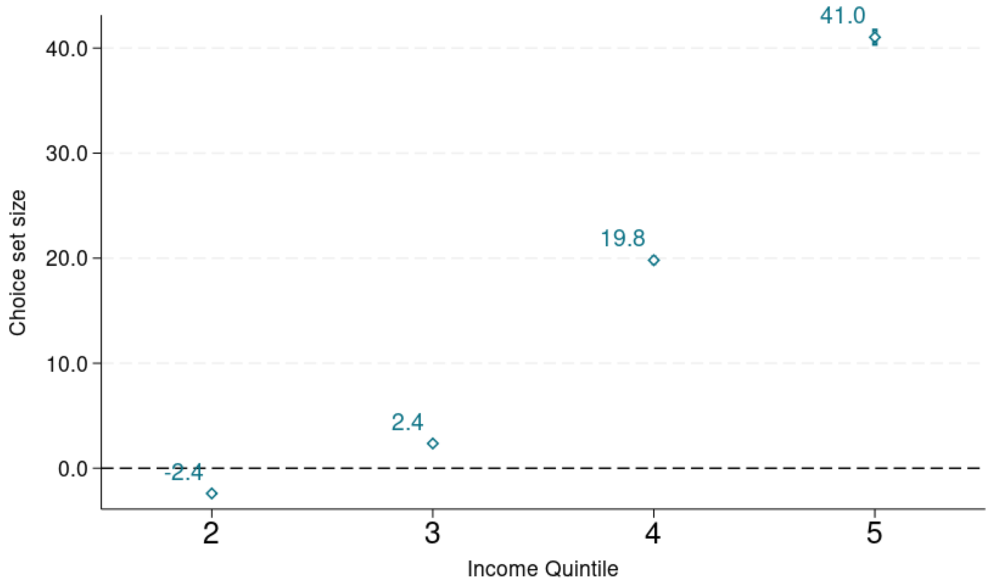

Figure 5: Variation in Total Options in Choice Set by Income Group

Notes: This figure plots the β_1 coefficients and 95 percent confidence intervals from Equation 2, which gives the change in the count of food pantries in the choice set of a customer living in each income quintile, relative to the count of pantries in the choice set of a household living in lowest income quintile neighborhood.

The results reveal disparities in pantry access even when controlling for population and proximity to Franklin County. The results indicate that households in the highest income quintiles have 41 more food pantries in their choice set relative to households in the lowest income quintiles. Additionally, households in the highest-income neighborhoods have more pantries of every type near their homes compared to households in the lowest-income neighborhoods, including 13 more nonprofit food pantries, five more pantries without visit restrictions, and 27 more pantries open on weekends.[17]

Finally, Table 6 considers how neighborhood income relates to a lack of access to pantries certain characteristics. Just over 3% of food pantry customers in low-income neighborhoods do not live near a nonprofit food pantry, for a total of 1,143 households without access. Given that nonprofit food pantries distribute significantly more food than other types of food pantries, these customers may not have access to as much food as other households. On the other hand, all households in the highest two income quintiles have access to at least one nonprofit food pantry in their choice set.

One of the most striking differences is the number of households in low-income neighborhoods

[17] I test the sensitivity of this result to different choice set radii in Appendix B. The tests show that the number of food pantries within a fifteen mile radius increases with income quintile, similar to the twenty mile radius. Within a ten mile radius, households in highest-income neighborhoods have three more food pantries than those in the lowest income quintiles. Within a five mile radius, households in the lowest income quintile have just three more food pantries in their choice set compared to households in the highest income quintiles, even though the number of customers in the lowest income group is five times larger than the number of customers in the highest income group.

without access to a food pantry that does not restrict the number of days customers can visit; over 10,000 households in the lowest-income neighborhoods do not have access to a food pantry without visit restrictions, which is nearly one third of all households in the lowest-income neighborhoods. There are just over 7,000 food pantry customers living in high-income neighborhoods total, and all but four percent live near at least one pantry without restrictions on the number of visits. Visit limits usually reflect situations where demand for charitable food exceeds the supply, pointing toward more restrictive budgets in the lowest-income neighborhoods.

Table 6: Percent of Customers Lacking Nearby Pantries with Specific Characteristics (by Tract Income Quintile)

	Income quintile of customer's census tract				
	1	2	3	4	5
	Panel A. Type of pantry				
Nonprofit	3.12	1.25	2.63	0.00	0.00
Church	0.00	0.00	0.02	0.03	0.80
Branch	16.00	14.16	14.00	5.49	1.66
	Panel B. Open frequency				
Open weekly	0.23	0.31	0.20	0.00	0.00
	Panel C. Weekend availability				
Open on weekends	1.01	0.64	0.51	0.00	0.00
	Panel D. Visit restrictions				
Weekly Cap	0	0	0	0	0
No Cap	27.74	34.80	16.90	11.31	4.06

Notes: Table 6 presents the percent of food pantry customers living in each income quintile that do not have a pantry within twenty miles of their residence with certain characteristics. Panel A breaks down the percent of customers without access by pantry type, and Panel B shows the percent that do not have access to a pantry that is open weekly. Panel C shows the percent of people that do not have a pantry open on Saturday or Sunday. Panel D shows the percent of people without access to a pantry that allows weekly visits or does not restrict visit frequency. (Source: author's calculations using MOFC data.)

Although food pantry customers are more likely to live in neighborhoods with lower median incomes, these households have fewer food pantries near their residence and face more restricted access in visiting the nearby pantries. Pantry characteristics, such as hours of operation and visit limits, are largely determined by the funding available to purchase food, rather than by the unobserved preferences of customers. Therefore, differences in service design across different neighborhoods can be treated as plausibly exogenous.

To quantify how these differences in pantry characteristics translate into utility for customers in different neighborhoods, I estimate a demand model that leverages variation in pantry choice sets available to different households. This allows me to identify customer preferences for observable pantry characteristics and assess how the existing geographic distribution of food pantries affects consumer welfare across income quintiles.

6 Demand Estimation

To investigate if variation in food pantry access leads to differences in the welfare gained from visiting a pantry, I estimate a discrete choice model that allows for heterogeneous consumer preferences. Each week, customers make a discrete choice between visiting (i) one of the food pantries within a 20 mile radius of their home location;[18] (ii) visiting a produce market; or (iii) an "outside option," of sourcing all meals from supermarkets, restaurants, and other locations. Formally, let $\mathcal{J}_i$ denote the set of food pantries located within 20 miles of customer i's home location, along with an option to visit a produce market. Then customer i faces a discrete choice between these nearby pantries (indexed by $j \geq 2$), a produce market (indexed by $j = 1$), or the "outside option" (indexed by $j = 0$). The customer, then, will choose the option that maximizes her utility.

Customer i's conditional indirect utility u for choosing pantry j during week t is represented by:

$$u_{ijt} = \boldsymbol{x_{ijt}}\boldsymbol{\beta}_i - \alpha_i D_{ij} + \varepsilon_{ijt}, \tag{3}$$

where $\boldsymbol{x}_j$, comprises a vector of pantry characteristics, including the type of pantry (nonprofit, church, mobile/produce markets), restrictions on the number of visits per month, pantry open times during week t, and the amount of food in different categories (produce, dairy, etc.) that the customer might expect to receive per visit.[19] I also include the count of SNAP-retailers within a five mile radius of the customer's home location[20] to allow preferences to vary based on access to the outside option. A higher concentration of nearby food retailers makes it easier for customers to substitute between a food pantry and a food retailer, and therefore including the count of nearby retailers captures outside

[18] The choice set is adjusted to account for a food pantry's open times such that a customer is only choosing among the pantries open at least one day in week t. For example, if a pantry is only open the first week of the month, that pantry is only included in a customer's choice set during the first week of the month.

[19] Because customers typically do not know what is available at the pantry before visiting, I create this variable by taking the total amount of food ordered by each pantry annually and dividing it by the number of annual visits. This reflects the type of food that is *typically* available at the pantry.

[20] To identify nearby food retailers, I use data from the USDA's Historical SNAP Retailer Locations (U.S. Department of Agriculture, Food and Nutrition Service 2025a), which includes the latitude and longitude of retailers that accept SNAP benefits. I match each customer's home location with all food retailers within a five mile radius of their home location. Retailers that accept SNAP must sell or stock a certain amount of staple food items, including cereals, dairy, meat, fruits and vegetables. Using SNAP retailers excludes some retail options, such as restaurants or grocery retailers that do not meet SNAP requirements.

option access.[21]

The customer's utility is decreasing in the one-way, Euclidean distance D_{ij} from the customer's home to the food pantry. In Equation (3), the coefficient α_i measures customer i's sensitivity to distance.[22] Because food pantries offer food free to their customers, travel time is the only observable direct cost that customers face. Finally, customer i exhibits idiosyncratic likes or dislikes ε_{ijt} for pantries j at time t, which I assume are independently and identically distributed according to a Gumbel distribution.

I allow customer i's preferences to depend on a vector of household-level demographics H_{it}, including household size and neighborhood income quintile. Including household size allows me to capture how preferences vary with different levels of a household's need for food; customers in larger households may prefer pantries with different characteristics than customers in smaller households, for example. Finally, allowing preferences to vary by income quintile allows me to identify if customers living in different income quintile neighborhoods experience different sensitivities to travel or different preferences for food pantry characteristics.

Letting h index various household demographics, distance sensitivity is specified as:

$$\alpha_i = \alpha + \sum_h \alpha_h H_{it}^h. \tag{4}$$

In addition, I allow customers' tastes for pantry characteristics to vary by customer demographics as well. Specifically, a customer's taste $\boldsymbol{\beta}_{ik}$ for pantry characteristic k is given by:

$$\boldsymbol{\beta}_{ik} = \boldsymbol{\beta}_k + \sum_h \boldsymbol{\beta}_{kh} H_{it}^h. \tag{5}$$

This model identifies how variation in food pantry service design and the amount of food distributed impacts the benefit that customers from different neighborhoods derive from each visit to a food pantry. I assume that the customer's idiosyncratic preferences, ε_{ijt}, for food pantries are uncorrelated with the explanatory variables in the utility function. As discussed in Section 4, pantry characteristics, such as hours of operation and visit restrictions, are largely determined by funding constraints rather than customer preferences. Similarly, I assume that households do not locate based on access to particular food pantries.[23] Taken together, these assumptions suggest that pantry characteristics are plausibly exogenous when estimating customer utility.

Another assumption is that the distance cost that customers face is the travel from their home

[21] Appendix Table 3 details differences in household size and food retailers by income quintile.

[22] Other costs to food pantry service may include the time spent waiting for food at the pantry, childcare costs, foregone labor hours, or the stigma associated with visiting a food pantry.

[23] This assumption is commonly made in research on school-choice (see Agarwal and Somaini (2018) and Abdulkadiroğlu, Agarwal, and Pathak (2017)) as well as in the existing research on food pantries (Byrne and Just 2023).

location to the food pantry. It is possible that households visit a food pantry in a multi-stop trip, such as from work, also known as trip-chaining. Evidence from grocery shopping literature indicates most households visit the grocery store directly from home, and finds that only 8% of grocery store trips are directly from work or part of a trip chain from work, 28% of grocery store trips are part of a trip chain to and from home, and 64% of grocery store visits are directly from home (Ver Ploeg et al. 2015).

Visiting a food pantry is not equivalent to visiting a grocery store because the restrictions that pantries impose make it difficult for customers to visit from work or other activities. Visiting a food pantry can also be a time-consuming process; although my data does not include information on wait times, Gose (2023) studied food pantries in Atlanta and found that customers waited between ten minutes to two hours to receive food. Conversations with food pantries in the MOFC network confirm that wait times can be lengthy for customers in the MOFC region as well, particularly when the pantry opens. Therefore, households that would like to pick up food from a food pantry probably need to schedule around the distribution times rather than their own schedules.

7 Results

Table 7 reports the estimated coefficients from a model without the demographic interactions to demonstrate how food pantry characteristics shape the level of utility derived from a food pantry visit on average.[24] Broadly, the estimates reveal patterns in food pantry preferences related to the (i) opportunity cost of visiting the food pantry, (ii) the food pantry's service design, and (iii) the concentration of local retailers, or the outside option, that a customer can choose from.

The results indicate that households prefer pantries that are closer to home, as expected. Because travel distance represents the primary cost of visiting a pantry in this setting, this finding suggests that households seek to minimize travel costs, all else equal. Households also favor pantries with distribution times in the mornings or evenings and on Fridays, while distribution times on other days have comparatively small effects on pantry choice. Translating these preferences into distance equivalents, customers would be willing to travel an additional 1.2 miles to visit a pantry open in the mornings or evenings, and an additional 1.7 miles to visit a pantry open on Fridays.[25]

Compared to distribution times, the amount of food offered per visit does not impact utility significantly, as shown in Panel C of Table 7. Customers may slightly prefer pantries that offer more bread, dairy, juice or other beverages, and snacks per visitor over pantries that offer more shelf-stable food and non-food necessities, such as toothpaste, diapers, or detergent.[26] Panel D of Table 7 shows

[24] A table of the base coefficients estimated from a model with the demographic interactions is available in Table 4.

[25] To translate the parameters to distance equivalents, I take Using these parameters,($\frac{\beta}{\alpha}$), where α is the distance coefficient.

[26] Snacks include items like pudding, desserts, and potato chips, but also items like salad dressing and pizza dough. Shelf-stable food includes canned fruits and vegetables, pasta, and frozen meals like pizza or burritos. Dairy includes

Table 7: Coefficient Estimates for Model without Demographic Interactions

	Point estimate	Standard error
	Panel A. Travel cost	
Distance × − 1	0.259	0.000
	Panel B. Pantry flexibility	
No cap on groceries obtained	–0.691	0.006
Limit one visit per week	–1.871	0.006
Open mornings	0.317	0.003
Open afternoons	0.073	0.003
Open evenings	0.313	0.003
Unknown open hours[a]	–0.780	0.006
Open Sundays	0.090	0.006
Open Mondays	–0.349	0.002
Open Tuesdays	–0.063	0.003
Open Wednesdays	0.153	0.003
Open Thursdays	–0.082	0.003
Open Fridays	0.429	0.003
Open Saturdays	–0.120	0.003
	Panel C. Food per customer	
Bread per visitor (lb)	0.012	0.000
Shelf stable food per visitor (lb)	–0.024	0.000
Fresh food per visitor (lb)	–0.003	0.000
Dairy products per visitor (lb)	0.045	0.000
Meat per visitor (lb)	–0.008	0.000
Snacks per visitor (lb)	0.031	0.001
Non-dairy beverages per visitor (lb)	0.011	0.000
Non-food necessities per visitor (lb)	–0.025	0.000
Unknown no. of visits[b]	–0.926	0.003
	Panel D. Pantry type	
Church	–0.056	0.004
Mobile pantry or produce market	–0.926	0.003
Nonprofit	0.306	0.003
	Panel E. Retail availability	
Outside option × no. nearby grocers	–0.019	0.000
Outside option × no. nearby local food stores	0.091	0.002
Outside option × no. nearby small retailers	–0.003	0.000
Outside option × no. nearby supermarkets	0.114	0.001

Notes: This table reports coefficient estimates for a conditional logit model of food pantry choice with neighborhood income–invariant preferences (see Equation (3)). Concerning pantry type (Panel D), the omitted type of pantry is branch locations. The rightmost column reports heteroskedasticity-robust standard errors.

[a] Open hours cannot be inferred because pantry does not report visit times.

[b] When the number of weekly visits is unknown, this variable is defined as one and the per-customer food variables are set equal to zero.

that customers also have a stronger preference for nonprofit pantries and would travel an additional 1.2 miles to visit a nonprofit pantry all else equal.

Finally, Panel E of Table 7 shows how increasing the number of nearby food retailers affects the value of the outside option. Customers who live near more supermarkets, defined as large retailers with more than ten checkout lanes that sell groceries and other merchandise, or local food stores, including specialty stores (e.g. bakeries, butchers, or produce stands), farmers markets, and food co-ops, derive more benefit from the outside option. One interpretation of this result is that ample nearby retailers give customers attractive alternatives to the food pantry, so choosing to visit the pantry despite the outside options suggests that each food pantry visit provides a high value to the customer. Alternatively, more supermarkets and local food stores may improve the pantry itself; for example, if a local bakery donates day-old pastries to their nearby food pantry, this may make the food pantry's offerings more valuable to the customer. By contrast, the concentration of dollar stores and convenience stores does not meaningfully affect the value of the outside option. This suggests that households seldom substitute between food pantries and small retailers. The same seems to be true of grocery stores, defined as stores that primarily stock groceries rather than groceries and other merchandise.

Table 8 presents the estimates including the demographic interactions (the α_h's and $\boldsymbol{\beta}_{kh}$'s), and reveals how changing household characteristics shift preferences for pantry characteristics. The distance-related coefficients suggests that travel sensitivity increases with neighborhood income. Even among households below 200% of the federal poverty line, those in wealthier neighborhoods may face higher opportunity costs of travel, making proximity more important.

Higher-income households also show stronger preferences for pantries that distribute in the afternoons or on Fridays, compared with lower-income households. This suggests that timing flexibility matters more for households with higher opportunity costs. Preferences for pantry type also varies by income quintile, as shown in Panel D of Table 8, which reveals that households in neighborhoods in the second or third income quintiles actually have a stronger preference for church pantries compared to households in the lowest income quintiles.

milk, yogurt, cheese, butter, and eggs.

Table 8: Coefficient Estimates for Model with Demographic Interactions

		Demographic interactions (β_{kh}'s and α_h's)					
		Income quintile of customer's census tract				Household size	
Pantry characteristics	Base coefficients ($\boldsymbol{\beta}$ and α)	2	3	4	5	log(size)	Unreported
	Panel A. Travel cost						
	Panel A. Travel cost						
Distance × − 1	0.223	0.018	0.023	0.053	0.056	0.008	0.497
	0.001	[0.001]	[0.001]	[0.001]	[0.001]	[0.000]	[0.010]
	Panel B. Pantry flexibility						
No cap on groceries obtained	−0.664						
	0.006						
Limit one visit per week	−1.800					0.018	−3.325
	0.006					[0.003]	[0.107]
Open mornings	0.294						
	0.003						
Open afternoons	−0.121	0.277	0.131	0.421	0.330		
	0.005	[0.006]	[0.006]	[0.007]	[0.010]		
Open evenings	0.288						
	0.003						
Unknown open hours	−0.707					−0.121	2.624
	0.007					[0.004]	[0.006]
Open Sundays	0.068						
	0.006						
Open Mondays	−0.328						
	0.002						
Open Tuesdays	−0.072						
	0.003						
Open Wednesdays	0.167						
	0.003						
Open Thursdays	−0.062						
	0.003						
Open Fridays	0.320	0.094	0.209	0.150	0.198		
	0.004	[0.007]	[0.006]	[0.007]	[0.010]		
Open Saturdays	−0.090					−0.018	−1.236
	0.004					[0.004]	[0.127]

Table 8 (continued)

		Demographic interactions (β_{kh}'s and α_h's)					
		Income quintile of customer's census tract				Household size	
Pantry characteristics	Base coefficients ($\boldsymbol{\beta}$ and α)	2	3	4	5	log(size)	Unreported
	Panel C. Food per customer						
Bread per visitor (lb)	0.011						
	0.000						
Shelf stable food per visitor (lb)	−0.025					0.000	−0.436
	0.000					[0.000]	[0.007]
Fresh produce per visitor (lb)	−0.004						
	0.000						
Dairy products per visitor (lb)	0.044						
	0.000						
Meat per visitor (lb)	−0.007						
	0.000						
Snacks per visitor (lb)	0.031						
	0.001						
Non-dairy beverages per visitor (lb)	0.011						
	0.000						
Non-food necessities per visitor (lb)	−0.023						
	0.000						
Unknown no. of visits[b]	−1.351						
	0.003						
	Panel D. Pantry type						
Church	−0.224	0.413	0.421	−0.076	−0.621		
	0.005	[0.006]	[0.006]	[0.008]	[0.013]		
Mobile pantry or produce market	−1.351						
	0.003						
Nonprofit	0.246						
	0.003						

Notes: This table presents estimates of the interaction terms in a conditional logit model of food pantry choice (see Equations (4) and (5)). USDA store types are aggregated following Shannon (2022). Heteroskedasticity-robust standard errors appear in brackets.

7.1 Consumer Surplus and Willingness to Travel

The parameters identified in the fully interacted model capture how customer preferences vary across different demographics. Using these preferences, I compare differences in consumer surplus and willingness to travel between households living in different income quintiles, allowing me to determine how the geographic distribution of food pantries affects the value customers derive from each visit. The surplus for a household in income quintile A is given by:

$$\begin{aligned} \mathrm{E}[CS \mid i \in A] &= \mathrm{E}\left[\frac{1}{\alpha_i} \max_{j \in \mathcal{J}_i} \{\boldsymbol{x_{ijt}} \boldsymbol{\beta}_i - \alpha_i D_{ij}\}\right] \\ &= \mathrm{E}\left[\frac{1}{\alpha_i} \log\Big(\sum_{j \in \mathcal{J}_i} \exp(\boldsymbol{x_{ijt}} \boldsymbol{\beta}_i - \alpha_i D_{ij})\Big)\right], \end{aligned} \tag{6}$$

where A indicates the set of households in quintile A. Equation (6) allows for variation across individuals within particular income quintiles, such as households within a particular income quintile with heterogeneous distance preferences depending on household size. Typical consumer surplus calculations give the difference between the highest price a customer would be willing to pay and the price they actually pay for a good or service. Because food pantries are free, this calculation gives the difference between the farthest distance a customer would be willing to travel to visit pantry j and what they actually travel to visit pantry j. In other words, consumer surplus is the number of additional miles an average household in each income quintile would be willing to travel before they were indifferent between visiting a particular food pantry or produce market, the inside option, or purchasing all meals from a grocery retailer, the outside option. Customers that derive a greater benefit from visiting a food pantry are willing to travel farther because the benefits of visiting outweigh the cost of travel. However, if a customer is more sensitive to travel distance, they may not be willing to travel as far as a customer who is less sensitive to travel distance.

Table 9 compares the consumer surplus derived by households in different income quintiles, along with the predicted number of visits and distance traveled.[27] The table indicates that households in all quintiles benefit from access to a food pantry, and they gain approximately the same amount of consumer surplus per visit; households would be willing to travel an additional 1.1 to 1.2 miles to access their chosen food pantry before they would choose to purchase all groceries from a local retailer, regardless of their neighborhood income. However, households in the highest income neighborhoods travel more than double the distance than households in the lowest income neighborhoods. Households in the lowest-income neighborhoods are predicted to travel 3.3 miles each way, and would tolerate a 1.1 mile increase, for a total of 4.4 miles to access their chosen food pantry. Compare this to households in the highest income neighborhoods; these households are predicted to travel 7.9 miles

[27] Appendix Table 5 reports the average observed visits and distance traveled. I report the predicted results to ensure the results are comparable to the counterfactual analysis in Section 7.2.

Table 9: Customer Welfare

Income quintile of census tract	Surplus from food pantries (miles)	Predicted welfare-relevant outcomes: Distance per regular-pantry visit (miles)	Regular-pantry visits per year[a]	Mobile-pantry visits per year[a]
1	1.12	3.26	9.40	1.19
	(0.69)	(3.02)	(6.52)	(2.34)
2	1.10	5.86	9.38	1.52
	(0.73)	(4.13)	(7.03)	(2.64)
3	1.15	6.69	10.08	1.41
	(0.75)	(4.07)	(6.98)	(2.26)
4	1.18	6.99	11.87	1.21
	(0.76)	(3.42)	(8.00)	(2.14)
5	1.14	7.87	12.27	1.03
	(0.57)	(3.02)	(6.64)	(1.96)

Notes: This table compares customer surplus, travel distance, and frequency of pantry visits according to the income quintiles of the census tracts where customers live. The annual frequency of regular (mobile) pantry visits is computed as the sum of observed regular (mobile) pantry visits, divided by the number of years elapsed between the earliest and latest observed visit to a pantry of any type. Standard errors are reported in parentheses.

[a] Conditional on thirty or more days elapsing between earliest and latest trip dates

each way to reach a food pantry, farther than the lowest income neighborhoods would be willing to travel, and would still travel an additional 1.1 before they would choose the outside option. In total, households in the highest income neighborhoods would be willing to travel 9 miles each way to visit their chosen food pantry before they would choose the outside option. Moving from the lowest income neighborhood to the highest income neighborhood would increase willingness to travel by over 100%. Additionally, households in the highest income neighborhoods are predicted to visit the food pantry more frequently than customers in any other neighborhood, with a total of 2.9 additional visits annually.

Although customers living in the highest income neighborhoods are predicted to travel farther, these households are also more sensitive to traveling longer distances than households in low-income areas. If households in high-income neighborhoods and low-income neighborhoods were visiting identical pantries the same distance from their residence, households in high-income neighborhoods would gain less surplus from each visit because of a stronger preference for nearby pantries. The results suggest that differences in willingness to travel more likely stems from the variation in the service design of the pantries in different choice sets, rather than variation in preferences. By traveling farther, households in high income neighborhoods can access pantries that provide enough additional benefit to offset their travel sensitivity, while households in low-income neighborhoods do not have access to pantries that provide enough benefit for them to increase their travel distance by much.

Section 5 established that there are fewer and more restrictive pantries in low-income areas than high-income areas, which led to the question of how this impacts the value that customers derive from their visit to the pantry. The analysis from the demand estimation shows that customers in lower-income areas receive less value from visiting the food pantry, suggesting that the restrictions imposed on customers in low-income areas lead to reductions in utility. Next, I conduct a counterfactual simulation to determine if redistributing funding from high-income areas to low-income areas would increase value for customers in low-income areas, which would ultimately demonstrate that donor- and volunteer-generated funding allocations limit the capacity of pantries in low-income areas.

7.2 Counterfactual Simulation

In this section, I explore whether increasing funding for food pantries in low-income areas would improve aggregate welfare for food pantry customers. I reallocate funds from pantries in high-income areas to pantries in low-income areas, allowing pantries in low-income areas to open more frequently and during times that customers prefer. The goal of this exercise is to demonstrate that welfare-improving funding allocations exist, rather than solve for an optimal funding allocation. If customer welfare can be improved by reallocating funding, then the donor- and volunteer-generated funding distribution may fail to fully serve customers in low-income areas.

For this exercise, I focus on redistribution among pantries located in rural areas, meaning that pantries located in Franklin County are excluded.[28] I focus on a subset of pantries in low-income areas that: (i) are infrequently open on Fridays or evenings and (ii) serve a higher-than-average volume of customers. These pantries would receive additional resources to open on Fridays or evenings during weeks where the pantry is already open at least one day. The funding comes from savings generated by closing food pantries in high-income areas on all Wednesdays or afternoons that they are currently open. To minimize the harm from closing the pantries, I choose a subset of pantries that serve a lower-than-average volume of customers. Opening the low-income pantries during the more popular times between 2018-2023 would increase expenditure by approximately \$595,088, and savings from the closures would allow \$614,089 to be redistributed to the lower income pantries. For details on how I estimate the predicted change in food pantry funding, see Appendix C.

Estimates in Table 7 show that customers prefer food pantries that are open on Fridays and in the evenings, motivating the redistribution of funds to allow pantries in low-income areas to increase the number of weeks they are open on a Friday or in the evenings. Table 10 shows that pantries mostly serving customers in quintile two are open ten Fridays per year on average, while pantries mostly serving customers in quintiles three are open 33 Fridays per year. Similarly, pantries serving customers

[28]Recall that although all of the customers in this analysis live in the 19 rural counties that MOFC serves, some choose to visit pantries within Franklin County if they live nearby. Because I do not include Franklin County customers in my overall welfare analysis, I cannot account for how changing pantry characteristics for a pantry in Franklin County would affect the welfare of a customer in Franklin County.

Table 10: Pantry Characteristics by Income Quintile

Income Quintile	Total Pantries	Average weeks open per year	Average weeks open on a Friday per year	Average weeks open at least one evening per year
1	2	26.4	18.6	0.4
		(15.6)	(12.7)	(0.74)
2	66	30.8	10.1	6.6
		(20.7)	(15.6)	(12.1)
3	48	32.6	32.6	11.5
		(19.5)	(13.2)	(17.4)
4	8	29.4	6.6	8.4
		(22.7)	(12.0)	(13.9)
5	8	37.1	20.1	13.0
		(17.0)	(21.6)	(18.5)

Notes: Table 10 breaks down the income quintile assigned to each pantry. A pantry is assigned an income quintile based on the population-weighted average income quintile of the census tracts with a population centroid within twenty miles of the food pantry. The table shows the total number of pantries assigned to each income quintile, the average number of weeks per year the pantries are open, and the average number of weeks per year the pantries are open on a Friday or in the evening. (Source: author's calculations using MOFC and ACS data.)

in quintile two are rarely open in the evenings, at just under seven evenings per year. Pantries serving customers in quintile three and five are open between 11 and 13 evenings per year, or around one evening per month. This suggests that increasing the number of weeks pantries are open during these preferred times in low-income areas could increase welfare overall.

Table 11 gives the change in consumer welfare under the new regime. Consumer surplus increases by 4–5% for customers living in neighborhoods in the first through third income quintiles. Customers in quintile four experience a 2.5% decrease in consumer surplus as a result of the redistribution of resources and customers in quintile five experience less than a 1% decrease in surplus. The welfare improvements are driven by increases in the predicted frequency that customers visit the pantry due to the improved selection of distribution times. Improving welfare for the customers in low-income areas is relatively low cost at around $600,000 over a six-year period and only involves small adjustments in pantry characteristics. Larger adjustments, such as increasing distribution hours or reducing visit restrictions could result in even greater welfare improvements. Ultimately, identifying any welfare-improving funding structure suggests that relying on donors to determine which food pantries receive the most resources does not provide the highest level of welfare for food pantry customers. Instead, these results show that small changes in the funding distribution, guided by customer rather than donor preferences, can lead to welfare gains for households in the lowest-income areas, highlighting the potential for more equitable resource allocation.

Table 11: Changes in Customer Welfare under Alternative Funding Distribution

Income quintile of census tract	Surplus from food pantries (miles)	Predicted welfare-relevant outcomes: Distance per regular pantry visit (miles)	Regular pantry visits per year[a]	Mobile pantry visits per year[a]
1	0.06	–0.01	0.42	–0.01
	(0.12)	(0.17)	(0.81)	(0.02)
2	0.05	–0.01	0.45	–0.01
	(0.15)	(0.22)	(1.02)	(0.03)
3	0.05	0.06	0.40	–0.01
	(0.14)	(0.21)	(0.97)	(0.02)
4	–0.03	0.04	–0.28	0.01
	(0.08)	(0.16)	(0.61)	(0.01)
5	–0.01	0.02	–0.15	0.00
	(0.03)	(0.08)	(0.27)	(0.01)

Notes: This table reports changes in various measures of customer welfare under the counterfactual funding transfers described in Section 7.2. The annual frequency of regular (mobile) pantry visits is computed as the sum of observed regular (mobile) pantry visits, divided by the number of years elapsed between the earliest and latest observed visit to a pantry of any type. Standard errors are reported in parentheses.

[a] Conditional on thirty or more days elapsing between earliest and latest trip dates

8 Conclusion

This paper analyzes the relationship between local giving and the availability of charitable services in a geographic area. I begin by documenting differences in food pantry access between households in high- and low-income neighborhoods. Households in high-income neighborhoods live near over 40 more food pantries than households in low-income neighborhoods, even after adjusting for population and access to urban areas. Customers in high-income areas also live near more pantries with a desirable service design, such as flexible visit times.

The descriptive analysis points toward differences in food pantry access that could lead to disparities in consumer welfare. While pantry characteristics are largely determined by funding, unobserved factors, such as historical pantry practices, could still influence service design. Nevertheless, these factors are unlikely to correlate systematically with individual customer preferences, supporting the plausibility of the exogeneity assumption. The demand estimation shows that households in high-income neighborhoods are willing to travel farther to reach a food pantry than households in low-income neighborhoods even though households in higher-income areas experience more disutility from travel. This implies that customers in high-income areas are willing to pay a higher price for a higher quality visit, and that they derive more value per-visit. Because five times as many customers live in low-income neighborhoods compared to high-income neighborhoods, improving access for customers in low-income neighborhoods could lead to significant welfare improvements for a large portion of the population.

The analysis of the status-quo points toward variation in food pantry quality that favors customers in high-income neighborhoods. The demographics of the high-income areas are consistent with the profile of donors and volunteers to food pantries, suggesting that local-giving may be driving the disparities in food pantry access. In a counterfactual analysis, I show that welfare-improving funding structures exist with small adjustments to the amount of funding each pantry receives. I simulate opening high-volume pantries serving low-income neighborhoods on popular days and closing low-volume pantries in high-income neighborhoods on less popular days, according to preferences derived using the random utility model. I find that the new funding structure increases consumer surplus for customers in quintiles one, two, and three between 4-5%. Byrne and Just (2023) show that each pantry visit is worth between \$40 and \$60, so a 4-5% increase adds \$2-3 per visit, or approximately the average cost of an additional meal (Feeding America 2025a). MOFC estimates that households in their region miss between 3 and 4 meals per week, and so small welfare gains can begin to close the meal gap.

More broadly, this study suggests that relying on local giving to provide charitable social service will result in unequal charitable service distribution. Households in areas with more donors and volunteers will receive better care, while households in areas with fewer donors and volunteers will remain underserved. Policies assuming that cuts to federal safety net programs will encourage charitable organizations to step in fail to recognize that these organizations depend on adequate support to meet increased demand. This paper shows that the organizations with the most resources are concentrated in higher-income areas, while charities in lower-income areas have a larger customer base and fewer resources.

While food pantries in higher-income neighborhoods provide more value per visit, access to food pantries improves welfare in all areas, regardless of neighborhood income. Private food assistance provides a small, but meaningful, amount of support to households in need of food, and in speaking to food pantries across the MOFC service area, all pantries felt they were falling short of meeting the demand in their area. Redistributing resources from high-income areas to low-income areas would improve welfare overall for pantry customers, but would ultimately decrease welfare for some needy households living in high-income areas. In addition, donors likely gain more utility from supporting their neighbors, and therefore redistributing funding would harm donors or could lead to decreases in overall giving.

Alternative solutions to disparities in high-quality food pantry access, and charitable service access in general, could involve increasing outside funding, such as government funding or grant funding, for pantries in low-income areas. Without paid staff, small, all-volunteer organizations may not have the time or expertise required to apply for large grants that could significantly improve welfare in their region. Improvements in data collection, such as the data collected by MOFC, could allow policymakers to identify organizations poised for high-impact improvements without requiring grant-writing skills from those organizations.

Another approach is to allow intermediary organizations, like food banks, to identify underfunded organizations and redistribute the resources accordingly. For example, MOFC currently identifies organizations in underserved areas that are capable of expansion and supports them with marketing materials and additional produce to increase charitable food access in their service area. The Greater Chicago Food Depository, a large food bank in the Chicago area, also implemented a creative solution to expensive shipping costs; the food bank provided small grants to partner food pantries that were capable of storing large volumes of food. The grants allowed the pantries to purchase refrigerated vehicles that they could then use to travel to the food bank to pick up food orders for other pantries in their region. The smaller pantries, then, only needed to travel to the grant-funded pantry to pick up food, rather than pay to have the food shipped all the way from the bank.

In addition to showing that relying on donors to fund charitable social services leads to lower levels of aggregate welfare than alternative funding structures, I also contribute to the small literature on food pantries by describing the preferences of households relying on food pantries for some of their meals. Households prefer nonprofit over church-based pantries, favor distribution times on Fridays and in the mornings or evenings, and prefer pantries offering more dairy and snacks per visit. Preferences for food pantry service design vary by the customer's neighborhood income and also by the customer's household size. Finally, the local food environment also influences the benefit derived from visiting a food pantry; customers with a higher concentration of supermarkets or local retailers near their home derive more benefit from the outside option of shopping at a grocery retailer, suggesting that vibrant grocery shopping options may draw food pantry customers toward the outside option and away from visiting the pantry. On the other hand, access to more small retailers, like convenience stores, does not shift the value of the outside option for food pantry customers.

To my knowledge, this paper is the first quantitative analysis of demand for food pantries using multi-county data on food pantry utilization. However, this paper is limited to households who select in to visiting a food pantry, therefore excluding households who qualify for services but cannot access any food pantry or choose not to visit. In addition, this paper assumes that the cost of visiting a food pantry is the Euclidean distance traveled to the food pantry. Although the Euclidean distance is likely correlated with travel times, the actual distance traveled to each food pantry is unknown, and therefore my estimates are a lower bound for the travel costs associated with visiting a pantry. Further, I am unable to account for the variation in wait times that customers face when visiting a pantry, which could increase the cost of visiting. For these reasons, I generate a lower bound to the value of visiting a food pantry in miles, rather than dollars. Byrne and Just (2023) finds that food pantries provide an annual benefit of \$600 to \$1,000 per customer; my work complements that research by showing that the benefits provided by pantries likely vary by geographic location.

In 2016, MOFC estimated that charitable food provided 5% of the meals needed by low-income households in the 20 county region, while government provided meals, including SNAP, WIC, TANF, and free/reduced-price lunch, provided 29%. Feeding America reports that the personal budget shortfall that food insecure households face increased by 55% between 2020 and 2023 (Feeding America 2025b). However, the findings also show that two out of five households facing food insecurity do not qualify for SNAP benefits, and therefore these households may depend more on charitable services. Recent cuts to federal programs will make it more difficult for households to receive food benefits along with other federal social services. State-level cuts to food banks and food pantries, such as recent cuts in Ohio (Sollinger 2025), will restrict the ability of charitable services to respond to the increase in need. This research indicates that while charitable services provide an important resource for low-income households, variation in donor support leads capacity-constraints for some organizations. Alternative funding structures that use existing, donor-provided resources and prioritize customer preferences would improve customer welfare overall.

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Supplementary Appendix

A Tables

Appendix Table 1: Food Pantry Orders: Branches without MOFC

	Panel A. Total quantity ordered
Weight (lb)	151,664.4
	(226,771.5)
Price ($)	13,464.4
	(18,256.5)
	Panel B. Quantity ordered by food category (%)
Bread	3.5
	(5.9)
Shelf-stable	29.7
	(16.7)
Fresh foods	44.8
	(24.1)
Dairy	6.0
	(4.9)
Meat	12.3
	(8.5)
Snacks	10.1
	(6.9)
Non-dairy beverages	7.6
	(7.6)
Non-food necessities	4.3
	(4.8)
Observations (pantry-year)	24

Notes: This table shows the amount of food in pounds that all branch organizations ordered, excluding the two locations operated by the Mid-Ohio Food Collective. (Source: author's calculations using MOFC data.)

Appendix Table 2: Food Pantry Orders by Nonprofit Type in 2022

	990	990-EZ	990-N	Nonfiler
	Panel A. Total quantity ordered			
Weight (lb)	397,077.3	187,355.6	187,443.9	149,856.8
	(501,252.3)	(360,267.5)	(462,234.7)	(264,332.3)
Price ($)	15,371.1	10,030.8	5,036.4	5,351.2
	(20,110.1)	(18,379.42)	(7,286.1)	(6,555.2)
	Panel B. Quantity ordered by food category (lb)			
Bread	6.1	7.9	4.7	3.4
	(6.7)	(11.8)	(7.8)	(6.2)
Shelf-stable	17.8	27.0	28.3	26.4
	(11.9)	(18.2)	(18.4)	(13.3)
Fresh foods	57.7	46.7	38.9	39.6
	(21.3)	(22.0)	(18.8)	(20.6)
Dairy	6.5	6.3	5.9	5.7
	(3.9)	(4.4)	(5.0)	(3.9)
Meat	12.2	9.8	14.3	14.5
	(9.0)	(6.0)	(6.1)	(9.5)
Snacks	8.3	10.0	11.8	12.8
	(6.2)	(6.4)	(6.5)	(7.2)
Non-dairy beverages	5.0	6.0	6.1	9.5
	(4.7)	(5.6)	(5.6)	(8.1)
Non-food necessities	4.9	4.8	5.7	5.7
	(8.0)	(4.6)	(8.0)	(6.2)
Observations (pantry-year)	158	45	75	101

Notes: This table breaks down food pantry orders from nonprofit organizations by nonprofit tax-filing type. I exclude 2023 as not all organizations' tax filings were available at the time of writing this paper. (Source: author's calculations using MOFC data.)

Appendix Table 3: Household Size and Retail Food Availability by Tract Income Quintile

	Income quintile of Customer's census tract				
	1	2	3	4	5
	Panel A. Household size				
Customer-reported household size	2.5	2.6	2.6	2.7	3.0
	(1.9)	(1.8)	(1.8)	(1.9)	(2.0)
	Panel B. Retail food availability				
Number nearby grocers	1.3	1.8	0.7	0.6	2.1
	(0.8)	(4.1)	(0.8)	(0.8)	(4.9)
Number nearby local food stores	0.9	0.7	0.4	0.4	0.3
	(0.9)	(0.9)	(0.7)	(0.7)	(0.6)
Number nearby small retailers	19.4	18.0	11.8	8.0	12.3
	(13.8)	(15.6)	(10.5)	(9.1)	(16.6)
Number nearby supermarkets	3.9	3.5	2.1	1.5	2.7
	(3.3)	(3.2)	(2.4)	(2.2)	(4.1)

Notes: This table presents summary statistics about household size (as reported by MOFC customers), as well as the availability of retail food options within five miles of a customer's home, according to the income quintile of customers' census tracts. (Sources: MOFC and USDA).

B Figures

Appendix Table 4: Estimated Base Coefficients (β_k's and α)

	Point estimate	Standard error
	Panel A. Travel cost	
Distance × − 1	0.223	0.001
	Panel B. Pantry flexibility	
No cap on groceries obtained	−0.664	0.006
Limit one visit per week	−1.800	0.006
Open mornings	0.294	0.003
Open afternoons	−0.121	0.005
Open evenings	0.288	0.003
Unknown open hours[b]	−0.707	0.007
Open Sundays	0.068	0.006
Open Mondays	−0.328	0.002
Open Tuesdays	−0.072	0.003
Open Wednesdays	0.167	0.003
Open Thursdays	−0.062	0.003
Open Fridays	0.320	0.004
Open Saturdays	−0.090	0.004
	Panel C. Food per customer	
Bread per visitor (lb)	0.011	0.000
Shelf-stable food per visitor (lb)	−0.025	0.000
Dairy products per visitor (lb)	0.044	0.000
Fresh produce per visitor (lb)	−0.004	0.000
Snack food per visitor (lb)	0.031	0.001
Meat per visitor (lb)	−0.007	0.000
Non-dairy beverages per visitor (lb)	0.011	0.000
Non-food necessities per visitor (lb)	−0.023	0.000
Unknown no. of visits[a]	−1.351	0.003
	Panel D. Pantry type	
Church	−0.224	0.005
Mobile pantry or produce market	−1.351	0.003
Nonprofit	0.246	0.003
	Panel E. Retail availability	
Outside option × no. nearby grocers	−0.015	0.000
Outside option × no. nearby local food stores	0.104	0.002
Outside option × no. nearby small retailers	−0.004	0.000
Outside option × no. nearby supermarkets	0.104	0.001

Notes: This table presents base coefficient estimates for a conditional logit model of food pantry choice (see Equation (3)). Concerning pantry type (Panel D), the omitted type of pantry is branch locations. The rightmost column reports heteroskedasticity-robust standard errors.

[a] When the number of weekly visits is unknown, this variable is defined as one and the per-customer food variables are set equal to zero.

[b] Open hours cannot be inferred because pantry does not report visit times.

Appendix Table 5: Observed Travel Distance and Pantry Visit Frequency

Income quintile of census tract	Distance per regular pantry visit (miles)	Regular pantry visits per year[a]	Mobile pantry visits per year[a]
1	2.8	9.0	1.3
	(4.0)	(9.1)	(4.0)
2	4.3	9.3	1.5
	(4.4)	(9.6)	(4.3)
3	5.8	10.0	1.1
	(5.2)	(9.7)	(3.7)
4	6.1	11.4	1.1
	(4.9)	(10.8)	(4.2)
5	7.5	12.5	1.2
	(5.0)	(11.7)	(4.9)

Notes: This table compares observed travel distance, and frequency of pantry visits according to the income quintiles of the census tracts where customers live. The annual frequency of regular (mobile) pantry visits is computed as the sum of observed regular (mobile) pantry visits, divided by the number of years elapsed between the earliest and latest observed visit to a pantry of any type. Standard errors are reported in parentheses.

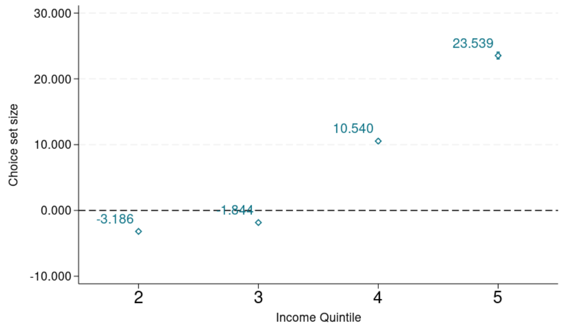
[a] Conditional on thirty or more days elapsing between earliest and latest trip dates.

C Predicted Funding Changes

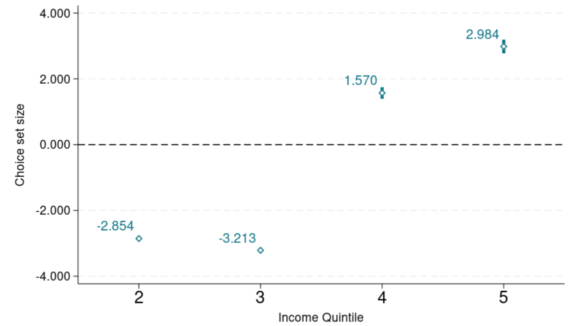
To estimate the cost of opening food pantries in low-income areas and the savings from closing food pantries in high-income areas, I first identify the *pantry* income quintile as the income quintile of the people likely served by the pantry and/or the income quintile of potential supporters of the pantry. Specifically, I use the weighted average of the income quintiles with a population centroid within 20 miles of the pantry. By this definition, there are two pantries that primarily serve customers in quintile one, 66 pantries primarily serving customers in quintile two, 48 primarily serving quintile three, and eight primarily serving both quintiles four and five. Excluding Franklin county removes 135 pantries that rural customers chose, all located in quintiles three or above.

Food pantries face both fixed and variable costs when providing food to the community. I assume that the amount of money each pantry spends on food in a given month represents the variable costs that pantries face. I treat other costs, such as staff and rent, as fixed and I assume these costs do not change if the pantry opens or closes on additional days. I exclude fixed costs in the cost-per-visit.

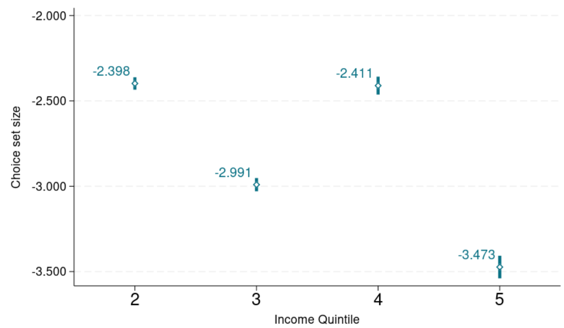
To calculate the cost-per-visit, I divide the total amount spent on food by pantry j in month t by the total number of visits to pantry j that occurred in month t. I multiply the number of weekly visits by the cost-per-visit to estimate the weekly cost of serving customers. For pantries open on Fridays or in the evening, I calculate the share of their visits that take place on Fridays/evenings. I then predict the share of visits that would occur at pantries not currently open on Fridays or evenings using a beta



Panel A. 15-mile threshold



Panel B. 10-mile threshold



Panel C. 5-mile threshold

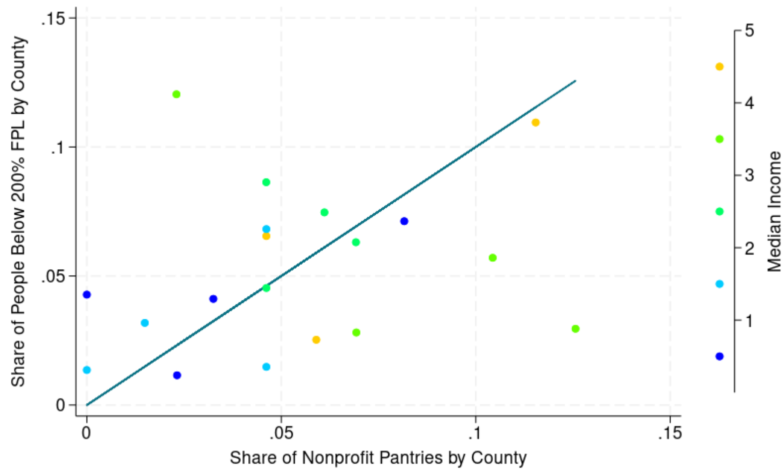
Appendix Figure 1: Variation in Total Options in Choice Set by Income Group

Notes: This figure plots the β_1 coefficients and 95 percent confidence intervals from Equation 2 using alternative definitions of the food pantry choice set. Each graph plots the change in the count of food pantries in the choice set of a customer living in each income quintile, relative to the count of pantries in the choice set of a household living in lowest income quintile neighborhood.

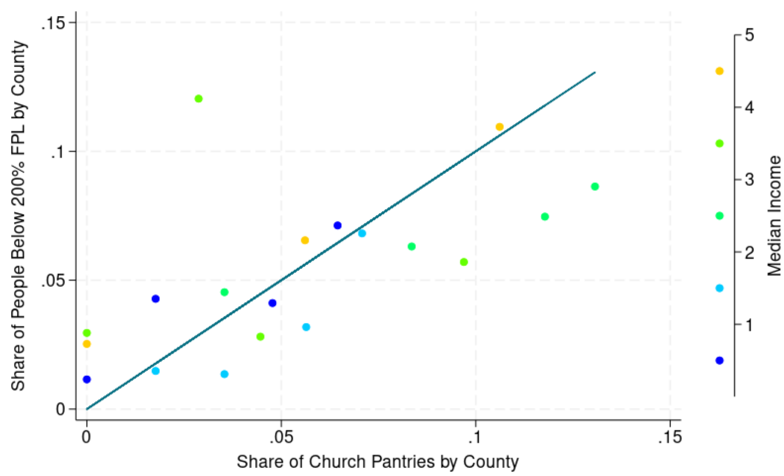
regression, represented by:

$$g(y_{jt}) = \boldsymbol{x}_{\boldsymbol{jt}}\boldsymbol{\theta} + \boldsymbol{\tau}_t + \gamma_j, \tag{7}$$

where $y_j \in \{0, 1\}$ is the share of visits on a Friday or in the evenings. This specification does not include pantries that are not open on Fridays or in the evenings or pantries that are only open on Fridays or in the evening in a given week. I also include a vector of pantry characteristics, $\boldsymbol{x}_{\boldsymbol{j}}$, including indicators for pantry type (church, or nonprofit), day-of-the week the pantry is open, and time-of-day the pantry is open. I include the pantry-census-tract population of individuals between ages 36 and 64, which MOFC reports as the age range where most volunteers fall, to control for the availability of volunteer labor for a particular pantry. I include year and month fixed effects, $\boldsymbol{\tau}_t$, to account for unobservable patterns in pantry utilization related to the year and month the pantry is open. Finally, I include pantry fixed effects to account for unobservable, time-invariant pantry characteristics.



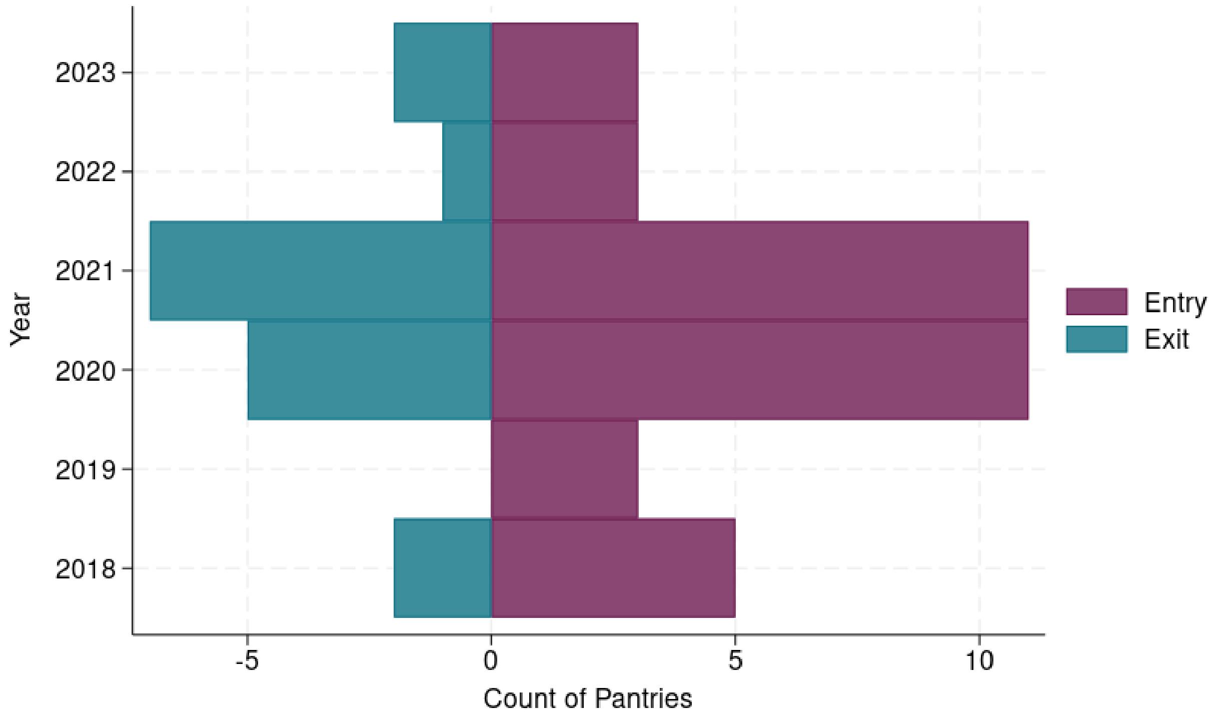
Panel A. Share of Nonprofits and Share of Pantry-Eligible Households



Panel B. Share of Churches and Share of Pantry-Eligible Households

Appendix Figure 2: Distribution of Church and Nonprofit Pantries by County

Notes: The figure plots the share of households in the MOFC region below the 200% of the federal poverty line residing in each county against the share of nonprofit or church-based food pantries in each county, and a 45 degree line. Points above the line have a disproportionately high share of individuals eligible for food pantry services. Points below the line have a disproportionately high share of food pantries. The points are colored according to the income quintile of the county.



Appendix Figure 3: Entry and Exit of Pantries by Year

Notes: This figure shows the total number of pantries that enter or exit the sample by year.

I calculate the estimated cost increase by multiplying the predicted weekly visits on Fridays or evenings by the pantry's weekly cost. Similarly, I calculate the actual cost-per-week for pantries that are open on Wednesdays or in the afternoon by multiplying the actual share of weekly visits that occur during these times by the pantry's weekly costs. I then choose the subset of pantries in low-income areas that are (i) infrequently open on Fridays (evenings), defined as open on a Friday (evening) for less than half of the weeks that the pantry is open; and (ii) a pantry with a higher-than-average volume of customers, relative to the other low-income pantries that are infrequently open on Fridays or in the evenings. This includes 16 food pantries eligible for Friday openings, half of which are church pantries, seven small nonprofit organizations, and one branch location. 18 pantries are eligible for evening openings, including eight churches, three branches, six small nonprofits, and one mid-sized nonprofit. Because the pantries are largely churches and small nonprofits, which are typically all-volunteer operations, the labor costs associated with the additional hours would involve recruiting more volunteers rather than hiring new staff. Though the list of pantries that would open on Fridays and pantries that would open during the evenings are distinct, eight pantries are on both lists.

I calculate the expected savings that could be redistributed to low-income pantries if pantries in quintiles three, four, and five that are frequently open on Fridays or in the evenings were to close on Wednesdays and during the afternoons. I choose to focus on pantries that are frequently open on Fridays or evenings because this would allow customers to continue to visit the pantry on the most popular day and time. For pantries that would close, I focus on low-volume pantries, or pantries that serve a lower-than-average volume of customers. Eight pantries would experience afternoon closures in the counterfactual scenario and eleven would experience Wednesday closures. Only one pantry appears on both lists.