Who Goes to Farmers Markets? Food Desert Gaps, Structural Demand, and Policy Design*

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Abstract

Farmers markets are touted as a solution to food access disparities in under-resourced communities. However, systematic evidence on who actually attends them and which policy interventions enhance their utilization remains limited. To answer that question, we link nationwide cell-phone mobility data to neighborhood socioeconomic characteristics, including food desert status, estimate a structural destination-choice model, and evaluate the effectiveness of potential policy interventions. Four findings emerge. First, food desert residents visit farmers markets less frequently and travel farther, choosing markets that are economically similar, but not racially similar, to their neighborhoods. Second, a decomposition attributes 70% of the visitation gap between food desert and non-food desert residents to differences in demand, 20% to supply, and 10% to market attributes. We find that urban gaps reflect both travel costs and socio-demographic fit, while rural gaps are primarily driven by high travel costs and sparse supply. Third, policy simulations indicate that universal acceptance of the Supplemental Nutrition Assistance Program (SNAP) would close about 18% of the gap, universal evening operations about 33%, and adding one representative market per food desert community nearly 58%, with especially large rural gains. Fourth, a benefit-cost analysis shows that SNAP acceptance delivers the highest return per dollar. These policy insights contribute to the debate over how to effectively reduce food access disparities in under-resourced communities.

Keywords: Farmers markets, food deserts, mobility data, destination-choice modeling, food access policy

JEL Codes: Q13, Q18, C81

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1 Introduction

Access to affordable and nutritious food remains deeply uneven across the United States. Large regions, particularly low-income, rural, and racially marginalized communities, are classified as food deserts, where residents must travel long distances to reach full-service grocery stores (Woolf and Braveman, 2011; Neff et al., 2009). Previous studies suggest that these spatial inequities in food access closely mirror patterns of diet-related health outcomes. Such disparities in the retail food environment reinforce broader health and socioeconomic inequalities, contributing to inter-generational cycles of disadvantage (Larson, Story, and Nelson, 2009; Walker, Keane, and Burke, 2010). Recognizing these persistent gaps, federal and state governments have launched an array of initiatives to reshape local food environments. These policies span supply-side programs such as grants and loans for farmers markets, community gardens, and mobile markets, as well as purchasing-power interventions that expand affordability through acceptance of the Supplemental Nutrition Assistance Program (SNAP) and Special Supplemental Nutrition Program for Women, Infants, and Children (WIC) benefits or matching incentives like Double Up Food Bucks (U.S. Department of Agriculture and Service, 2022b,a; U.S. Department of Agriculture, 2023; U.S. Department of Agriculture and Service, 2023; Network, 2023). Complementary infrastructure investments, including new transit routes, food-oriented zoning, and public-private food hubs, aim to connect under-resourced communities to healthier options (Allcott et al., 2017; Gittelsohn et al., 2014; Beaulac, Kristjansson, and Cummins, 2009; Cummins, Flint, and Matthews, 2014). Collectively, these efforts reflect a growing recognition that both proximity and economic accessibility matter for achieving equitable nutrition outcomes.

Evidence from changes in access to traditional grocery stores suggest that simply increasing physical proximity produces only limited behavioral change. For example, Amin, Badruddoza, and McCluskey (2025) find that consumers do substitute toward healthier grocery stores when they become more accessible, but these responses are modest and occur only within short travel distances. Allcott et al. (2019) show that when a new supermarket opens, most of the inflow comes from other full-service grocers located farther away rather than from nearby, less healthy retailers. Their simulations suggest that supply expansions explain only about ten percent of nutritional disparities. Complementing these empirical patterns, Bronnenberg and Ellickson (2015) and Courtemanche and Carden (2011) document that travel costs, time constraints, and cultural or social fit meaningfully

shape where households shop and what they buy. This evidence indicates that while proximity matters, access alone is insufficient because persistent behavioral and structural frictions often limit the extent to which healthy retail options are actually utilized.

Against this backdrop of limited substitution and persistent barriers, farmers markets have emerged as a more adaptive and community-centered response to the shortcomings of traditional grocery interventions. Unlike conventional supermarkets, farmers markets can operate flexibly, such as appearing in under-resourced neighborhoods, adjusting hours to local needs, and fostering direct connections between consumers and nearby producers. Many also accept SNAP benefits and offer incentive programs such as matching dollars, further expanding access for low-income households. These characteristics make farmers markets a promising avenue for advancing health equity while supporting small and medium-sized farms (La Trobe, 2001a; Pitts et al., 2013; Low et al., 2015; Jilcott Pitts et al., 2017). At the same time, they represent a unique form of localized supply that can potentially bridge economic, social, and spatial divides in food access.

However, evidence on the effectiveness of farmers markets in reducing nutritional disparities is mixed. While some studies link proximity to improved access and dietary quality, others identify persistent barriers, including transportation, inconvenient hours, prices, and cultural differences, that limit participation in low-income communities (Freedman et al., 2016; Farmer et al., 2019b; Garrity et al., 2024). Most existing work relies on localized surveys, which restrict generalizability and provide little insight into who uses farmers markets and which attributes drive participation among food desert (FD) populations (Conner et al., 2010; Logozar and Schmit, 2009; Freedman et al., 2016). These limitations have hindered rigorous assessment of whether and how farmers markets contribute to reducing nutritional inequality at scale.

Our paper contributes to this discussion by providing national-scale evidence on disparities in the accessibility and utilization of farmers markets, analyzing around 4,000 market locations across the continental United States. We begin by assembling a comprehensive dataset of farmers market visitation by identifying market locations from mobility-based POI data and validating them against authoritative sources, including state directories, USDA's Farmers Market Directory, SNAP retailer listings, Google Maps, and Facebook. Aggregating all visits from 2019-2022 yields a panel of 14 million census block group (CBG)-market-quarter observations, providing a detailed characterization

of market attendance across diverse communities.

Descriptive patterns reveal persistent disparities. Residents of FD communities visit farmers markets substantially less often, travel 20% farther to their nearest market and 15% farther to alternatives within 30 miles, yet are no less likely than non-FD residents to visit their closest market. This suggests that the primary barrier is not awareness but the higher generalized travel costs and opportunity costs faced by FD communities. Moreover, FD visitors disproportionately select markets that are economically familiar but racially or ethnically dissimilar to their home neighborhoods, and these markets tend to exhibit greater racial and income diversity. Taken together, these patterns reveal very different underlying mechanisms, indicating that these spatial and social dimensions may play an important role in shaping the observed visitation gaps.

To understand the drivers of the visit gaps, we estimate a random-coefficient logit model of market choice that incorporates travel costs, market attributes, and demographic and income fit. Estimated preferences vary markedly by community type. A 10 percentage-point increase in racial-ethnic distance between home and market neighborhoods reduces visitation by 9%. Large markets that operate in the evening attract substantially more visitors. We also find that SNAP acceptance significantly increases market attractiveness, with non-FD communities exhibiting even larger responses than FD communities. One potential explanation is that non-FD households may derive stronger pro-social or virtue-signaling benefits from supporting SNAP-authorized markets, making any stigma less influential in their choices.

Using estimates from this model, we adapt the decomposition framework in Allcott et al. (2019) to quantify the sources of FD–non-FD gaps in utilization. Demand-side factors account for most of the disparity: differences in travel preferences explain roughly 70% of the gap, preferences for market attributes about 10%, and supply availability and accessibility the remaining 20%. Within the demand component, travel cost sensitivity is the primary contributor, followed by socio-demographic fit, with distinct geographic patterns: gaps among urban residents reflect both travel and fit preferences, while rural community gaps stem primarily from high generalized travel costs and sparse market availability.

To isolate which community characteristics most strongly predict demand differences, we apply the Gelbach decomposition holding supply constant across communities (Gelbach, 2016). Lower

educational attainment emerges as the strongest correlate of reduced visitation, suggesting that information frictions or planning barriers remain salient even when access is equalized.

Finally, we use a structural model to evaluate three policy interventions: universal SNAP acceptance, universal evening hours, and adding one representative market in each FD choice set. SNAP acceptance closes 18% of the gap, evening hours 33%, and adding a representative market nearly 58%, with especially large gains in rural areas. Welfare simulations show that SNAP acceptance delivers the highest benefit per public dollar, while adding new markets yields larger absolute gains at higher cost; evening hours are most effective in areas with strong predicted evening demand. These findings suggest a sequencing of interventions: prioritize SNAP acceptance as a low-cost baseline, expand market supply in high-need rural communities (and targeted urban locations), and extend hours where partnerships can mitigate operating costs.

We provide four distinct contributions. First, we broaden the scope of research on food environments by providing the first nationwide empirical analysis of farmers' markets and their role in food utilization disparities. Although some studies examine farmers markets, this work is almost entirely localized while the broader food environment literature has focused mainly on supermarkets, corner stores, and fast-food outlets, leaving farmers markets essentially absent from large-scale analyses of national patterns and disparities across diverse communities (Galvez et al., 2008; Hallum et al., 2020; Horowitz et al., 2004; Lytle, 2009; Powell et al., 2007; Raja, Morgan, and Hall, 2017; Rhone et al., 2019; Zenk et al., 2005b). More importantly, prior work has largely focused on the intensive margin of how often people visit farmers markets, providing little systematic evidence on the extensive margin of who actually visits farmers' markets. Leveraging four years of nationwide cellphone mobility data linked to community socio-economic and food access characteristics, we provide the first national characterization of farmers market visitation and document substantial disparities, with farmers markets disproportionately utilized by residents of non-FD communities.

Second, we move beyond access to examine how communities choose among available markets and what drives differences in realized visitation. Prior research has typically emphasized geographic proximity to healthy food outlets but has provided little evidence on how households sort across multiple markets or which mechanisms explain observed utilization gaps (Jilcott Pitts et al., 2017; Freedman et al., 2016; Conner et al., 2010; Zhen et al., 2013). Using nationwide mobility data, we

observe actual destination choices and adapt the decomposition framework of Allcott et al. (2019) to separate the FD–non-FD visitation gap into supply-side differences in market availability and demand-side differences in preferences for travel costs, market attributes, and social and economic fit. This approach shows that demand-side mechanisms account for most of the disparity, while supply differences play a smaller but meaningful role.

Third, our work contributes to the broader food assistance literature by quantifying the value of SNAP acceptance specifically in the farmers market setting. While extensive SNAP research has focused on impacts on food security, household spending, and overall retail access (Fox, Hamilton, and Lin, 2004; Meyerhoefer and Yang, 2011; Somsen, 2010; Bitler et al., 2015; Kropf et al., 2007), little is known about its role in shaping participation in farmers markets. Our model estimates that SNAP-accepting markets are valued in both FD and non-FD communities, and simulation results show that universal SNAP adoption in FD communities could close 18% of the visitation gap at relatively low cost (benefit-cost ratio ≈ 62). This provides direct evidence that targeted SNAP expansion at farmers markets can be a cost-effective intervention to increase utilization.

Fourth, our study contributes to the literature on mobile location data applications by introducing a novel framework for measuring the distributional impacts of local public goods using structural demand estimation (Amin, Badruddoza, and McCluskey, 2025; Cervigni, Hickling, and Olaru, 2022; Horn et al., 2023; Jin et al., 2023; Lin et al., 2025; Oje et al., 2025). Prior work has used cell phone GPS data to examine resource use patterns, such as restaurant choice (Athey et al., 2018) and daily trip choices (Abbiasov et al., 2022), but has not applied these methods to local food markets or systematically linked them to equity-oriented policy simulations. We integrate mobility data with a discrete choice model to simulate three policy interventions. Results underscore that in urban areas, improvements to existing markets (e.g., evening hours) can yield substantial welfare gains, whereas in rural areas, increasing local supply has much larger effects. This approach provides a generalizable blueprint for using mobility data to diagnose inequities, decompose their drivers, and simulate targeted interventions.

2 Background and Data

2.1 Background

Farmers markets have experienced remarkable growth in the U.S., increasing by 492% between 1994 and 2018 (Metz and Scherer, 2022).[1] This surge aligns with broader consumer interest in sustainable agriculture, environmental stewardship, and local alternatives to industrialized food production (Hinrichs, 2000; Feenstra, 1997; Lyson, 2004; Alkon, 2008; Slocum, 2007). Farmers markets bring fresh, locally sourced produce directly to communities (La Trobe, 2001a; Oberholtzer, Dimitri, and Schumacher, 2012). This accessibility reduces transportation barriers that often prevent low-income individuals from accessing nutritious foods, and can positively impact food affordability in underserved communities (Larsen and Gilliland, 2009; Warsaw et al., 2021; Young et al., 2013; Pitts et al., 2013; Low et al., 2015; Jilcott Pitts et al., 2017). By providing local residents with easier access to fresh foods, farmers markets can play a crucial role in mitigating nutritional disparities.

Food assistance programs such as SNAP and WIC provide targeted aid to low-income families, and are accepted at various retail outlets, including supermarkets and farmers markets (Bitler et al., 2015; Oliveira, 2009; Kropf et al., 2007). The Farmers Market Nutrition Program (FMNP) is additionally designed to encourage WIC recipients and low-income seniors participating in SNAP to purchase fresh produce from local food outlets (Somsen, 2010). This initiative not only enhances nutrition among vulnerable populations but also supports small farmers and bolsters local economies. Similarly, incentive programs such as Double Up Food Bucks (DUFB) match SNAP benefits spent on fruits and vegetables at farmers markets and other outlets, effectively doubling their purchasing power while directing resources to local producers (Fair Food Network, 2013). For instance, FMNP offers financial incentives, such as providing two dollars back for every five dollars spent at participating markets (Weninger and Just, 1997).

Despite these benefits, several challenges hinder the accessibility and utilization of farmers markets by low-income populations (Freedman et al., 2016; Young et al., 2013; Dimitri et al., 2015).

[1] More recent sources indicate over 8,700 markets in the country today, although growth has slowed compared with the rapid early phase of expansion (Witzling, Shaw, and Wolnik, 2025).

For example, Farmer et al. (2019a) revealed that 42% of WIC and SNAP recipients who shopped at farmers markets did so less frequently than they desired, primarily because they preferred the convenience of purchasing all their groceries from a single location. Additionally, 35% reported that farmers markets were not conveniently located, which discouraged regular visits. Among those who did not shop at farmers markets, 73% cited a preference for one-stop shopping at traditional grocery stores, and 33% perceived the prices at farmers markets to be prohibitively high. Prior research has also highlighted that inconvenient hours of operation limit access for working families, further constraining the ability of low-income populations to shop at farmers markets (Zhen et al., 2013; Singleton, Sen, and Affuso, 2017; Grigsby-Toussaint et al., 2020).

Social and psychological barriers also contribute to the underutilization of farmers markets by low-income individuals (Pilgeram, 2012, 2011). The public nature of transactions at farmers markets, often involving token systems to convert SNAP and WIC benefits into market currency, can eliminate the anonymity provided by Electronic Benefit Transfer (EBT) cards in grocery stores. This lack of privacy may cause discomfort for beneficiaries who prefer more discreet transactions. Furthermore, Pilgeram (2011) has highlighted that farmers markets are frequently patronized by middle or upper-middle class, White consumers, which can make these spaces feel unwelcoming to low-income shoppers and people of color. Addressing these social and logistical challenges is essential to ensuring that farmers markets become more inclusive and serve as valuable resources for all community members, especially those relying on food assistance programs.

While farmers markets are primarily known for offering fresh, locally produced fruits and vegetables, they also commonly feature a broader mix of goods that extend beyond unprocessed produce. Many markets sell value-added and processed food products such as baked goods, jams, pickles, cheeses, and prepared foods, reflecting the diverse production capacities of small-scale farms and local food entrepreneurs (Hinrichs, 2000; La Trobe, 2001b). In addition to food items, farmers markets frequently include non-food products like handmade crafts, body care items, plants, and flowers, which help vendors diversify income streams and attract a wider customer base. Because farmers markets predominantly offer fresh and locally produced and processed foods, visitation serves as a behavioral measure of engagement with healthier food environments rather than a direct measure of healthy food consumption. Although some visitors attend markets for recreational or

social purposes, patterns of visitation still provide informative signals about households' access to, and interaction with, healthier food options.

2.2 Data

Our primary dataset consists of a panel of farmers market visits obtained from GPS-based cell phone pings gathered from a variety of mobile devices in the U.S., covering the period from 2019 to 2022, provided by Advan.[2] Each mobile device in the dataset is associated with a unique identifier and a sequence of recorded "stays" at different points of interest (POIs). To protect data privacy, Advan aggregates this information to the level of CBGs, and we are able to observe aggregated weekly or monthly visits to farmers markets from a device's home location.[3] We only focus on points of interest (POIs) within the tagged category "farmers market." Advan provides monthly data on the distribution of market visitors' home CBG, and to track the quarterly visits from each CBG (origin) to a farmers market (destination), we decompose this data and then aggregate the number of visitors at a market from a CBG to a given quarter.[4]

However, not all locations tagged by Advan as "farmers markets" conform to the traditional definition of a marketplace where local farmers directly sell their produce. To address potential misclassification errors, we first restrict the sample to POIs whose names contain the term "farm," ensuring closer alignment with venues that plausibly reflect farm-related market activity. We then remove POIs associated with farm stands and community-supported agriculture (CSA) programs, as

[2] One concern about cell phone data is the potential for location errors. The mobile GPS positioning can achieve an accuracy of 5 meters (roughly 16.5 feet). Although some urban markets may be located in dense areas where GPS accuracy could be reduced, we expect any resulting measurement error to be largely random and thus unlikely to systematically bias our estimates. To further assess this concern, we conduct robustness checks by imposing alternative minimum-visit thresholds for market inclusion; the results, presented in Online Appendix B.1, confirm that our main findings remain stable.

[3] The visitor's home locations are determined by analyzing 6 weeks of data during nighttime hours (between 6 pm and 7 am). Advan requires a sufficient amount of evidence (total data points and distinct days) to assign a home (common nighttime) geohash-7 for the device, which is then mapped to a CBG, census tract, and county of origin.

[4] We adopt a quarterly frequency as a trade-off between capturing meaningful temporal variation and avoiding excessive short-term fluctuations. farmers markets tend to operate seasonally, with attendance influenced by harvest cycles and weather patterns. Therefore, quarterly aggregation smooths out transitory spikes or dips caused by specific events (e.g., a single rainy weekend), while still allowing us to observe seasonal trends throughout the year.

well as locations operating seven days a week, which are more indicative of permanent retail stores than traditional, periodic farmers markets. These refinements are necessary because not all POIs tagged by Advan as "farmers markets" conform to the conventional definition of sites where local farmers directly sell their products. Several tagged locations correspond to chain stores such as Sprouts Farmers Market or to specialty grocers that function more like conventional retail outlets. Our final sample therefore focuses on locations most consistent with traditional farmers market activity.

To ensure the accuracy of our panel dataset, we validate our identified markets using a variety of authoritative sources, each contributing unique and essential details about farmers markets. The USDA Farmers Market Directory, managed by the Agricultural Marketing Service, offers a comprehensive national directory that includes operating hours and product offerings. SNAP retailer listings from the USDA's Food and Nutrition Service identify markets accepting SNAP benefits. Google Maps and Facebook Marketplace contribute geographic validation and add information on market days, vendor lists, and special events. Additionally, several states maintain farmers market directories with precise locations and operational specifics.[5]

We cross-reference each market listed in the Advan dataset with geographic data from the aforementioned sources to ensure that we are excluding misclassified entities like chain grocery stores. Specifically, we used fuzzy matching techniques to align the addresses and names from the Advan data with those listed in our external directories. This meticulous matching resulted in over three thousand verifications between the farmers markets and those recorded by Advan. To further refine our validation, we geocoded these locations to facilitate distance calculations using the Haversine distance formula, which allowed us to uncover additional matches that were not initially evident through address and name matching alone. These processes and their methodologies are detailed in Online Appendix A.1.

However, each dataset has certain limitations and incompleteness, requiring us to integrate information across sources to build a fuller picture. For instance, we primarily rely on SNAP retailer listings from the USDA's Food and Nutrition Service (FNS) to confirm whether markets accept

[5] These states are Connecticut (available here), California (available here), New York (available here), Texas (available here), Maryland (available here), Florida (available here), and Colorado (available here).

SNAP benefits, an important indicator of service to low-income populations. For markets that cannot be matched to the SNAP dataset, we cross-check their SNAP status using the USDA Farmers Market Directory.[6] Advan's data provides details like operating hours for some markets, allowing us to determine if a market operates during established hours, such as nighttime or weekends. When Advan's data lacks information on operating hours, we complement it with data from Facebook or Google to develop comprehensive market profiles.

To the end, we successfully matched 3,983 farmers markets, incorporating detailed information such as geolocation, city, state, ZIP code, market size (polygon area), and key operational attributes including SNAP acceptance, nighttime operating hours, and weekend availability, all summarized in Table 1. We also compared these statistics with those from the National Farmers Market Management Survey (NFMMS) to validate our findings against national trends (Table A1). This comparison showed a slightly higher but relatively close alignment in geographic dispersion and operational characteristics, such as the weekday and weekend operations, highlighting the representativeness and reliability of our sample.

Due to the aggregated nature of the data collected by Advan, direct personal details about the device holders, such as socioeconomic characteristics, are not available. Therefore, we rely on characteristics of the CBG in which the device's home is located to infer demographic information about the cell phone users.[7] We utilize demographic data from the Open Census, which provides cleaned and packaged American Community Survey data, alongside the Food Access Research Atlas from the USDA, to infer the socioeconomic status and other attributes of individuals based on their

[6] A limitation of this approach is that SNAP acceptance is treated as time-invariant over our study period. In reality, some markets may begin or discontinue SNAP participation, but these changes are not captured in the available data. This static definition can attenuate estimated effects if the true variation in SNAP participation over time is meaningful. We discuss further in Section 4.

[7] As neighborhood segregation has been increasing over time (Fogli and Guerrieri, 2019), assigning residents the sociodemographic characteristics of the census tract in which they reside is generally appropriate (Moss et al., 2021). Most Americans (97%) own a cellphone, which reduces to 85% for smartphones specifically (Pew Research Center, 2024). There appears to be little sociodemographic heterogeneity as smartphones are owned by 76% of those with the lowest income and 61% of those over the age of 65 (Pew Research Center, 2024).

home CBG.[8] Specifically, we define the racial and ethnic composition, income status, and urban share of a CBG using specific classification rules. For ethnicity, a CBG is classified as Hispanic if the majority of its population is Hispanic, following the majority rule. Racial classification is then determined through a relative comparison rule, where a CBG is considered the majority of a particular race if it has a higher percentage of that race compared to others. A CBG is classified as having a high income if its median household income is above the national median. Finally, we use the USDA ERS Food Access Research Atlas definition of a "food desert," which classifies areas as low-access if they are both low-income and have a substantial share of residents living more than one mile from the nearest supermarket/supercenter/large grocery store in urban areas or more than ten miles in rural areas (U.S. Department of Agriculture, Economic Research Service, 2023).

To complement our primary datasets, we incorporate three types of data to enhance the accuracy of our analysis. First, we collect daily average temperature and precipitation measures for each 2.5 $\times$ 2.5 mile grid across the contiguous U.S. from the Parameter-Elevation Regressions on Independent Slopes Model (Daly et al., 2009). The PRISM model, utilizing daily weather station data and accounting for factors such as elevation and wind direction, provides interpolated weather measures essential for controlling for the impact of weather on farmers market trips.

Second, gas cost data are sourced from the AAA website, which provides daily national and state-level average gas prices by type (regular, mid-grade, premium, and diesel). We extract this data using the Wayback Machine to retrieve daily snapshots since 2019, aggregating them to monthly averages per state. We calculate the travel costs based on the monetary travel cost and the opportunity cost of time. Specifically, we first estimate the travel distance and duration from the centroid of a CBG to a farmers market using the Open Source Routing Machine (OSRM)[9]. The visitor's opportunity cost of time in a CBG is measured using the common assumption that it is one-third of the wage rate implied by the CBG's average annual income (Lupi, Phaneuf, and

[8] Open Census data from Advan simplifies access to Census data by pre-cleaning and packaging it into user-friendly files based on the American Community Survey. Each file encompasses over 7500 attributes such as income, age, and education.

[9] In some cases, the open source routing machine failed to calculate the travel distance and duration. Instead, we calculated the haversine distance between origin and destination and used the ratio of 1.4 to impute the travel distance and travel time based on observed data.

von Haefen, 2020). Under these assumptions, the total travel costs (TC) are the sum of travel and time-related expenses:

$$TC_{ijt} = 2 * (gs_{st} + f_t) * Dist_{ijt} + 2 * \gamma \frac{Medinc_i}{2080} Time_{ijt} \quad (1)$$

where $Dist_{ijt}$ is the one-way distance between the centroid of a CBG and the market; gs_{st} reports the state-level average gas cost at year t; f_t denotes the marginal maintenance cost, repair cost, and depreciation from AAA reports; we assume $\gamma = 1/3$ indicating the share of the value of travel time used to account for the cost of leisure time, and $medinc_i$ is the median annual income in the visitor's CBG. The median income is divided by 2,080, the number of full-time hours potentially worked in a year. Lastly, annual national crude oil prices from 2019 to 2022, obtained from the U.S. Energy Information Administration (EIA), are utilized to address potential endogeneity issues in our farmer's market travel cost estimates. Together, these complementary datasets provide a robust framework for precisely estimating and analyzing farmers market demand.

Following previous studies on travel distance to farmers market (Jilcott Pitts et al., 2017), we restrict our study to short-distance trips within 30 miles.[10] After defining the choice sets, we calculate the market shares of each farmers market using the following procedure. We first define the market size of farmers market demand for each CBG per quarter. We assume an individual could make 26 market visits over a quarter (once per weekend day and holiday). The potential market size of each CBG is then calculated by multiplying the number of residing devices of the CBG by 26. The trip share of any farmers market within a given CBG-quarter is then defined as the ratio of the trips made to each market by visitors from the CBG to the CBG's total market size. To obtain theoretically consistent market shares for demand estimation, we apply an empirical Bayesian estimator to all markets, including those with zero observed visits, as discussed later in Section 4. The remaining share of the CBG market, which consists of all visits that occurred to locations other than farmers markets, is classified as the outside option share.

With these linkages and assumptions, we construct aggregate data of actual farmers market

[10] The 30-mile threshold is based on the unadjusted means and standard deviations reported in Appendix Table A2. The majority of trips fall well below 30 miles, making it a reasonable upper bound for defining short-distance trips.

choices for each CBG in the U.S. Our final estimation data set consists of 13,716,129 observations corresponding to CBG/market/year-quarter combinations where sampling occurred from 2019 to 2022. These observations are constructed from individual cell phone devices in 161,504 CBGs across the nation. Table 1 shows the summary statistics of farmers market visits in our sample from 2019 to 2022, averaged over farmers market and year-quarter. Residents, on average, traveled 8.39 miles and took 0.25 hours for a one-way-trip visit, with average travel costs of approximately $10.59.[11]

3 Who Visits Farmers Markets?

We first study disparities in farmers market access and use between FD and non-FD communities. We focus on several key metrics specifically designed to measure disparity in farmers market access and utilization across different communities. By examining both average visits per capita and visits per capita to the nearest farmers market, we quantify the level of engagement among various groups, identifying potential social or economic barriers to access for underrepresented populations. Analyzing average travel distance and distance to the nearest farmers market reveals how a lack of nearby market access could contribute to these disparities in utilization.

Considering racial, ethnic, and income factors, we follow Backstrom and Woodward (2023) in using the Euclidean distance between the racial/ethnic composition (or income) of two locations as a summary measure of demographic difference. This metric captures the overall magnitude of compositional dissimilarity across multiple groups in a single value, making it well-suited for comparing diverse communities. In addition, we incorporate the measure of experienced racial and income isolation proposed by Athey et al. (2020), which reflects the extent to which individuals are exposed primarily to others of the same group in the places they visit. For experienced isolation, we use whether or not a device is from a majority non-Hispanic White block group to define "White" and "non-White" users and whether the median household income of a CBG is above the national median

[11] To alleviate potential concerns about the representativeness of our GPS-based sample, extensive comparisons are made in Online Appendix A.2, demonstrating that our dataset aligns closely with the time-use patterns and travel behavior reported in other farmers market surveys.

value to define "high-income" and "low-income" users.[12] By evaluating the degree to which consumers from different racial and income backgrounds attend the same market, we can explore how social and psychological barriers affect attendance at these markets.[13] Collectively, these metrics provide a comprehensive view of both social and physical factors contributing to disparities in farmers market access and utilization.

Panel A of Table 2 shows a clear participation gap. On average, residents of FD communities make 0.132 visits per device compared to 0.174 for non-FD residents, a difference of 0.042 (t=20.09). When we anchor the comparison to each community's nearest market, the gap shrinks to 0.007 (t=7.88). This sharp reduction indicates that most of the participation shortfall comes from differences in access to preferred markets rather than an unwillingness to use markets. The small residual gap that remains is plausibly linked to other frictions, such as whether the nearest market is farther away, whether payment systems are convenient, or whether consumers feel comfortable in the space.

Panel B of Table 2 reinforces this access story with distance patterns. FD neighborhoods are physically farther from their nearest market: 8.367 miles compared to 7.128 miles for non-FD communities (t=-22.56). Among those who do visit, FD residents also travel farther in practice: 9.548 miles compared to 8.932 miles (t=-11.51). This means FD households face a double burden. The higher baseline distance raises the cost of making a trip to the nearest farmers markets, and it also makes trips to other markets less feasible because each visit requires more time, fuel, or transit. This explains why distance depresses participation both at the extensive margin (whether someone goes at all) and at the intensive margin (how often residents go when they have more choices).

Panel C of Table 2 sheds light on economic fit and demographic alignment. Farmers markets frequented by FD residents are more racially and ethnically dissimilar from their home neighborhoods than those visited by non-FD residents (36.323 vs. 32.306; t=-20.47), but they are more similar in terms of income (25.416 vs. 35.617; t=43.54). The same pattern appears when we look at nearest markets, which indicates that part of this difference is built into the structure of supply. The fact

[12] A majority non-Hispanic White block group is defined as a CBG in which more than 50 percent of residents identify as non-Hispanic White in the American Community Survey.

[13] The definition and methodologies are detailed comprehensively in Online Appendix A.3 and Online Appendix A.4 of our study.

that realized visits tilt even further toward income similarity suggests that economic fit, meaning how well markets align with household budgets and local economic characteristics, plays a role in shaping destination choice, which is in line with findings in (Pilgeram, 2011).

Panel D of Table 2 captures the experience once residents arrive at a market. FD visitors encounter lower racial isolation (34.152 vs. 40.541; t=30.31) and lower income isolation (46.385 vs. 50.990; t=19.52) compared to non-FD visitors, indicating the composition of shoppers they encounter is more diverse. In some ways, this can be a strength, as FD residents experience more varied social and economic interactions. However, prior work suggests that diversity does not always translate into comfort. The public nature of farmers market transactions, especially token systems for SNAP and WIC, can reduce privacy and make low-income shoppers feel stigmatized, and markets are often perceived as spaces dominated by middle- and upper-class White consumers (Pilgeram, 2011, 2012). These factors can dampen the extent to which diversity is experienced as inclusion.

Taken together, these results show that one of the major drivers of disparities is access, as FD residents have to travel further to reach farmers' markets. Improving geographic access through better siting, mobile markets, or transit connections should therefore deliver the largest gains. But there is also a persistent gap that suggests barriers remain even when a market is physically reachable. These barriers could be tied to economic fit, such as whether prices and payment options align with household budgets, and to social comfort, such as whether shoppers feel welcome in the market environment. Addressing these issues would entail targeted strategies such as expanding SNAP and WIC acceptance, adjusting hours toward evenings and weekends, diversifying product offerings, or working with community organizations to build trust and inclusion.

4 Model and Estimation

The descriptive patterns in Table 2 highlight where the disparities lie, but they do not by themselves reveal how much each factor contributes to the observed differences. Results of average visits, nearest-market benchmarks, travel distances, and economic fit all suggest that both geography and alignment with household characteristics shape participation. Yet these patterns may also be correlated with one another. For instance, longer distances could coincide with differences in racial

or income alignment, making it difficult to separate their independent effects.

To address this, we now turn to a discrete choice framework that formalizes the decision of whether and where to visit a farmers market. This model allows us to quantify how sensitive visitation is to travel distance, to demographic alignment between neighborhoods and markets, and to other sources of heterogeneity across communities. By moving from descriptive comparisons to a structural setting, we can better isolate the relative importance of access and fit, and we can then simulate how changes in market availability or characteristics would affect participation among FD communities.

4.1 Demand Model

We model households' decisions to visit farmers markets using a discrete-choice framework following Berry (1994). In each period, households from CBG i choose among a set of available farmers markets j or an outside option, which represents any non-farmers market activities.[14] We define each market as a CBG-quarter combination and assume that consumers make static, myopic choices, optimizing their current utility without considering future changes in travel cost or market attributes.

Households weigh several key factors when deciding where to visit. The first is generalized travel cost, which includes both time and fuel expenses and therefore represents an implicit price of visiting more distant markets. The second involves market and neighborhood attributes such as SNAP acceptance, evening hours, market size and variety, urban location, and whether the market is situated in a FD area. The third concerns social and economic fit, as households may prefer markets that align with their socioeconomic characteristics or community identity, even when travel distances are similar.

[14] Traditional food retailers are treated as part of the outside option. While supermarkets and grocery stores compete for similar food expenditures, our focus is on isolating the determinants of farmers market visitation and accessibility. Future extensions could explicitly model substitution between farmers markets and traditional retailers to quantify broader competitive dynamics.

The utility function of consumer i to farmers market j in year-quarter t is as follows:

$$\begin{aligned} V_{ijt} &= \delta_{ijt} + \mu_{ijt} + \epsilon_{ijt} \\ &= \delta_{ijt} + \sigma_{tc}\, t_{ijt}\, \nu_i^{tc} + \sigma_{race}\, r_{ij}\, \nu_i^{tc} + \sigma_{inc}\, y_{ij}\, \nu_i^{tc} + \epsilon_{ijt}, \end{aligned} \tag{2}$$

where δ_{ijt} represents the mean utility of farmer's market j for consumer from CBG i, ϵ_{ijt} follows i.i.d. Type-I extreme value distribution, and μ_{ijt} denotes the CBG-specific preference deviation from the mean utility. $\nu_{i,tc}$ is standard normal draw; t_{ijt}, r_{ij}, and y_{ij} denotes the travel costs, racial/ethnic distance, and income distance from CBG i to farmer's market j at time t.[15] Each visitor i makes a discrete choice and chooses the market j at time t that maximizes her/his random utility U_{ijt}. The discrete choice model allows opting out. Thus, an "outside good" is introduced into the model. The outside good in our case is all other activities that do not qualify as farmer's market trips. The mean utility δ_{ijt} is defined as:

$$\delta_{ijt} = \beta_1 t_{ijt} + \beta_2 r_{ij} + \beta_2 y_{ij} + \eta_j + \phi_i + \tau_t + \omega_{jt} + \xi_{ijt}, \tag{3}$$

where ω_{jt} denotes the weather condition at market j and year t. We characterize temperature and precipitation using a binning approach. In particular, we create sets of dummies where average temperature and precipitation fall into one of 10 decile bins. We include alternative specific constants (η_j) for each market to capture time-invariant unobserved market attributes, year-quarter fixed effect τ_t to control seasonality and year trends, and ϕ_i fixed effects to capture unobserved demographic variables that influence the demand for farmers markets.

Following Murdock (2006), we recover consumers' preferences for farmers market attributes by regressing the estimated alternative-specific constants (ASCs) on observed market characteristics,

[15] Because market fixed effects absorb time-invariant differences across markets (e.g., parking, vendor mix, baseline safety), identification of the racial/ethnic and income distance coefficient comes from within-market variation across origins. However, we cannot fully separate racial/ethnic or economic "fit" from origin-market-specific unobservables, such as outreach, social networks, or perceived comfort, that may be correlated with racial or income similarity. The coefficient should therefore be interpreted as capturing a broader social-fit channel rather than a fully identified causal taste for race or income.

including home county fixed effects to control for unobserved demographic and geographic factors:

$$\eta_j = \mathbf{z}_j'\boldsymbol{\gamma} + \zeta_c + v_j, \tag{4}$$

where $\mathbf{z}_j = [\text{SNAP}_j,\ \ln(S_j),\ \text{Weekend}_j,\ \text{Night}_j,\ U_j]'$ is the vector of market characteristics, $\boldsymbol{\gamma}$ is the associated coefficient vector, ζ_c denotes the home county fixed effect, and v_j is the idiosyncratic error term.[16]

Under the assumption that the idiosyncratic utility components are independently and identically distributed with the type I extreme value distribution, the probability that a utility-maximizing visitor i chooses market $j \in \{1, \ldots, J\}$ in period t is:

$$\text{share}_{jt} = \int \frac{\exp\left(\delta_{jt} + \mu_{ijt}\right)}{\sum_{k=1}^{J} \exp\left(\delta_{kt} + \mu_{ikt}\right)}\, d\nu_i, \tag{5}$$

where δ_{jt} is the mean utility of market j in period t, μ_{ijt} represents individual-specific deviations from mean utility, and ν_i denotes the distribution of random taste parameters across visitors.

The term $k = 0$ in the denominator denotes the *outside option*, representing all alternatives other than the observed farmers markets. Its market share is:

$$\text{share}_{0t} = 1 - \sum_{j=1}^{J} \text{share}_{jt}. \tag{6}$$

4.2 Handling Zero Market Shares

A common challenge in modeling demand is the occurrence of zero market shares, where some product sales record no observed purchase from specific markets during certain periods (Earle and Kim, 2024; Gandhi, Lu, and Shi, 2023; Ackerberg and Rysman, 2002; Quan and Williams, 2018). This issue is particularly prevalent in studies of retail markets using discrete-choice demand models, where infrequent purchases, niche product offerings, or limited consumer awareness can lead to

[16] Because the alternative-specific constants are estimated from millions of underlying choice observations per market, the sampling error in the first-stage estimates is extremely small. As in Murdock (2006) and related two-step demand applications, this implies that first-stage estimation noise contributes negligibly to the uncertainty in the second-stage coefficients, so standard clustered inference remains valid without further correction.

observed zero sales. Berry, Linton, and Pakes (2004) highlights that traditional demand models often assume positive market shares for all products, making them less suited for datasets with frequent zero observations. Moreover, sampling errors in small datasets or survey-based approaches can further distort demand estimation, exacerbating the challenge of accurately capturing consumer preferences.

To overcome this challenge, previous researchers modified data by aggregation or selective trimming, sometimes unknowingly, leading to potential selection bias and distorted demand estimates that affect policy simulations (Dubé, Hortaçsu, and Joo, 2021). In our context, the presence of zero market shares raises concerns about potential sampling and measurement errors. If visits are missed due to sampling limitations, then we potentially underestimate actual demand and distort the estimated effect of key variables.

To mitigate the issue, we apply empirical Bayes posterior mean estimation, as proposed by Li (2019). This method refines the visit probability estimates and ensures compatibility of our demand model with the estimation framework of Berry (1994), which requires strictly positive market shares. In practice, to maintain key heterogeneity across markets (CBG-year-quarter), we construct each market's empirical Bayes prior using a set of similar markets. Specifically, we define similar markets as the 50 closest in travel distance.[17] The market shares for the same farmers market from these similar markets serve as the prior distribution. We then fit this observed distribution using a Beta-Binomial model, apply a Bayesian approach to estimate the posterior distribution, and predict the adjusted market shares based on the posterior distribution. This method enables flexible adjustments by shrinking observed zero market shares toward expected positive values in comparable markets, reducing potential downward bias in demand caused by sampling errors and

[17] The choice of 50 balances two goals: (i) borrowing enough observations to estimate a stable Beta prior, and (ii) keeping the pooled markets geographically and behaviorally close so that implicit travel costs are comparable. Travel distance here serves as a proxy for the "price" of visiting a site, so restricting to CBGs with similar distances ensures that the prior reflects similar effective costs.

providing a more accurate representation of true behavior.

$$K_{jc} \sim \text{Binomial}(N_c, s^0_{jc}), \tag{7}$$
$$s^0_{jc} \sim \text{Beta}(\lambda^1_{jc}, \lambda^2_{jc}).$$

To estimate the hyperparameters and construct the prior Beta distribution for the Bayesian approach, we use visitation data from similar markets $l \in P_c$, where P_c represents a set of markets with similar travel distances or demographic characteristics. The hyperparameters λ^1_{jc} and λ^2_{jc} are estimated by maximizing the log-likelihood over these similar markets:

$$f(K_{jl}, l \in P_c | \lambda^1_{jc}, \lambda^2_{jc}) = \prod_{l \in P_c} \binom{N_l}{K_{jl}} \frac{\Gamma(\lambda^1_{jc} + \lambda^2_{jc})\Gamma(\lambda^1_{jc} + K_{jl})\Gamma(N_l - K_{jl} + \lambda^2_{jc})}{\Gamma(\lambda^1_{jc})\Gamma(\lambda^2_{jc})\Gamma(N_l + \lambda^1_{jc} + \lambda^2_{jc})}. \tag{8}$$

The posterior distribution of the trip probability s_{jc} also follows a Beta distribution, with the posterior mean given by:

$$\hat{s}_{jc} = \frac{\lambda^1_{jc} + K_{jc}}{\lambda^1_{jc} + \lambda^2_{jc} + N_c}. \tag{9}$$

We use the strictly positive posterior means $\hat{s}_{jc}$ as the adjusted market shares. In large markets, the empirical Bayes posterior is very similar to the observed shares because the observed sales dominate the prior.[18]

4.3 Identification and Estimation

We use the panel structure and the mean-utility specification in (3). For the first-stage demand system, the parameter vector is

$$\theta_2 \equiv (\beta_1, \beta_2, \beta_3), \tag{10}$$

[18] A Monte Carlo simulation in Cheng and Wan (2025) demonstrated that the empirical Bayes (EB) posterior-mean correction yields unbiased recovery of travel-cost parameters and mean utilities under sparse cellphone mobility data, whereas conventional treatments (e.g., dropping zeros or adding constants) produce attenuation or instability. See more details in Online Appendix E.

where $(\beta_1, \beta_2, \beta_3)$ load on the travel cost d_{ijt}, demographic distances r_{ij} and income distance y_{ij}, respectively, in equation (4).

A key concern is that the observed travel cost t_{ijt} co-moves with unobserved market–time shocks ξ_{jt}. As emphasized in recent recreation-demand work (Bradt, 2025), endogeneity can arise from two sources: measurement error in per-mile fuel costs, reflecting local fuel-price heterogeneity or imprecise price assignment to travelers, and residential sorting, in which households with particular tastes for amenities choose locations with systematically different travel costs. Either issue would bias the estimated travel-cost coefficient if unaddressed.

To address these concerns, we instrument d_{ijt} with the interaction of the average crude oil price with origin-state dummies, $z_{ijt}^{\text{oil}} \equiv p_t^{\text{oil}} \times \mathbf{1}\{\text{state}(i) = s\}$, to allow fuel-cost pass-through, taxes, and supply-chain conditions to vary across states. These interactions generate plausibly exogenous, time-varying shifts in the marginal cost of travel that apply uniformly to all markets within a state. After conditioning on our rich set of fixed effects, this variation is orthogonal to market-time demand shocks and therefore satisfies exclusion.

Crude oil-based instruments address both sources of endogeneity. First, they mitigate measurement error in per-mile fuel costs by separating travel costs from potential mismeasurement in assigning local fuel prices to devices. Second, they help address residential sorting because oil price fluctuations provide short-run variation in driving costs that is unrelated to the long-run amenity-driven reasons households choose their residential locations. As a result, the instrument isolates exogenous variation in travel costs that is not confounded by either fuel-price mismeasurement or sorting-based correlations between travel distances and unobserved tastes.

Next, we consider the SNAP acceptance variable, SNAPj. We construct SNAPj by matching markets to the FNS SNAP retailer listings and, when a direct match is unavailable or ambiguous, by cross-checking against the USDA Farmers Market Directory and other public listings. Two measurement challenges arise. First, our matching relies on fuzzy name/address algorithms and nearest-neighbor rules, which may result in occasional mismatches across data sources. Second, coverage is uneven across time: while the FNS data report start and end dates, the Directory provides only snapshots, so we measure SNAPj as effectively time-invariant over our sample even though adoption or discontinuation may occur within the period. If misclassification were classical,

the coefficient on SNAPj in the market-attribute regression would be attenuated toward zero. In practice, however, errors are plausibly nonrandom, for example, smaller or more remote markets are more likely to have incomplete records, so the direction of bias is a priori ambiguous.[19]

To address these two sources of potential mismeasurement, we implement two sets of robustness checks. First, to account for possible mismatches from fuzzy name or address matching, we re-estimate using alternative matching rules that vary the allowable string similarity score and distance cutoff. This ensures that our results are not sensitive to the tolerance level in the matching algorithm. Second, to account for unobserved within-year changes in SNAP authorization, we restrict the sample to markets with consistent SNAP status across all available sources over the study period. This stable subset isolates long-run authorization from potential misclassification due to timing discrepancies. Across both checks, the estimated SNAP coefficients remain positive and similar in magnitude, indicating that our conclusions are unlikely to be driven by mismeasurement in SNAP status.

Finally, we estimate the demand parameters by generalized method of moments (GMM) using moment conditions that set the instrumented residuals to zero. Let Z_{tc} collect the demand-side instruments (including dist_{ij} and $p_t^{\text{oil}}\times$ state dummies) and let $\xi(\theta_2)$ denote the market-time unobservable implied by the mean-utility equation once observed covariates and fixed effects are partialled out. Identification requires

$$\mathbb{E}[Z_{tc}\,\xi(\theta_2)] = 0. \tag{12}$$

For a given $\theta_2 = (\beta_1, \beta_2, \beta_3)$, we recover $\xi(\theta_2)$ by inverting the share system via a standard contraction mapping so that the model-predicted (weighted) shares match the observed (weighted) shares.

We implement a two-step GMM. In the first step, we use $A_{tc}^{(0)} = I$ and obtain a preliminary estimate $\widehat{\theta}_2^{(1)}$. We then estimate the covariance of the sample moments using heteroskedasticity- and serial-correlation-robust, multiway clustered residuals (clustered by origin CBG i and destination

[19] Other sources of potential error include reporting lags, name or address changes, and supplemental lists based on market self-reporting. Because these discrepancies cannot be systematically validated against ground truth, we treat them as additional sources of unobserved noise in the construction of SNAP_j.

market j across t), and update the optimal weighting matrix to $A_{tc}^{*} = \widehat{\Omega}^{-1}(\widehat{\theta}_2^{(1)})$. The final estimate solves

$$\widehat{\theta}_2 \;=\; \arg\min_{\theta_2} \; \xi(\theta_2)' \, Z_{tc} A_{tc}^{*} Z_{tc}' \, \xi(\theta_2). \tag{13}$$

We report first-stage diagnostics for the instruments (e.g., Kleibergen–Paap F-statistics).[20]

4.3.1 Other Demand Estimation Considerations

A final set of considerations concerns the use of GPS-based mobility data in demand estimation and in model assumptions.

First, smartphone ownership is high nationally but remains modestly lower among older and lower-income populations. If these groups are underrepresented in the mobility panel or engage in less detectable travel, the data may understate their true engagement with farmers' markets. Because such selection is more likely among populations facing greater travel constraints, this bias again works against finding large disparities. Additionally, home CBGs are inferred from nighttime clustering over a 6-week window. Individuals with irregular schedules, multiple residences, or seasonal mobility may be misclassified. Misclassification is more likely among economically vulnerable or highly mobile populations and may further reduce the measured frequency of visits originating from disadvantaged communities.

These factors tend to bias visitation measures downward for the very populations that face the strongest access constraints. Consequently, our structural estimates should be interpreted with the understanding that measurement error works mostly in a conservative direction. Any disparities we document represent lower-bound estimates of underlying differences in market utilization across FD and non-FD communities.

Additionally, our demand model treats the outside option as an aggregate category that includes grocery shopping at supermarkets or other food retailers, non-food trips, and the decision not to make a trip. Because we do not model substitution across individual retailers, the logit structure should be

[20] Computationally, we iterate the contraction until the maximum change in mean utility is below 10^{-8}, use stabilized log-sum-exp to avoid overflow in the share inversion, and standardize covariates entering the nonlinear inversion for numerical stability.

interpreted as describing which farmers' market consumers choose, conditional on deciding to visit a farmers' market, rather than a full model of substitution within the broader food retail environment. Prior work shows that new supermarkets primarily draw customers from other full-service grocers within very short distances rather than from farmers' markets (Amin, Badruddoza, and McCluskey, 2025; Allcott et al., 2019), reflecting the distinct role that farmers' markets play as intermittent, specialty venues offering local or artisanal products.

Building on this evidence, we assume that substitution patterns between farmers' markets and other food retailers remain relatively stable over our study period. In our setting, the average nearest farmers' market is located more than three miles from a CBG centroid, making short-distance retail competition less relevant. Under this structure, the outside option appropriately absorbs grocery-store visits and non-shopping activities, and our welfare and policy simulations should be interpreted as incremental improvements in farmers' market access or attributes holding the broader retail environment fixed. This conditional-choice framework provides a conservative interpretation of consumer behavior without imposing strong assumptions about cross-format substitution.

4.4 Results

Table 3 summarizes demand estimates from a homogeneous-tastes logit (setting $\sigma = 0$) and from our preferred random-coefficients (R.C.) logit, which allows for heterogeneity in preferences between FD and non-FD consumers. In the all sample, the travel-cost coefficient is negative and precisely estimated. Instrumenting generalized travel cost with geometric distance and the interaction of crude oil prices with state dummies yields a travel-cost estimate very close to the OLS logit result, indicating that any endogeneity in observed travel costs is limited after conditioning on rich fixed effects and controls. Moving to the R.C. logit, the mean travel-cost effect remains of similar magnitude and sign, while the deviation (standard deviation) is statistically different from zero, confirming meaningful taste heterogeneity in the disutility of travel.

Demographic distances show a clear pattern. Racial/ethnic distance enters the mean utility negatively and robustly across specifications, consistent with a tendency to visit markets whose visitor composition is closer to that of the origin CBG. We view this pattern as consistent with a social-fit mechanism, encompassing comfort, familiarity, and other unobserved factors correlated

with racial composition, rather than as clear evidence of a pure taste parameter for race. By contrast, income distance is sensitive to specification: it is negative in the homogeneous logit but is not robustly different from zero in the R.C. mean, and we do not detect strong heterogeneity in responses to income distance. Together, these results suggest that racial/ethnic composition differences are a more salient barrier to visitation than income composition differences, once we allow for random coefficients.

In the subgroup estimates, both the mean travel-cost effect and the mean racial/ethnic-distance effect are larger in magnitude for non-FD neighborhoods than for FD neighborhoods, and the dispersion of the corresponding random coefficients is smaller in FDs. This pattern is consistent with more constrained choice sets in FDs: with few viable markets and high baseline frictions, households' behavior converges toward selecting the nearest feasible option, compressing both average sensitivities (to distance and to composition) and cross-household heterogeneity. By contrast, in better-served areas with thicker choice sets, households respond more strongly on both margins and exhibit greater heterogeneity in the trade-offs they are willing to make.

Table 4 reports the second-stage regressions of market fixed effects, η_j, on time-invariant market attributes. In columns (1)-(4) we use η_j from the all-sample R.C. logit and vary the set of controls and fixed effects; columns (5)-(6) repeat the specification separately for FD and non-FD neighborhoods. If the fixed effects soak up the unobserved factors that might otherwise be correlated with these attributes, the coefficients can be interpreted as the causal contribution of each attribute to market attractiveness. We view the estimates in this light, while acknowledging that some residual unobserved heterogeneity may still remain.

Three patterns are robust in the all-sample results. First, *SNAP acceptance* is positively associated with baseline market appeal across specifications. The magnitude declines as we add richer controls and county fixed effects, but the sign and significance are stable, consistent with SNAP authorization being valued by visitors. Second, *night operation* becomes positive and significant once location confounders are absorbed; conditional on county fixed effects, evening hours are associated with higher appeal, consistent with improved temporal access for working households. Third, *market size* (log size) is strongly and consistently positive, indicating sizable gains from variety/scale. Finally, *Urban share* is positive in the all-sample specification with the richest controls, pointing to higher

baseline appeal in more urban catchments.

The subgroup estimates highlight meaningful differences. For FD neighborhoods, SNAP acceptance remains positively associated with market appeal, though only marginally significant, while night operation and market size continue to play central roles. The urban-share coefficient is small and imprecise, suggesting that simply being in a more urbanized area does not, by itself, raise baseline appeal for low-access consumers. For non-FD neighborhoods, SNAP acceptance and market size are both strongly positive, night operation remains beneficial, and urban share is clearly positive. Taken together, these patterns suggest that in low-access areas, the largest gains come from expanding feasibility on the extensive margin, adding temporal access through evening hours, and ensuring sufficient scale, whereas in non-FD areas, both access and program features (notably SNAP) matter more for baseline appeal.

Before turning to the estimates, it is useful to note that whether FD households value SNAP authorization more or less than non-FD households is theoretically ambiguous. On the one hand, FD households may place greater value on SNAP authorization because it directly expands the set of feasible shopping opportunities and reduces the frictions they face in accessing fresh foods. Prior work shows that low-income households experience substantial time, transportation, and information constraints when shopping for healthy foods (Zenk et al., 2005a; Ver Ploeg et al., 2012; Bitler and Haider, 2011), and that SNAP benefits meaningfully expand their set of accessible retailers in constrained environments (Wilde, 2013; Gregory and Deb, 2015). Stigma concerns may also be less severe at farmers' markets than in conventional retailers, where stigma associated with SNAP use has been well documented (Moffitt, 1983; Currie and Grogger, 2001). These forces suggest a priori that SNAP acceptance could be particularly valuable for FD households. On the other hand, consumers in better-served and higher-income areas may attach expressive or identity-related value to SNAP participation at farmers' markets, for example, through social-image or virtue-signaling motives, which would imply higher WTP among non-FD communities (Sexton and Sexton, 2014; Griskevicius, Tybur, and van den Bergh, 2010; Ariely, Bracha, and Meier, 2009).

With this ambiguity in mind, we translate the estimated coefficients into implied WTP. For FD neighborhoods, dividing the SNAP coefficient by the corresponding travel-cost coefficient (0.093/0.1494) yields an MWTP of roughly \$0.62. For non-FD neighborhoods, the same ratio

(0.148/0.1518) results in an MWTP of about $0.98. These values indicate that non-FD communities are willing to incur nearly a full dollar of extra travel cost to reach SNAP-authorized markets, while FD communities are willing to bear only about two-thirds of that cost. Taken together, these differences suggest that, on balance, identity- or image-related motives likely play a stronger role for better-served households than the functional access benefits that matter more for FD residents.

We then examine how measurement errors of market visits may affect the accuracy of our estimates. While it might seem reasonable to assume that a closed market would have zero recorded visits, that's not always the case. Even during closures, we may observe a small number of visits due to market staff, maintenance personnel, or untracked activity. Additionally, GPS inaccuracies or the market's proximity to other businesses can result in misclassified visits. These issues highlight the importance of setting a minimum visit threshold that helps filter out such noise while still capturing true consumer activity. Following an approach by Crane et al. (2022), we analyze patterns in visitor activity to infer the likelihood of market closures, presenting our findings in Appendix Table B1, which suggests that measurement errors minimally impact our estimates.

We also conduct a number of robustness checks, which are presented in Appendix Online Appendix C. First, we run our IV logit model with alternative racial/ethnic and income diversity definitions, including the absolute values of the differences between the Black and Hispanic population proportions, indicator terms equal to 1 if the market's Black and Hispanic population proportions are greater than those at the visitor's home origin, and positive Black and Hispanic differences in Appendix Table C1. In general, these results show similar insights on the impact of racial/ethnic and income diversity on farmers market travel behavior. One concern about our sample is whether 30 miles is a reasonable cutoff for farmers market's choice set. We next re-estimate our model with alternative trip cutoffs, including 10, 15, 20, and 25 mile cutoffs in Appendix Table C2. We find that the coefficient of travel costs converges to -0.154 as the cutoff increases, suggesting that 30 miles is a reasonable cutoff. We also explore alternative definitions of market size in Appendix Table C3. While our baseline defines market size as the total number of market visitation occasions from a CBG in a given month, we test variations where consumers may have more or fewer decision occasions per quarter. Our results remain robust across these specifications.

As noted previously, the non-uniform spatial distribution in our device sampling could skew

results if left uncorrected. We experiment with incorporating sample weights that are calibrated using the presumed home locations of the devices. Specifically, we compute weights based on the deviation between the observed number of devices and the actual population at three geographic levels: CBG, county, and state. That is, for each device, we assign a weight equal to the population-to-device ratio at its home CBG, county, or state. Appendix Table C4 reports results from models using each of these weighting schemes, with each column corresponding to one geographic level. We find that incorporating these sampling weights slightly reduces the magnitude of the travel cost coefficients, though results are generally consistent, thereby enhancing the validity of our findings.

Another concern is that our findings could be driven by measurement error in the construction of the SNAP variable, either from mismatches in the market-retailer linkage or from markets whose SNAP status changes over time. To address the first issue, we vary the tolerance thresholds for name similarity and centroid distance in the matching algorithm. As shown in Appendix Table C5, the estimated effect of SNAP remains positive and statistically significant across all matching scores and distance cutoffs, with magnitudes tightly clustered around the baseline. To address the second issue, we exclude markets that either begin or end SNAP participation after specific years, thereby focusing on markets with stable SNAP status over the study window. Table Appendix Table C6 shows that the SNAP coefficients are similarly robust in sign, significance, and magnitude across these exclusion rules. Taken together, these results demonstrate that our conclusions are not artifacts of fuzzy matching, reporting discrepancies, or transitional markets, but rather reflect a stable underlying relationship between SNAP acceptance and market attractiveness.

5 Can Farmers Markets Reduce Food Utilization Disparity?

5.1 Decomposing Visit Differences into Supply versus Demand Factors

To understand the drivers of disparities in farmers market usage between FD and non-FD communities, we adapt the conceptual framework of Allcott et al. (2019) to our structural setting and mobility data. Our goal is to separate the observed gap in visits into *supply-side* factors (market availability and travel variables) and *demand-side* factors (preferences for market characteristics and travel). Breaking the gap into access and preference components makes it clear which force is doing

more of the work, and therefore whether improving supply or easing demand-side barriers would have the bigger payoff.

We first use nearest-neighbor matching to pair each FD neighborhood with a non-FD neighborhood that has similar demographics, including income, racial composition, education, and vehicle ownership. Matching details are provided in Appendix Section Online Appendix D. This ensures that any differences identified in the decomposition are not driven by demographic composition. The matched non-FD neighborhood for FD neighborhood i is denoted $m(i)$.

Let $u_{ij}(\mathcal{C}, \theta^T, \theta^A)$ denote the deterministic component of utility for a representative device in neighborhood i visiting farmers market j, given the choice set $\mathcal{C}$ with associated travel costs, travel-preference parameters θ^T, and market-attribute preference parameters θ^A (e.g., SNAP acceptance, evening hours, market size, weekend operation). For any market j in the choice set $\mathcal{C}$, the choice probability is given by the logit formula:

$$P_{ij}(\mathcal{C}, \theta^T, \theta^A) \;=\; \frac{\exp\left[u_{ij}(\mathcal{C}, \theta^T, \theta^A)\right]}{1 + \sum_{k \in \mathcal{C}} \exp\left[u_{ik}(\mathcal{C}, \theta^T, \theta^A)\right]}, \tag{14}$$

where the outside option is normalized to zero utility.

Expected quarterly visits per device in neighborhood i are:

$$V(\mathcal{C}, \theta^T, \theta^A) \;=\; M_i \sum_{j \in \mathcal{C}} P_{ij}(\mathcal{C}, \theta^T, \theta^A), \tag{15}$$

where M_i is the market size, measured as the average number of trips per device to all farmers markets in the neighborhood's choice set.

We define FD objects $(\mathcal{C}_i^{FD}, \theta^{T,FD}, \theta^{A,FD})$ and non-FD objects $(\mathcal{C}_i^{N}, \theta^{T,N}, \theta^{A,N})$ for each matched pair $(i, m(i))$. The overall baseline gap in visits between matched non-FD and FD CBGs is:

$$\Delta = \frac{1}{|\mathcal{I}|} \sum_{i \in \mathcal{I}} \left[\, V(\mathcal{C}_i^{N}, \theta^{T,N}, \theta^{A,N}) - V(\mathcal{C}_i^{FD}, \theta^{T,FD}, \theta^{A,FD}) \,\right]. \tag{16}$$

We then conduct a sequential decomposition, replacing components of the FD demand system with those of their matched non-FD counterparts in the order of supply, then market attributes, and

finally travel preferences. First, we replace the FD supply (choice sets and travel variables) with non-FD supply:

$$S = \frac{1}{|\mathcal{I}|} \sum_i \Big[V(\mathcal{C}_i^N, \theta^{T,FD}, \theta^{A,FD}) - V(\mathcal{C}_i^{FD}, \theta^{T,FD}, \theta^{A,FD}) \Big]. \tag{18}$$

Next, we replace market-attribute preferences:

$$D_A = \frac{1}{|\mathcal{I}|} \sum_i \Big[V(\mathcal{C}_i^N, \theta^{T,FD}, \theta^{A,N}) - V(\mathcal{C}_i^N, \theta^{T,FD}, \theta^{A,FD}) \Big]. \tag{19}$$

Finally, we replace travel preferences:

$$D_T = \frac{1}{|\mathcal{I}|} \sum_i \Big[V(\mathcal{C}_i^N, \theta^{T,N}, \theta^{A,N}) - V(\mathcal{C}_i^N, \theta^{T,FD}, \theta^{A,N}) \Big]. \tag{20}$$

We further decompose D_T into three components: (i) *travel cost preference* (D_T^t), capturing differences in the marginal disutility of travel costs; (ii) *demographic distance preference* (D_T^r), reflecting differences in sensitivity to racial and ethnic composition distance; and (iii) *income distance preference* (D_T^y), representing differences in sensitivity to income composition distance.

By construction,

$$\Delta \approx S + D_A + D_T^t + D_T^r + D_T^y, \tag{21}$$

and we report shares S/Δ, D_A/Δ, D_T^t/Δ, D_T^r/Δ, and D_T^y/Δ.

Understanding whether the determinants of farmers market usage gaps differ across community types is essential for designing targeted interventions. Rural communities may face greater geographic and transportation barriers, while urban communities may experience more intense competition from alternative food retailers. Identifying these differences can help policymakers and practitioners prioritize strategies that are most effective for specific populations. To investigate these potential differences, we extend the decomposition framework to examine heterogeneity across community types. We conduct our visit gap analysis separately for rural and urban neighborhoods.[21] For each

[21] We classify a neighborhood as *urban* if at least 50% of its population resides in Census-defined urban areas, based on the 2010 Census Urban Area population share; *rural* otherwise.

subgroup, Rural and Urban, we compute the overall FD–non-FD visit gap Δ_g and its components S_g, $D_{A,g}$, and $D_{T,g}$. We then compare the proportional contributions of supply, market attributes, and travel preferences across these subgroups to assess whether the drivers of the usage gap vary systematically by rurality.

Figure 2 shows the normalized contributions of each component to the FD–non-FD visit gap. The bar heights are scaled so that all components sum to one, allowing direct comparison of their relative importance in explaining visitation disparities. For all neighborhoods combined, store availability and access account for about 20% of the total gap, reflecting spatial inequities in market distribution and travel cost. Store characteristics preferences explain roughly 10% of the gap, capturing differences in valuation of SNAP acceptance, evening operation, and market size. The remaining 70% is explained by travel preferences, which we further divide into travel cost, demographic distance, and income distance preferences. Travel cost preference alone accounts for the largest share of the gap, followed by demographic distance preference and, to a lesser extent, income distance preference.

Patterns differ across community types. For urban neighborhoods, demand preference remains the dominant factor explaining FD–non-FD disparity, as preference for travel cost and demographic distance play a more prominent role. In rural neighborhoods, preference for travel cost still explains a substantially larger share of the gap, while demographic and income distance preferences contribute relatively little; the supply-side component is larger in rural than in urban areas. This combination suggests that rural disparities are more likely driven by fewer proximate markets. As a result, policies that directly reduce travel time and cost, such as increasing market density, improving transportation infrastructure, or providing travel subsidies, may be especially effective in rural areas. In addition, because demographic and income distance preferences are less salient in rural settings, interventions that focus solely on socio-demographic alignment may have limited impact unless paired with measures to reduce geographic isolation.

While not directly comparable to Allcott et al. (2019), as we focus on market visits rather than their healthy purchasing index, the broad pattern of supply and demand factors remains informative. In Allcott's supermarket setting, demand-side preferences overwhelmingly explained disparities (about 90%), and supply-side factors played only a minor role. In our farmers market setting, demand preferences still dominate, but supply-side access accounts for a larger share of the

gap. Importantly, our framework extends the decomposition by incorporating demographic and income distance preferences alongside travel costs, allowing us to capture how socio-demographic fit and spatial frictions shape market utilization. This added dimension reveals that disparities are not only about product variety or price, but also about whether farmers markets align with the social and economic profiles of surrounding communities. This pattern suggests that, relative to supermarkets, farmers markets may offer greater potential for reducing disparities through supply-side interventions (e.g., improving market access or characteristics, or increasing market density). However, given the large role of travel costs and socio-demographic preferences, particularly in rural areas, effective strategies will likely require a combination of physical access improvements and targeted demand-side engagement.

5.2 Using Observables to Explain Demand Differences in Farmers Market Visits

The previous section showed that demand-side behavior, rather than supply differences, accounts for most of the disparity in market visits between FD and non-FD areas. To isolate demand-side behavioral differences from supply disparities, we simulate a counterfactual in which non-FD neighborhoods face the same market availability and travel structure as FD neighborhoods. To begin, for each non-FD neighborhood c, we replace its observed supply attributes with those from FD neighborhoods while keeping its demographic characteristics unchanged.

Under this scenario, the probability of visiting market j from neighborhood c is:

$$P_{ijt}^{\text{eq-supply}} = \frac{\exp\left(V_{ijt}^{\text{FD-supply}}\right)}{\sum_{k \in \mathcal{J}_{it}^{\text{FD-supply}}} \exp\left(V_{ikt}^{\text{FD-supply}}\right)}, \tag{22}$$

where $V_{jc}^{\text{FD-supply}}$ is the systematic utility using FD supply attributes (location, travel distance, hours) and the original taste parameters θ_t and attribute sensitivities θ_a of CBG c.

The predicted total visits per device are:

$$\hat{y}_{it} = M_{it} \sum_{j \in \mathcal{J}_{it}^{\text{FD-supply}}} P_{ijt}^{\text{eq-supply}}, \tag{23}$$

with M_c denoting the market size for neighborhood c.

To identify which observable characteristics drive the difference in market visits between FD and non-FD communities, once each FD is paired with a comparable non-FD food environment, we apply the decomposition method of Gelbach (2016), following the implementation in Allcott et al. (2019), to attribute changes in the FD coefficient to specific covariates.

Consider the baseline regression of visits per device (or the log share of farmers market trips) on the FD indicator:

$$\hat{y}_{it} = \alpha \, \mathrm{FD}_i + \mu_t + \varepsilon_{it}, \tag{24}$$

where μ_t are time fixed effects. Let X_{it}^1 denote the set of potential mediators (e.g., education, income, vehicle access, age structure, work-from-home share, internet access, and race shares), and X_{it}^0 any remaining controls held fixed across specifications (e.g., CBG FE or urbanization controls, as applicable). The "full" regression is

$$\hat{y}_{it} = \tilde{\alpha} \, \mathrm{FD}_i + \gamma^\top X_{it}^1 + \eta^\top X_{it}^0 + \mu_t + u_{it}. \tag{25}$$

Following Gelbach (2016), define $\hat{\Gamma}$ as the coefficient vector from the auxiliary regression of FD_i on the mediators,

$$\mathrm{FD}_i = \hat{\Gamma}^\top X_{it}^1 + \zeta^\top X_{it}^0 + \mu_t + v_{it}. \tag{26}$$

Then the contribution of mediator $v \in X^1$ to the baseline FD–visit relationship is

$$\hat{\pi}_v \;=\; \frac{\hat{\gamma}_v \hat{\Gamma}_v}{\hat{\alpha}}. \tag{27}$$

Intuitively, $\hat{\pi}_v$ measures how much of the baseline FD coefficient is "explained" by demographic characteristic v; the sum of $\hat{\pi}_v$ over all mediators equals the change in the FD coefficient when moving from (26) to (27). We report point estimates and confidence intervals for $\hat{\pi}_v$ using the bootstrapping method.

Figure 3 summarizes the estimated $\hat{\pi}_v$. Four patterns emerge. First, *educational attainment* (share with a bachelor's degree or higher) accounts for by far the largest single contribution to the

FD–visit relationship, on the order of five percentage points of the baseline coefficient. Second, *vehicle access* (share without a vehicle) also contributes meaningfully, consistent with mobility constraints mediating visitation differences even after holding supply fixed. Third, *income* (log median income) makes smaller but positive contributions. Fourth, the contributions of *work-from-home share*, *internet access*, and *race shares* (White, Black) are close to zero once the full set of mediators is included, suggesting limited additional explanatory power through these channels for the FD–visit relationship in our setting.

These Gelbach attributions indicate that most of the demand-side visit gap can be explained by *human-capital* and *transportation* channels, rather than by broadband access or racial composition, once other characteristics are held constant. Because these are correlations rather than causal effects, the patterns should be interpreted cautiously. Still, the association with education is consistent with the possibility that information, awareness, or planning frictions may influence market participation, suggesting that clearer communication of EBT/SNAP acceptance, multilingual signage, or predictable scheduling could help lower cognitive or planning burdens. The correlation with vehicle access similarly points to transportation constraints as a potential barrier; options such as locating markets closer to low-access neighborhoods, offering mobile or pop-up markets, or improving transit connections may help address these constraints. Overall, these results are consistent with the broader evidence (Section 2) indicating that reducing general travel burdens and decision frictions may offer some of the more immediate avenues for improving equity in market participation, particularly in areas with low vehicle ownership.

5.3 Using Supply-side Interventions to Reduce Food Utilization Disparity

While our decomposition showed that differences in demand-side preferences were the dominant contributor to the FD–non-FD visit gap, supply factors still accounted for a meaningful share of the disparity. This suggests that well-designed changes to the local market environment could increase visitation from FD communities, even without altering underlying preferences. Policymakers generally have more control over market supply than consumer preferences, and we now explore how targeted supply-side interventions could reduce the utilization gap. We perform two complementary exercises on three policy scenarios that address well-documented barriers faced by FD communities:

(i) requiring all markets in FD choice sets to accept SNAP benefits, (ii) ensuring these markets operate during evening hours to better serve working households, and (iii) strategically adding one "average" market to each FD neighborhood's choice set to expand local supply.

We evaluate these scenarios using two complementary exercises. In the first exercise, we simulate the change in visitation implied by each intervention, holding the estimated preference parameters fixed. In the second, we translate these simulated changes in visitation into monetized welfare gains and compare them with approximate implementation costs. Across all scenarios, we recompute visit probabilities and total visits under the modified supply environment while keeping preferences constant.

Simulated Visitation Gains from Policy Interventions. The utility specification from the model Section is used to evaluate each intervention by modifying relevant market attributes, recomputing choice probabilities, and aggregating expected visits per device.

(1) Universal SNAP acceptance. In this scenario, for each j in FD choice sets with $SNAP_j = 0$, we set $SNAP_j^{(\text{SNAP})} = 1$. The induced change in the alternative-specific constant (ASC) is

$$\Delta ASC_{jc}^{(\text{SNAP})} \;=\; \gamma_1\big(SNAP_j^{(\text{SNAP})} - SNAP_j\big), \tag{28}$$

and the policy-adjusted utilities are

$$\delta_{ijt}^{(\text{SNAP})} \;=\; \delta_{ijt} + \Delta ASC_{jc}^{(\text{SNAP})}, \qquad V_{ijt}^{(\text{SNAP})} \;=\; \delta_{ijt}^{(\text{SNAP})} + \mu_{ijt} + \varepsilon_{ijt}. \tag{29}$$

For this augmented set, recomputed logit probabilities and total visits are:

$$P_{ikt}^{(\text{SNAP})} = \frac{\exp\big(V_{ikt}^{(\text{SNAP})}\big)}{1 + \sum_{\ell \in \mathcal{C}_i^{(\text{SNAP})}} \exp\big(V_{i\ell t}^{(\text{SNAP})}\big)}, \qquad V_i^{(\text{SNAP})} \;=\; M_i \sum_{k \in \mathcal{C}_i^{(\text{SNAP})}} P_{ikt}^{(\text{SNAP})}. \tag{30}$$

(2) Universal night operations. For each j in FD choice sets with $Night_j = 0$, set $Night_j^{(\text{Night})} = 1$.

The induced ASC change is

$$\Delta ASC_{jc}^{(\text{Night})} \;=\; \gamma_4\big(Night_j^{(\text{Night})} - Night_j\big), \tag{31}$$

and the policy-adjusted utilities are

$$\delta_{ijt}^{(\text{Night})} \;=\; \delta_{ijt} + \Delta ASC_{jc}^{(\text{Night})}, \qquad V_{ijt}^{(\text{Night})} \;=\; \delta_{ijt}^{(\text{Night})} + \mu_{ijt} + \varepsilon_{ijt}. \tag{32}$$

For this augmented set, recomputed logit probabilities and total visits are:

$$P_{ikt}^{(\text{Night})} = \frac{\exp\big(V_{ikt}^{(\text{Night})}\big)}{1 + \sum_{\ell \in \mathcal{C}_i^{(\text{Night})}} \exp\big(V_{i\ell t}^{(\text{Night})}\big)}, \qquad V_i^{(\text{Night})} \;=\; M_i \sum_{k \in \mathcal{C}_i^{(\text{Night})}} P_{ikt}^{(\text{Night})}. \tag{33}$$

(3) Adding an "average" market. Following Athey et al. (2018), we do *not* pool attributes into a single synthetic option. Instead, we use a *set* of representative ("average") markets and average the resulting visit gains. Let

$$\mathcal{J}_{\text{avg}} = \Big\{ j : \; |D_j - \bar{D}| \le 0.1\, SE(D) \Big\} \tag{34}$$

be the set of markets whose total demand lies within 0.1 standard errors of the sample mean. For each candidate $r \in \mathcal{J}_{\text{avg}}$, we add a copy j_r^* of that market to FD CBG i's choice set (with the candidate's observed attributes x_r and travel cost $TC_{ij_r^*t}$ computed to i), forming

$$\mathcal{C}_i^{+(r)} \;=\; \mathcal{C}_i \cup \{j_r^*\}. \tag{35}$$

For this augmented set, recomputed logit probabilities and total visits are:

$$P_{ikt}^{+(r)} = \frac{\exp\big(V_{ikt}^{+(r)}\big)}{1 + \sum_{\ell \in \mathcal{C}_i^{+(r)}} \exp\big(V_{i\ell t}^{+(r)}\big)}, \qquad V_i^{+(r)} \;=\; M_i \sum_{k \in \mathcal{C}_i^{+(r)}} P_{ikt}^{+(r)}. \tag{36}$$

Average total visits from adding new markets across the representative set are:

$$\overline{V}_i^{\,\text{add}} \;=\; \frac{1}{|\mathcal{J}_{\text{avg}}|} \sum_{r \in \mathcal{J}_{\text{avg}}} V_i^{+(r)}. \tag{37}$$

We report the policy effect for the "Add" intervention as the average $\overline{\Delta V}_i^{\text{add}}$ across FD neighborhoods (and, when normalized, as a share of the baseline FD-non-FD gap Δ).

To ensure that results are comparable across policies, we normalize each simulated visitation gain by the baseline FD-non-FD gap per device. Specifically, the metric reports the fraction of this gap eliminated under each intervention. Let V_i denote baseline visits for FD neighborhood i, and let V_i^N be the matched non-FD counterfactual (same matching set as in the decomposition section). The baseline FD-non-FD gap per device is

$$\Delta \;=\; \frac{1}{|\mathcal{I}_{FD}|} \sum_{i \in \mathcal{I}_{FD}} \big(V_i^N - V_i\big). \tag{38}$$

For each policy $p \in \{\text{SNAP}, \text{Night}, \text{Add}\}$, define the share of the gap closed as

$$\text{Intervention}_p \;=\; \frac{\frac{1}{|\mathcal{I}_{FD}|} \sum_{i \in \mathcal{I}_{FD}} \big(V_i^{(p)} - V_i\big)}{\Delta}. \tag{39}$$

Table 5 shows the simulation results. Across all neighborhoods, universal SNAP acceptance closes 18.4% of the baseline gap, night hours 32.8%, and adding a market 57.8%. The effects are generally larger in urban areas, with night hours closing 33.1% of the gap and market addition closing 42.1%. In rural neighborhoods, SNAP and night hours have smaller relative effects (16.6% and 28.4%, respectively), but adding a market yields a disproportionately large gain, over 280% of the baseline gap, reflecting the severe under-supply of markets in rural FD communities.[22]

These results highlight substantial heterogeneity in the potential effectiveness of supply-side interventions. In urban neighborhoods, both SNAP acceptance and night hours yield larger proportional gap reductions than in rural areas, reflecting that urban FDs typically have at least some proximate markets whose attractiveness can be enhanced. In contrast, the extreme effect of adding a market in rural neighborhoods, more than doubling baseline visitation, underscores the severity of supply shortages in these communities. In many rural FDs, the absence of any nearby market

[22] The large simulated effect in rural areas is likely to reflect how adding an "average" market sharply reduces generalized travel costs. Because the exercise applies preference parameters estimated from relatively sparse rural data and assumes the new market has attributes comparable to those of an average existing market, the magnitude of this result should be viewed with caution.

appears to be the primary constraint on utilization, so increasing local supply has an outsized impact. These differences suggest that policy priorities should be context-specific: incremental improvements to existing markets may be most impactful in urban settings, whereas rural areas may require direct expansion of market availability to meaningfully close utilization gaps.

Benefit-Cost Analysis of Policy Interventions. Unlike the analysis in the above subsection that was restricted to FD neighborhoods, all benefit and cost aggregates for the benefit-cost analysis are computed over the full sample. We broaden the aggregation to: (i) align market-level implementation costs with system-wide welfare effects, (ii) capture spillovers to non-FD areas within market catchments, and (iii) ensure comparability across policies whose affected populations differ in size and composition.

For add-market scenario, given that recomputing counterfactuals for all FD neighborhoods is computationally intensive, we implement the scenarios by siting one market near each of the ten urban FD neighborhoods with the lowest baseline visitation and one market near each of the ten rural FD neighborhoods with the lowest baseline visitation; program costs are tallied for 10 markets in each case, while benefits are averaged over all neighborhoods.[23]

We value welfare changes using compensating variation (CV) from the discrete-choice model. Let $\mathcal{C}_0$ and $\mathcal{C}_1$ denote baseline and policy choice sets (outside option normalized to zero), and $u_{ij}(\cdot)$ the systematic utility of option j for individual i. The per-capita CV for moving from $(\mathcal{C}_0, \theta_0^T, \theta_0^A)$ to $(\mathcal{C}_1, \theta_1^T, \theta_1^A)$ is

$$CV_i^{(p)} \;=\; \frac{1}{\lambda}\left[\ln\Big(1+\sum_{j\in\mathcal{C}_1}\exp\{u_{ij}(\mathcal{C}_1,\theta_1^T,\theta_1^A)\}\Big) - \ln\Big(1+\sum_{j\in\mathcal{C}_0}\exp\{u_{ij}(\mathcal{C}_0,\theta_0^T,\theta_0^A)\}\Big)\right], \tag{40}$$

where $\lambda \equiv -\hat{\beta}_1 > 0$ is the marginal utility of income implied by the estimated price/generalized travel-cost coefficient. We integrate over simulated tastes to obtain $\overline{CV}_i^{(p)}$. For each CBG i with

[23] We restrict siting to the ten urban and ten rural FD neighborhoods with the lowest baseline visitation to (i) keep the counterfactual enumeration computationally tractable; (ii) mirror a transparent, need-based siting rule a planner could implement with readily available data. Benefits are still averaged over the full sample, so market-level costs are aligned with system-wide welfare.

population w_i, we convert to annual benefits as $B_i^{(p)} = 4 \times 26 \times w_i \, \overline{CV}_i^{(p)}$.[24] We report *benefits per CBG* as $\frac{1}{|\mathcal{I}|} \sum_{i \in \mathcal{I}} B_i^{(p)}$ and *total benefits* as $\sum_{i \in \mathcal{I}} B_i^{(p)}$.

Implementation costs are annualized per market. For *SNAP acceptance* scenario, we assume a one-time wireless EBT/POS setup of $850 amortized over five years at 3% (CRF = 0.218), yielding $186/year, plus $900/year service fees, for $1,086 per market per year. For *night hours* scenario, we assume +8 evening hours per week for a 26-week season at a fully-loaded $50/hour, giving $10,400 per market per year. For *adding markets*, comprehensive budgets include annual operating expenses plus annualized capital items (3% over five years), totaling $110,505 per urban market and $34,471 per rural market.[25]

Table 6 shows that SNAP acceptance has the highest return, with a benefit-cost ratio of 62.17, benefits per CBG of $711, total benefits of $121.23 million, and total costs of $1.95 million. Extending night hours is positive but less cost-effective, with a benefit-cost ratio of 4.23, benefits per CBG of $498, total benefits of $84.88 million, and costs of $20.07 million. Adding ten urban markets yields a benefit-cost ratio of 6.86, with $7.62 million in benefits against $1.11 million in costs. Adding ten rural markets performs especially well given lower operating costs, with a benefit-cost ratio of 34.44, $11.71 million in benefits, and $0.34 million in costs.

These patterns are intuitive. SNAP is cheap to implement and removes a common barrier to participation, so even small per-visit gains scale up to large aggregate benefits. A new rural market tends to create larger welfare gains per dollar because access is thin and travel costs are high, while operating costs are relatively low. A new urban market helps but faces higher fixed and recurring costs and more nearby substitutes, which lowers the return per dollar. Night hours can be valuable where evening demand is strong, but the extra staffing and security costs quickly dominate in places with limited after-work traffic.

[24] $\overline{CV}_i^{(p)}$ is computed per decision occasion per individual (device). We multiply by 26 (the assumed number of decision occasions per device per quarter used in our market-size mapping) and by 4 (quarters per year), i.e., $4 \times 26 = 104$ occasions per device-year.

[25] Totals are derived from the itemized build in Appendix Table A6. Line items and magnitudes follow standard market budgeting guides and manager surveys (Ragland and Tropp, 2009; Hofmann and Dennis, 2007; Michigan Farmers Market Association, 2024). Annualization uses the capital-recovery approach consistent with OMB Circular A-94 (Office of Management and Budget, 2023).

Taken together, these results point to a practical sequence of actions: make SNAP acceptance universal first, because it is cheap and yields the largest return per dollar; expand access by adding rural markets in the highest-need places where the model indicates large gains at relatively low operating cost; add urban markets selectively in locations with strong predicted demand that can cover higher permitting, security, and sanitation costs (for example, dense, transit-served gaps); and extend night hours only where evening demand is demonstrably high or where partnerships lower staffing costs.

6 Conclusion

Neighborhood disparities in food access remain a persistent challenge for the US food system. Numerous strategies have been proposed to address this concern. Farmers markets offer potential benefits by providing direct access to fresh, locally sourced produce. However, despite substantial funding to support farmers markets, whether they successfully mitigate these disparities remains unclear. Here, leveraging cellphone mobility data on farmers market visits nationwide, we quantify the extent of travel behavior to farmers markets from 2019 to 2022. We link cell phone users with the socioeconomic and food access characteristics of their residential areas to assess disparities in accessibility and utilization of farmers markets across different communities.

Our analysis reveals large access and utilization disparities between FD and non-FD communities. FD residents make fewer total visits to farmers markets, must travel further to their nearest market, and travel longer distances overall to attend markets. However, they are just as likely to visit their nearest market, suggesting that broader transportation burdens and opportunity costs, rather than a lack of knowledge, constrain participation. Beyond distance, social and economic factors shape participation: FD consumers tend to visit markets that are more economically similar, but racially/ethnically dissimilar, to their home communities, and they experience lower levels of both racial and income segregation at these markets. These patterns suggest that FD residents are willing to engage in diverse market environments but face layered constraints, spanning geographic, economic, and cultural dimensions, that limit equitable access.

To better understand the drivers of these disparities, we developed a structural demand model

that integrates preferences for particular market attributes while accounting for variations in travel costs and demographic diversity. This model pinpointed key features that enhance market appeal, such as acceptance of SNAP benefits, increased market size, and extended night operations. Our analysis revealed that markets that align with these attributes, especially those accepting SNAP, are significantly more appealing to visitors. Moreover, factors such as racial/ethnic diversity between origin and destination and farmers market neighborhood attributes play crucial roles in shaping consumer behavior toward farmers markets.

Using the estimated model, we adapted Allcott et al. (2019) to our setting and showed that demand-side forces dominate the FD–non-FD visit gap, but that supply-side access remains economically meaningful. In our preferred decomposition, supply (availability and access) explains roughly one-fifth of the gap in visits between FD and non-FD consumers, market-attribute preferences about one-tenth, and the remainder, about 70%, reflects travel preferences. Decomposing the latter reveals that *travel cost* is the largest demand-side component, followed by *demographic distance* and a smaller contribution from *income distance*. These patterns differ across space: urban gaps reflect both travel costs and socio-demographic fit, whereas rural gaps are driven primarily by high generalized travel costs and sparse local supply.

To further isolate demand and supply causes of the visit disparity, we equalize supply across FD and non-FD neighborhoods and apply the Gelbach attribution. Vehicle access and educational attainment emerge as the largest endowment contributions, while coefficient effects, particularly the stronger positive link between income and visits in non-FD areas, explain most of the remaining demand-only gap. These results point toward mobility constraints, information frictions, and differences in time-budget trade-offs as key drivers, rather than purely compositional differences in the population.

We then study three practical supply-side interventions: universal SNAP acceptance, universal evening hours, and adding a representative market to FD choice sets. Simulations indicate meaningful gap closure even when preferences are held fixed. Across all neighborhoods, SNAP closes 18.4% of the baseline gap, night hours 32.8%, and adding a market 57.8%. Importantly, the spatial pattern of gains is heterogeneous: in urban areas, incremental improvements to existing markets (e.g., night hours) yield relatively large returns, whereas in rural areas, adding even one market produces a

transformative reduction in the gap, over 280% of the baseline difference, highlighting the severity of undersupply. This contrast reinforces that the same policy lever will not have uniform effects and that geographic targeting can significantly enhance efficiency.

Monetizing welfare via compensating variation and annualizing implementation costs, we find that SNAP acceptance delivers the highest return per dollar (benefit-cost ratio 62.17). Adding new markets also performs well, especially in rural areas (34.44) and, to a lesser extent, in urban areas (6.86), while extending night hours is positive but less cost-effective (4.23). Policy implications follow directly. Start by making SNAP acceptance universal because it is inexpensive and highly cost-effective. Expand spatial access next by adding rural markets in the highest-need places, potentially via mobile or seasonal formats to keep fixed costs down, and add urban markets selectively where predicted demand is strong enough to cover higher permitting, security, and sanitation costs. Extend night hours only where evening demand is demonstrably high or where partnerships lower staffing costs. Monitor outcomes such as SNAP redemptions, market attendance, vendor capacity, and spillovers to other healthy-food outlets, and use that evidence to adapt placements and hours over time so resources flow to the locations with the greatest equity and efficiency returns.

While our study offers valuable insights into the dynamics of farmers market visits and preferences, it is important to acknowledge certain limitations that could serve as avenues for future research. The data used in this analysis, primarily sourced from cellphone mobility records, might not fully represent the entire population, particularly the behavior of older adults or those in lower socioeconomic brackets. Additionally, applying differential privacy techniques to safeguard privacy may lead to a loss of detail, potentially obscuring subtle yet important patterns in market visitation. Another significant limitation is our approach to measuring experienced isolation, which relies on aggregate CBG data rather than individual visitor data, potentially masking variations within these groups. Recognizing these limitations, future research could explore more granular, individual-level data-collection methods, improve privacy-preserving techniques to maintain data fidelity, and develop refined metrics for social isolation that capture personal experiences more accurately. These areas of further investigation could improve our understanding of market behavior and inform more targeted, effective interventions to increase farmers market accessibility.

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Tables and Figures

Table 1: Summary Statistics of Farmers Markets in Advan

	Count	Mean	S.D.	Min	Max
Farmers Market Characteristics					
SNAP	3,983	0.36	0.48	0.00	1.00
Weekend Dummy	3,983	0.76	0.43	0.00	1.00
Nighttime Dummy	3,983	0.35	0.48	0.00	1.00
Area Size (1,000 m^2)	3,983	10.98	253.20	0.02	15,165.70
Food Desert Dummy	3,983	0.09	0.29	0.00	1.00
urban Share	3,983	0.79	0.36	0.00	1.00
Median Household Income ($k)	3,983	76.33	40.63	8.45	250.00
Hispanic (%)	3,983	12.81	17.05	0.00	100.00
White (%)	3,983	77.66	21.12	0.00	100.00
Travel Costs & Visits					
Travel Costs ($)	13,716,129	10.59	7.86	0.01	40.50
Regular Gas Prices (cent)	13,716,129	14.16	3.93	7.74	23.74
Depreciation (cent)	13,716,129	23.92	2.11	21.43	26.00
Maintenance (cent)	13,716,129	9.29	0.27	8.94	9.55
Median Household Income ($k)	13,716,129	84.83	44.26	2.50	250.00
Travel Distance (mile)	13,716,129	8.39	6.93	0.01	30.00
Travel Duration (h)	13,716,129	0.25	0.18	0.00	0.71
Visitors	13,716,129	3.22	12.41	0.00	3,406.00
Outside Options	13,716,129	3,619.53	4,199.66	22.00	52,000.00
Trip Share	13,716,129	0.00	0.00	0.00	0.15
Outside Share	13,716,129	0.98	0.03	0.38	1.00
No. of Residing Devices	13,716,129	141.59	163.55	1.00	2,000.00
Weather & Demographic Distance					
Mean Temparature (C)	13,716,129	14.82	7.91	-15.33	35.14
Precipitation (mm)	13,716,129	82.97	54.81	0.00	591.29
Racial/Ethnic Distance	13,716,129	37.34	26.45	0.00	165.47
Income Distance	13,716,129	41.69	35.98	0.00	238.49

Notes: Summary statistics of farmers markets and visits, 2019-2022. Farmers market characteristics include SNAP acceptance, weekend and nighttime operation, area size, and CBG demographics. Travel costs and visits are defined at the CBG-market-quarter level; costs combine round-trip fuel, maintenance, depreciation (AAA), and one-third of the CBG median wage, with distances and times from OSRM. Weather variables are from PRISM. Racial/ethnic and income distances are Euclidean differences between home and market CBG composition. For additional details, see Section 2.

Table 2: Travel Patterns of Visitors from FD and non-FD CBGs

	Average (All CBGs)	Average (FD CBGs)	Average (Non-FD CBGs)	Difference (t-value)
Panel A: Visits				
Average visits per device	0.170	0.132	0.174	0.042***
				(20.090)
Visits per device to nearest FM	0.082	0.075	0.082	0.007***
				(7.878)
Panel B: Travel Distance (Miles)				
Average distance	8.995	9.548	8.932	-0.616***
				(-11.507)
Distance to nearest FM	7.255	8.367	7.128	-1.238***
				(-22.559)
Panel C: Demographic Distance				
Racial/Ethnic distance	32.718	36.323	32.306	-4.016***
				(-20.473)
Racial/Ethnic distance to nearest FM	31.531	35.609	31.065	-4.544***
				(-22.424)
Income distance	34.570	25.416	35.617	10.201***
				(43.539)
Income distance to nearest FM	33.127	24.646	34.098	9.451***
				(39.321)
Panel D: Experienced Isolation				
Race isolation	39.881	34.152	40.541	6.389***
				(30.311)
Race isolation to nearest FM	52.972	47.855	53.558	5.703***
				(23.797)
Income Isolation	50.517	46.385	50.990	4.606***
				(19.517)
Income Isolation to nearest FM	42.886	35.678	43.716	8.037***
				(36.227)

Notes: Sample covers 2019-2022. FD represents food desert CBGs; non-FD denotes non food desert CBGs. Reported values are CBG-level means. "Visits per device" is the average number of farmers market (FM) visits per mobile device. Rows labeled "to nearest FM" are constructed using each CBG's geographically nearest FM (not necessarily the one actually visited). Travel distances (miles) are computed from the home-CBG centroid to the FM using the Open Source Routing Machine. Racial/ethnic and income distances are Euclidean differences between the characteristics of the home and market CBGs; the "to nearest FM" versions use the nearest market. Isolation indices measure within-group exposure at the market (higher values indicate greater exposure); "to nearest FM" evaluates the index at the nearest market. Differences are Non-FD minus FD, with t-statistics in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively. See Section 3 for details.

Table 3: Demand Estimates for Farmers Market Visits

	Logit OLS	Logit IV	Logit R.C.		
	All CBGs	All CBGs	All CBGs	FD CBGs	non-FD CBGs
Mean Valuations					
Travel Costs	-0.1438***	-0.1535***	-0.1499***	-0.1494***	-0.1518***
	(0.0004)	(0.0004)	(0.0019)	(0.0119)	(0.0027)
Racial/Ethnic Distance	-0.0098***	-0.0091***	-0.0091***	-0.0071***	-0.0097***
	(0.0001)	(0.0001)	(0.0008)	(0.0026)	(0.0007)
Income Distance	-0.0017***	-0.0017***	0.0012	-0.0012	-0.0004
	(0.0001)	(0.0001)	(0.0011)	(0.0230)	(0.0029)
Deviation Valuations					
Travel Costs			0.1028***	0.0686**	0.1059***
			(0.0015)	(0.0106)	(0.0013)
Racial/Ethnic Distance			0.0095	-0.0027	-0.0175
			(0.0109)	(0.1111)	(0.0159)
Income Distance			0.0013	0.0029	0.0127
			(0.0109)	(0.2262)	(0.0109)
Observations	13,716,129	13,716,129	13,716,129	921,847	12,782,864
Kleibergen-Paap F test		4320.9			
GMM Statistic			21,140	25,424	18,908

Notes: This table reports demand model estimates with and without visitor taste heterogeneity in travel and demographic distances. All specifications include farmers market fixed effects, CBG fixed effects, year-quarter fixed effects, and weather controls. The IV and random coefficients (R.C.) logit models instrument travel costs using the interaction of crude oil prices with state dummies (CPI-deflated to 2019 dollars). Standard errors are clustered at the CBG level and shown in parentheses. ***, **, * denote statistical significance at the 1%, 5%, and 10% levels, respectively. For additional details, see Section 4.

Table 4: Second-Stage Estimates of Farmers Market Characteristics

	All CBGs				FD CBGs	non-FD CBGs
	(1)	(2)	(3)	(4)	(5)	(6)
SNAP Dummy	0.326***	0.313***	0.221***	0.149***	0.093*	0.148***
	(0.049)	(0.050)	(0.044)	(0.044)	(0.052)	(0.044)
Weekend Dummy		-0.122**	0.012	0.038	-0.017	0.005
		(0.056)	(0.049)	(0.049)	(0.060)	(0.048)
Night Operation Dummy		-0.051	0.066	0.088**	0.126**	0.096**
		(0.049)	(0.044)	(0.044)	(0.053)	(0.044)
Log(Size)			0.443***	0.428***	0.386***	0.425***
			(0.015)	(0.015)	(0.019)	(0.015)
Food Desert Dummy				-0.118	0.042	-0.086
				(0.076)	(0.080)	(0.075)
Urban Share				0.415***	0.132	0.355***
				(0.062)	(0.091)	(0.061)
Observations	3983	3983	3983	3983	2975	3962
State FEs		Yes				
County FEs			Yes	Yes	Yes	Yes
R-sq	.232	.233	.396	.396	.297	.397

Notes: This table reports second-stage regressions using market fixed effects recovered from the random coefficients logit model. The dependent variable is the market-specific mean utility. Explanatory variables include SNAP acceptance, weekend and night operation, market size, food desert indicator, and urban share. All regressions include county fixed effects; columns (1)-(4) use the full sample, while columns (5)-(6) are split by FD and non-FD CBGs. Robust standard errors, clustered at the CBG level, are shown in parentheses. ***, **, * denote statistical significance at the 1%, 5%, and 10% levels, respectively. For additional details, see Section 4.

Table 5: Impact of Supply-Side Interventions on Visit Gap

Policy Simulations	ΔVisits per Capita	Current Gap	Gap Closed (%)
Panel A: All CBGs			
SNAP acceptance	0.005	0.025	18.4
Night hours	0.008	0.025	32.8
Add market	0.014	0.025	57.8
Panel B: Urban CBGs			
SNAP acceptance	0.005	0.025	18.5
Night hours	0.008	0.025	33.1
Add market	0.011	0.025	42.1
Panel C: Rural CBGs			
SNAP acceptance	0.003	0.019	16.6
Night hours	0.006	0.019	28.4
Add market	0.056	0.019	288.7

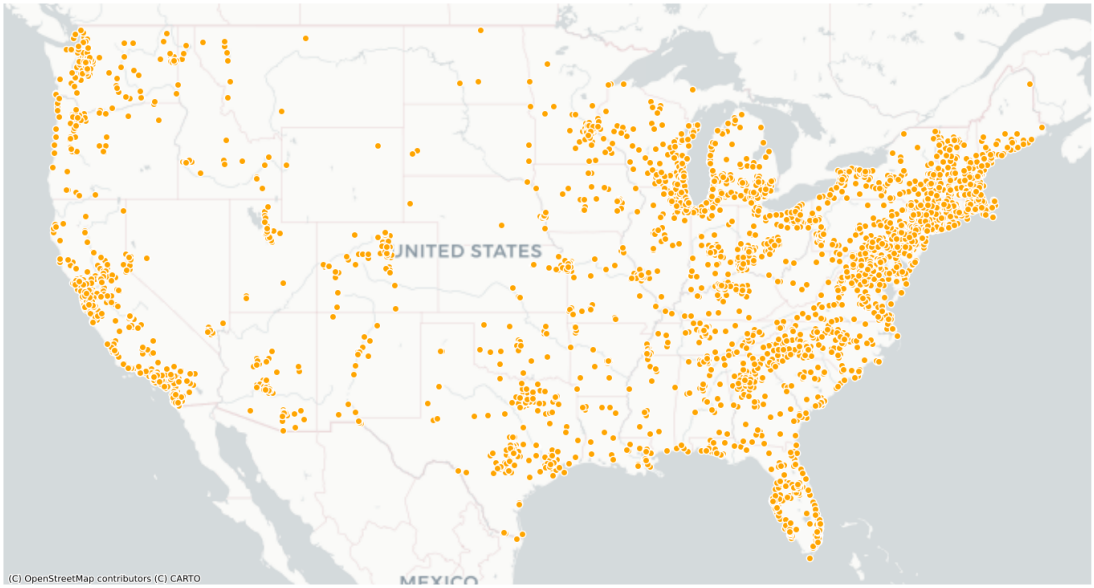
Notes: This table reports simulated changes in farmers market visits per capita under three supply-side interventions: universal SNAP acceptance, universal night operations, and adding one representative market in each food desert CBG. "Gap closed" is the share of the baseline FD-non-FD visit gap eliminated under each policy. Results are shown for all CBGs (Panel A), urban CBGs (Panel B), and rural CBGs (Panel C). For additional details, see Section 5.

Table 6: Benefit-Cost Analysis of Supply-Side Interventions

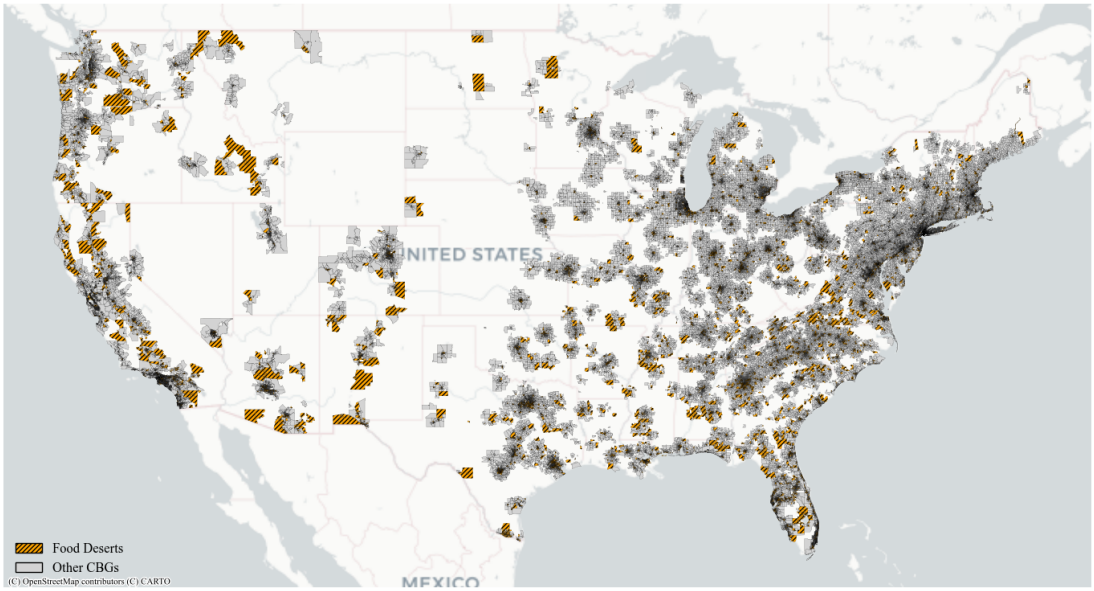
Policy	Benefits per CBG ($)	Total Benefits ($M)	Costs per Market ($)	Total Costs ($M)	Benefit–Cost Ratio
SNAP acceptance	711.30	121.23	1,086	1.95	62.17
Night hours	498.03	84.88	10,400	20.07	4.23
Add 10 urban markets	44.71	7.62	110,505	1.11	6.86
Add 10 rural markets	68.71	11.71	34,471	0.34	34.44

Notes: This table reports benefits and costs of three interventions targeted to farmers markets serving FD CBGs within a 30-mile radius: requiring SNAP acceptance, extending night hours, and adding new markets. Adding 10 urban (rural) markets places one market near each of the ten urban (rural) FD CBGs with the lowest baseline visitations. Benefits are expressed as monetized annual welfare gains. Costs are annualized per market. For SNAP, the $850 wireless POS setup cost is amortized over 5 years at a 3% discount rate and added to annual service fees ($900 per market). Night-hour costs assume 8 additional evening hours per week for 26 weeks, at $50/hour labor, yielding $10,400 per market annually. "Add market" costs include annual operating expenses plus annualized capital items amortized at 3% over 5 years (CRF=0.218). For additional details, see Section 5.

Figure 1: National Map of Farmers Markets in Advan and Served CBGs



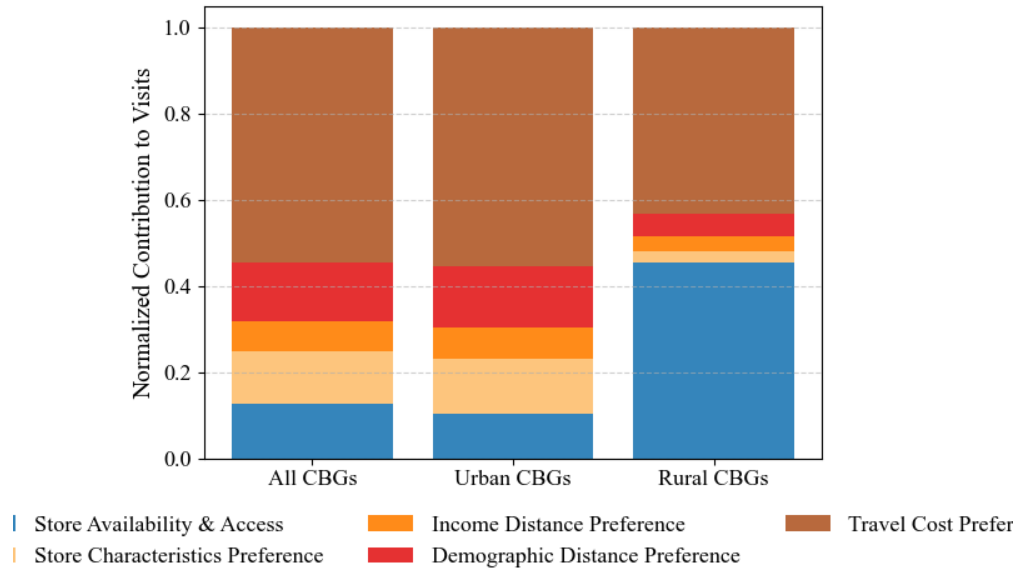
(a) Farmers Market Location



(b) Served CBGs

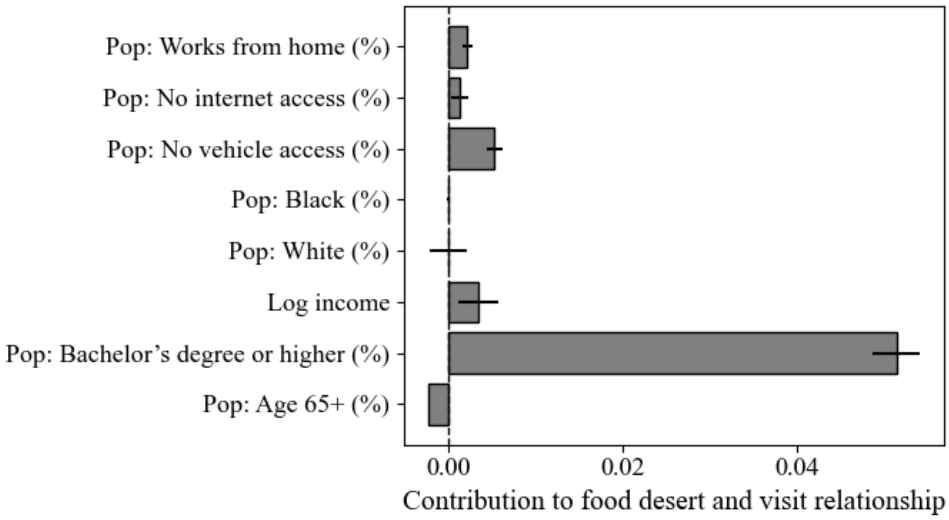
Notes: The figure illustrates the spatial distribution of farmers markets and CBGs they serve. Panel (a) displays the locations of farmers markets identified in the Advan dataset after validation using state directories, the USDA Farmers Market Directory, and other sources. Panel (b) shows CBGs with observed visits to these markets within a 30-mile radius. CBGs classified as food deserts, based on the USDA Food Access Research Atlas, are highlighted in orange. For additional details, see Section 2.

Figure 2: Decomposition of Demand and Supply Factors Driving FD–non-FD Market Visit Gap



Notes: This figure shows the normalized contribution of supply and demand components to the visit gap between FD and non-FD CBGs. Store availability and access capture supply-side factors, while preferences for store characteristics, travel cost, and demographic and income distance capture demand-side factors. Contributions are shown separately for all CBGs, urban CBGs, and rural CBGs. Values are normalized to sum to one within each group. For additional details, see Section 5.

Figure 3: Explaining the Relationship Between Food Desert and Market Visit Demand



Notes: This figure reports Gelbach decomposition results attributing the FD–non-FD gap in farmers market visits to observable community characteristics. Bars show the contribution of each covariate to the baseline gap, with 95% confidence intervals. Standard errors are obtained by bootstrapping. Education (share with a bachelor's degree or higher) and vehicle access account for the largest share of the explained demand-side gap, while income, age, internet access, and work-from-home status play smaller roles. For additional details, see Section 5.

Who Goes to Farmers Markets? Food Desert Gaps, Structural Demand, and Policy Design

Xibo Wan Cristina Connolly Sandro Steinbach

Appendices for Online Publication

These appendices supplement our article "Who Goes to Farmers Markets? Food Desert Gaps, Structural Demand, and Policy Design" with the following material:

- Online Appendix A includes additional details on spatial links across datasets, summary statistics of visit patterns to farmers markets in Advan and the National Farmers Market Managers Survey (NFMMS), and additional details of demographic distance and experienced isolation.
- Online Appendix B contains discussions on measurement errors, robustness checks, and alternative CBG classifications.
- Online Appendix C provides robustness checks on results from our preferred logit model, using alternative demographic distance definitions, alternative specifications, alternative travel distance cutoffs, alternative market sizes, alternative choice sets, and alternative sampling weights
- Online Appendix D presents the details of the matching process and the balance of Matching Covariates Before and After Matching.
- Online Appendix E details the Monte Carlo Simulation for Zero Market Share Corrections.

Online Appendix A Additional Details of Data and Methodology

Online Appendix A.1 Matching POIs of Farmers Markets

To perform an accurate analysis of farmers markets, we began by utilizing the Advan visits dataset, which provides detailed data on foot traffic to various points of interest (POIs), including potential farmers market locations. This dataset is instrumental in offering insights into the number of visits to a given location, allowing us to track trends in market attendance and activity levels. However, the Advan data alone lacks contextual details necessary to confirm whether a location is genuinely a farmers market, making it necessary to integrate additional sources to ensure accuracy.

- We incorporated data from state-level farmers market directories maintained by departments of agriculture. These sources provide highly accurate geographic locations and operational details such as market hours and seasonal schedules. While these directories are regionally focused and offer precise validation for matching markets in the Advan dataset, their geographic scope is limited to individual states.[26]

- To expand coverage, we used the USDA Farmers Market Directory, maintained by the Agricultural Marketing Service. This national dataset offers broad coverage across the U.S., capturing smaller or less formally listed markets. However, the USDA database may lack complete or up-to-date listings for some local markets, particularly those not self-reported by organizers.

- The FNS SNAP retailer listings from the Food and Nutrition Service added an important dimension to our data. These listings provide detailed information on farmers markets that accept SNAP benefits, facilitating identification of markets serving low-income and economically disadvantaged populations. Incorporating SNAP data allowed us to focus on markets that are actively operating and that play a crucial role in addressing food accessibility issues.

- To complement the official directories, we incorporated data from Google Maps and Facebook

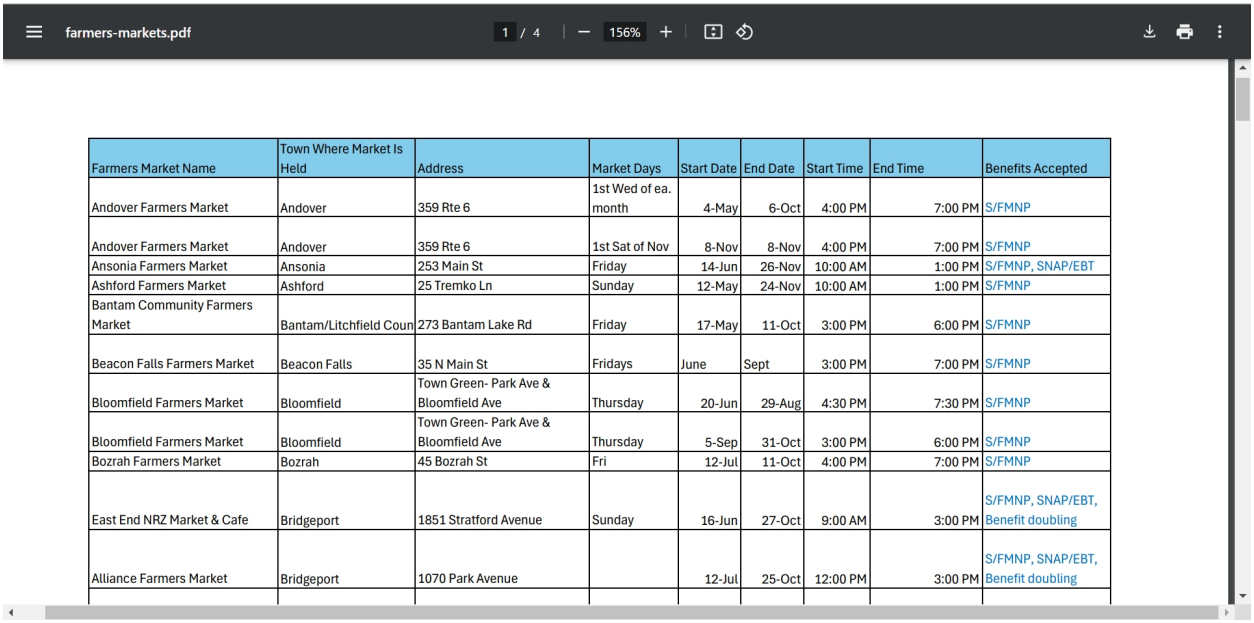
[26] See more details in here: https://www.cdfa.ca.gov/is/docs/CurrentMrktsCounty.pdf; https://portal.ct.gov/-/media/doag/adarc/farmers-markets/2024/farmers-markets.pdf; https://dem.ri.gov/sites/g/files/xkgbur861/files/programs/agriculture/documents/rimarkets.pdf; https://www.agriculture.nh.gov/publications-forms/documents/farmers-market-directory.pdf

Marketplace. These platforms offered valuable geographic validation, confirming the exact locations of markets and providing additional contextual information, such as market days, vendor lists, and special events. This data was critical for confirming that the markets in the Advan dataset were still operational and for detecting any discrepancies that may not have been apparent from the official sources.

The first step in our matching process involved using fuzzy matching techniques to align the addresses and names from the Advan data with those listed in the state directories, USDA Farmers Market Directory, and SNAP retailer listings. This method allowed us to identify potential matches based on similarities in market names and geographic locations, even when there were slight variations in spelling or formatting. By using this approach, we were able to establish a set of initial matches between the Advan data and the verified external sources.

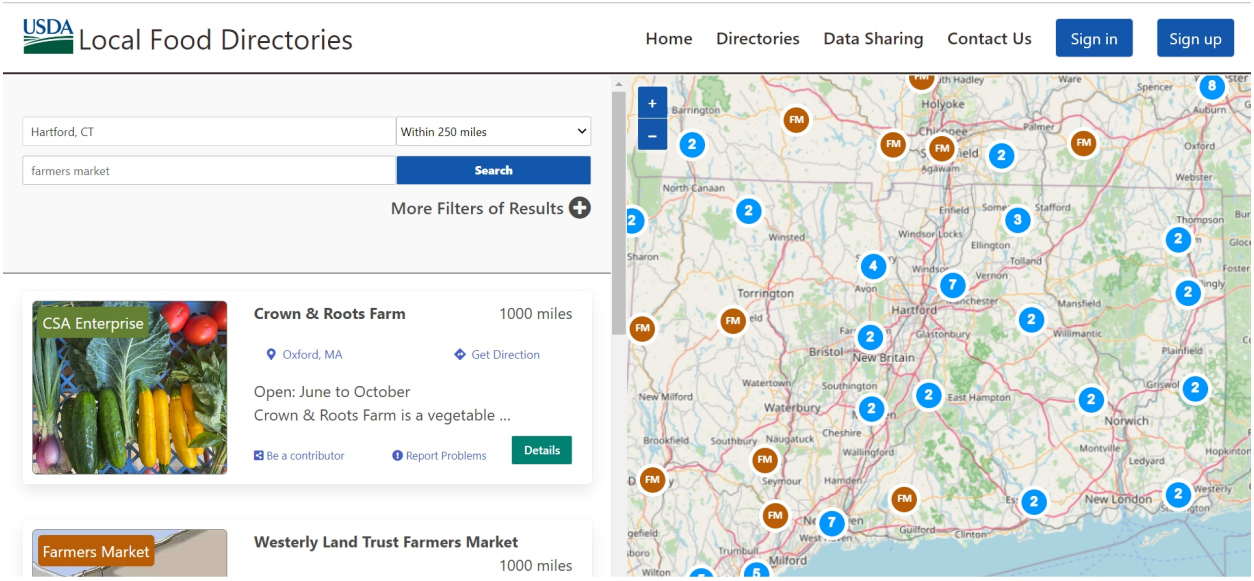
In the second step, we further refined the matching process by geocoding the locations and calculating the distances between the Advan-listed markets and those in the external sources using the Haversine distance formula. This method allowed us to account for instances where markets were close in proximity but may have had slightly different address formats. The distance-based approach helped uncover additional matches that were not immediately evident through name and address matching alone, resulting in a highly accurate final dataset of farmers markets.

Figure A1: **Additional Data Examples**

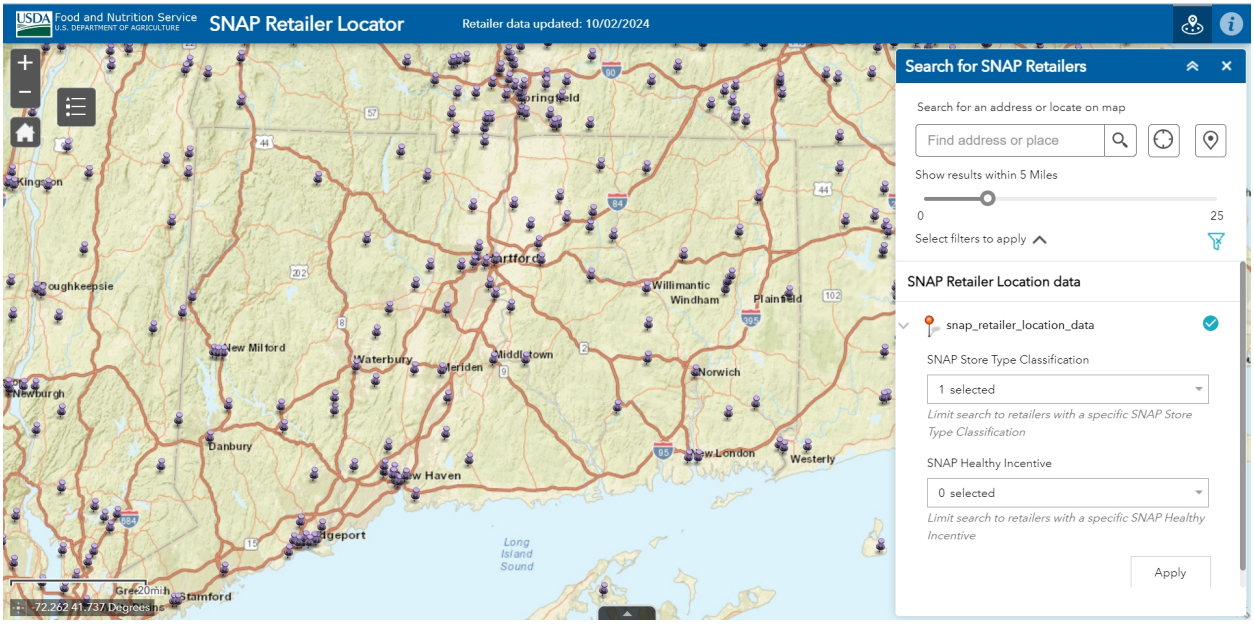


Farmers Market Name	Town Where Market Is Held	Address	Market Days	Start Date	End Date	Start Time	End Time	Benefits Accepted
Andover Farmers Market	Andover	359 Rte 6	1st Wed of ea. month	4-May	6-Oct	4:00 PM	7:00 PM	S/FMNP
Andover Farmers Market	Andover	359 Rte 6	1st Sat of Nov	8-Nov	8-Nov	4:00 PM	7:00 PM	S/FMNP
Ansonia Farmers Market	Ansonia	253 Main St	Friday	14-Jun	26-Nov	10:00 AM	1:00 PM	S/FMNP, SNAP/EBT
Ashford Farmers Market	Ashford	25 Tremko Ln	Sunday	12-May	24-Nov	10:00 AM	1:00 PM	S/FMNP
Bantam Community Farmers Market	Bantam/Litchfield Coun	273 Bantam Lake Rd	Friday	17-May	11-Oct	3:00 PM	6:00 PM	S/FMNP
Beacon Falls Farmers Market	Beacon Falls	35 N Main St	Fridays	June	Sept	3:00 PM	7:00 PM	S/FMNP
Bloomfield Farmers Market	Bloomfield	Town Green- Park Ave & Bloomfield Ave	Thursday	20-Jun	29-Aug	4:30 PM	7:30 PM	S/FMNP
Bloomfield Farmers Market	Bloomfield	Town Green- Park Ave & Bloomfield Ave	Thursday	5-Sep	31-Oct	3:00 PM	6:00 PM	S/FMNP
Bozrah Farmers Market	Bozrah	45 Bozrah St	Fri	12-Jul	11-Oct	4:00 PM	7:00 PM	S/FMNP
East End NRZ Market & Cafe	Bridgeport	1851 Stratford Avenue	Sunday	16-Jun	27-Oct	9:00 AM	3:00 PM	S/FMNP, SNAP/EBT, Benefit doubling
Alliance Farmers Market	Bridgeport	1070 Park Avenue		12-Jul	25-Oct	12:00 PM	3:00 PM	S/FMNP, SNAP/EBT, Benefit doubling

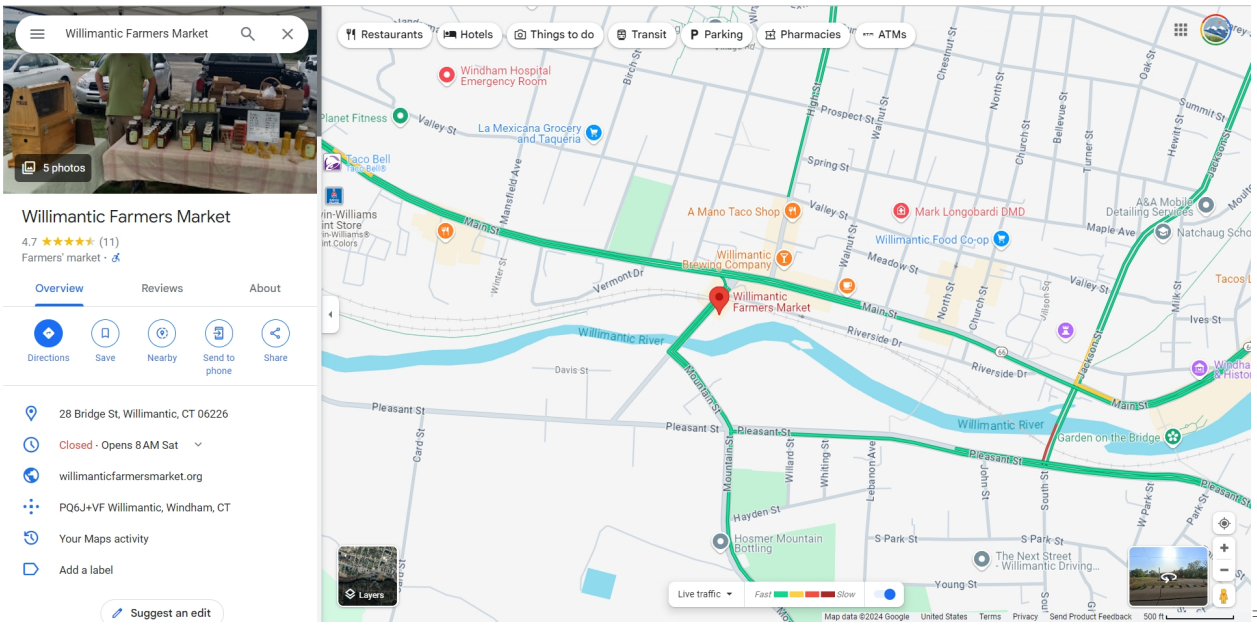
(a) state-level directories



(a) USDA Farmers Market Directory

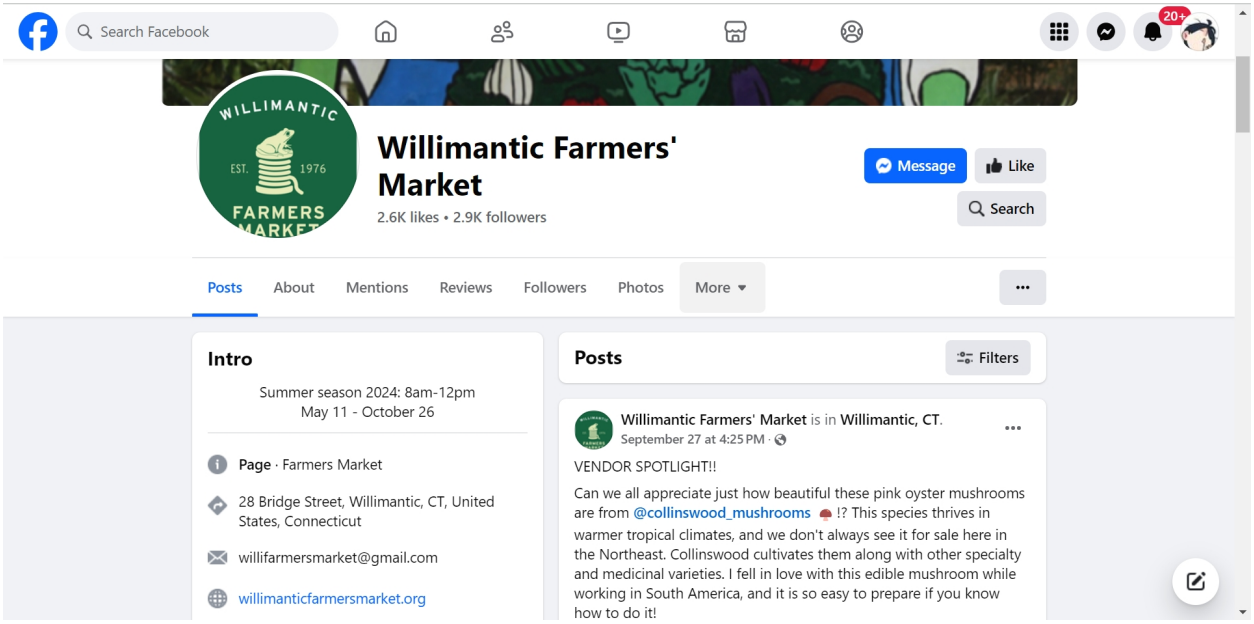


(b) USDA SNAP retailer



=12pt

(a) Google Map



(b) Facebook

Online Appendix A.2 Summary Statistics of Farmers Markets

The following tables present descriptive statistics to contextualize our analysis of farmers market access and visitation patterns. Panel A of Table A1 summarizes operational patterns and survey response rates from the 2019 USDA National Farmers Market Manager Survey (NFMMS), highlighting variation in market days by region. Panel B of Table A1 provides similar operational statistics derived from mobility data in the Advan sample. Table A2 reports unadjusted average travel distances to farmers markets by self-reported visit frequency, based on survey data from Jilcott Pitts et al. (2017). Tables A3-A5 summarize demographic characteristics of CBGs in the Advan sample using Census ACS data. Table A3 reports overall demographic comparisons between FD and non-FD CBGs. Table A4 presents demographics for CBGs where residents visited farmers markets during the study period. Table A5 compares demographics of CBGs with and without a farmers market presence. Together, these tables describe both market-level characteristics and spatial demographic variation relevant to understanding disparities in farmers market accessibility and usage.

Table A1: Summary Statistics of Farmers Markets in NFMMIS and Advan Data, 2019

Operation Day (%)	All	Northeast	Midwest	South	West
Panel A: NFMMS Data					
Monday	5.4	3.3	4.3	9.9	2.5
Tuesday	16.2	14.5	14.9	23.8	8.3
Wednesday	19.1	16.6	19.7	23.2	14.8
Thursday	19.8	15.0	21.7	23.6	16.4
Friday	14.0	15.9	11.4	16.4	12.2
Saturday	52.4	41.8	51.7	66.9	42.5
Sunday	10.6	13.8	6.6	8.3	16.2
Sample	5,883	1,089	1,918	1,792	1,084
Panel B: Advan Data					
Monday	10.66	11.33	12.31	12.92	7.96
Tuesday	18.87	18.76	21.72	20.15	18.58
Wednesday	24.41	25.09	28.35	24.70	20.35
Thursday	25.46	28.62	27.80	27.94	19.76
Friday	23.33	27.89	23.79	25.91	20.06
Saturday	59.29	59.93	64.18	67.75	55.75
Sunday	19.77	23.39	14.94	17.63	18.29
Sample	3,983	993	761	1,032	1,033

Notes: This table compares the distribution of farmers market operating days across regions using data from the 2019 National Farmers Market Managers Survey (NFMMIS, Panel A) and Advan mobility data (Panel B). Reported values are the percentage of markets operating on each day of the week. Regional breakdowns follow the U.S. Census Bureau definitions.

Table A2: Summary Statistics of Travel Distance to Farmers Markets

Frequency of farmers market shopping	Distance (in miles)		
	Obs	Mean	Standard Deviation
A few times per year or less	34	17.87	26.05
One to several times per month	39	9.13	11.02
Once a week	83	7.97	15.71
2 or more times per week	42	10.63	17.23

Notes: Statistics for each variable in Table A2 are obtained from Survey results in Jilcott Pitts et al. (2017).

Table A3: Demographic Statistics of CBGs in Advan

	All CBGs		non-FD CBGs		FD CBGs	
	Mean	SD	Mean	SD	Mean	SD
Population	1581.22	1045.73	1766.69	1259.25	1470.98	876.60
White (%)	72.12	26.12	76.64	23.18	69.43	27.36
Black (%)	13.34	22.08	12.19	20.71	14.02	22.82
Native (%)	0.61	2.71	0.58	2.82	0.63	2.64
Asian (%)	5.48	10.35	4.47	8.33	6.08	11.34
Hispanic (%)	17.43	22.81	12.99	18.39	20.07	24.70
Income ($k)	73.33	39.26	79.34	42.02	69.72	37.04
% HH. with no vihecle	9.37	14.24	5.50	7.96	11.68	16.48
Urban Share (%)	0.85	0.33	0.90	0.25	0.82	0.36

Notes: Demographic statistics are calculated using Census ACS data, restricted to CBGs included in the Advan sample. FD refers to food desert CBGs, while non-FD refers to non-food desert CBGs. SD denotes standard deviation.

Table A4: Demographics of CBGs with Farmers Market Visits in Advan

	All CBGs		non-FD CBGs		FD CBGs	
	Mean	SD	Mean	SD	Mean	SD
Population	1757.80	1511.09	1764.44	1511.19	1751.41	1511.16
White (%)	77.97	20.96	78.03	20.82	77.92	21.11
Black (%)	9.33	16.02	9.31	15.95	9.35	16.09
Native (%)	0.62	3.05	0.63	3.07	0.62	3.04
Asian (%)	5.28	9.36	5.27	9.30	5.29	9.41
Hispanic (%)	12.74	17.09	12.71	17.04	12.76	17.14
Income ($k)	76.50	40.90	76.65	41.14	76.35	40.68
% HH. with no vihecle	10.20	13.82	10.13	13.66	10.26	13.97
Urban Share (%)	0.79	0.37	0.80	0.36	0.78	0.38

Notes: Demographic characteristics are from Census ACS data, restricted to CBGs in the Advan sample at least visited farmers markets once during the study period. FD refers to food desert CBGs. SD denotes standard deviation.

Table A5: Demographics of CBGs by Farmers Market Presence in Advan

	All CBGs		CBGs w/ Markets		CBGs w/o Markets	
	Mean	SD	Mean	SD	Mean	SD
Population	1488.73	1023.90	1751.15	1503.90	1483.90	1012.30
white (%)	72.96	26.61	78.18	21.02	72.86	26.69
black (%)	13.40	22.75	9.24	16.00	13.48	22.85
native (%)	0.90	4.88	0.62	3.01	0.90	4.91
asian (%)	4.68	9.80	5.21	9.33	4.67	9.81
hispanic (%)	17.20	24.07	12.68	17.13	17.28	24.17
Income ($k)	68.46	37.72	76.56	40.76	68.31	37.64
% HH. with no vihecle	9.25	13.64	10.10	13.85	9.24	13.63
Urban Share (%)	0.79	0.38	0.78	0.38	0.79	0.38
Low Food Access	0.39	0.49	0.34	0.47	0.39	0.49

Notes: Demographic characteristics are from Census ACS data, restricted to CBGs in the Advan sample. Columns report means and standard deviations (SD) for CBGs with and without farmers markets.

Online Appendix A.3 Demographic Distance

To evaluate the extent to which the relative demographic distance between visitors' origins and farmers market locations influences market choices, we match the 2010 CBG boundaries utilized by Advan to 2010 Census economic and demographic data for each CBG. To develop our demographic diversity terms, we first calculate the proportions of White, Black, Hispanic, Asian, and Native American populations, and the average household income in the CBG of each visitor's origin and each market location. For each visitor, we then calculate the difference between their origin CBG and all markets in their choice set for each of these demographic values. These differences allow us to create four unique relative distance metrics, along with their equivalents for income:

- The Euclidean distance of the proportions of White, Black, Hispanic, Asian, and Native American populations between the market location and the visitor's home CBG.
- The absolute value of the differences in Black and Hispanic population proportions between the market location and the visitor's home CBG.
- Indicator variables equal to 1 if the market's Black and Hispanic population proportions are higher than those of the visitor's home CBG.
- Positive Black and Hispanic differences (i.e., truncated at zero), which represent the difference in the proportion of the population that is Black or Hispanic at the market location minus the proportion in the visitor's origin CBG.

Online Appendix A.4 Experienced Isolation

To estimate experienced income and racial isolation at farmers markets, we follow the methodology introduced by Athey et al. (2020). Experienced income isolation at a farmers market measures the difference between the proportion of lower-income visitors' interactions with higher-income visitors and the proportion of higher-income visitors' interactions with other higher-income visitors. Using GPS data, we define each device's exposure to members of each race and income group based on the time spent at each market and the demographic distribution of other visitors at that location.

For example, an income isolation measure of 0.5 would indicate that lower-income visitors have 50 percentage points fewer interactions with higher-income visitors compared to other higher-income visitors. These isolation metrics capture how visitors from different income and racial backgrounds interact in shared geographic spaces, though they may not fully correspond to meaningful social engagement. For instance, visitors from diverse racial and economic backgrounds may occupy the same physical space at a farmers market but not engage in direct social interactions, similar to the dynamic observed in schools or workplaces.

We compute experienced isolation for both race and income. For racial isolation, we follow Athey et al. (2020) by using designations based on the racial demographics of the visitor's CBG. Specifically, this provides a measure of isolation between visitors from predominantly White neighborhoods and those from predominantly non-White neighborhoods. For income isolation, we estimate individual income levels and categorize visitors based on whether their income is above or below the median income of their CBG, allowing us to assess the differences in exposure and interaction between higher- and lower-income visitors at farmers markets.

Online Appendix A.5 Annualized Costs of a Farmers Market

Table A6: Adding a Farmers Market: Annualized Build Cost (Urban vs. Rural)

	Urban		Rural	
A. Capital (one-time) items	*CapEx*	*Annualized*	*CapEx*	*Annualized*
Branding & wayfinding signage	$4,000	$874	$3,000	$655
Cones/barricades/traffic signs	$3,000	$655	$2,500	$546
Info/manager tent, tables, chairs	$2,000	$437	$2,000	$437
EBT/SNAP booth & POS hardware (non-proc.)	$1,200	$262	$1,200	$262
Storage (container/shed)	$3,000	$655	$2,000	$437
Portable lighting (evenings)	$2,500	$546	$1,800	$393
Power cords/cable ramps	$1,000	$218	$1,000	$218
Website & initial creative	$1,500	$327	$1,300	$284
Coolers/small cold-storage	$1,000	$218	$1,000	$218
Office/supplies	$1,000	$218	$1,000	$218
Shade structures/seating (activation)	,	,	$3,000	$655
Subtotal CapEx	$20,200	$4,411	$19,800	$4,323
B. Recurring operating items (annual)	*OpEx/yr*		*OpEx/yr*	
Site rent / permits / street closure		$15,600		$1,300
General liability insurance		$3,000		$1,500
Health & event permits		$2,000		$1,000
Staffing: manager		$18,720		$5,460
Staffing: assistant		$11,648		$3,432
Security / traffic control		$7,280		$936
Cleaning / custodian		$3,900		$1,040
Marketing / outreach		$10,000		$3,000
Waste & sanitation (dumpster/hauls)		$5,200		$1,560
Toilets & handwash (incl. water)		$9,300		$3,920
Power / utilities		$2,864		$1,000
Storage rental (off-site)		$3,000		$600
SNAP/EBT (amortized setup + service + fees)		$1,536		$1,266
Accounting / admin / legal		$2,000		$1,000
Subtotal OpEx		**$96,048**		**$27,014**
C. Roll-up (annual)				
Annualized CapEx (A)		$4,411		$4,323
OpEx (B)		$96,048		$27,014
Subtotal (A + B)		$100,459		$31,337
+ 10% contingency		$10,046		$3,134
Total annual cost per market		**$110,505**		**$34,471**

Notes: CapEx annualization uses the capital recovery factor $\mathrm{CRF}(r,n) = \frac{r(1+r)^n}{(1+r)^n-1}$ with $r = 3\%$, $n = 5$ years (CRF ≈ 0.21835); Annualized = CapEx $\times$ CRF, rounded to the nearest dollar. Urban assumes year-round weekly operations (52 weeks, ∼8 public hours/week) with typical city permits/closures; Rural assumes a 26-week season (∼6 public hours/week). Staffing lines are fully loaded (wages plus overhead) and include setup/teardown within hours. SNAP/EBT lines include amortized $850 setup (3%, 5y) + $900 service + modest per-transaction fees. Rural totals shown *without* a logistics trailer; adding a $5,000 trailer would increase Annualized CapEx by ≈ $1,092/yr.

Online Appendix B Additional Descriptive Evidence

Online Appendix B.1 Identifying Farmers Market Closure

While it may seem intuitive to categorize zero recorded visits as a market closure, there are several reasons why a non-zero threshold is more appropriate for this analysis. First, the Advan visit data is based on a sample of mobile devices, not the entire population, so some visitor activity may not be captured. Furthermore, even after a market has ceased regular operations, visits may still be recorded due to trips made by market organizers, vendors, or maintenance staff. These occasional visits could be linked to periodic activities such as clean-up or preparation for seasonal re-openings, even after a temporary closure. Another factor that supports the use of a non-zero threshold is the potential presence of visits from individuals unrelated to market operations, such as contractors, landlords, or other personnel maintaining the property. These incidental visits could continue even after the market has been permanently closed. Lastly, the inherent noise in GPS data warrants caution. Although Advan's tracking is generally precise, locations of nearby establishments can sometimes overlap, resulting in misidentification of visits to closed markets. This spatial noise can introduce errors, further justifying the need for a threshold that accounts for non-customer visits and potential data inaccuracies when identifying market closures.

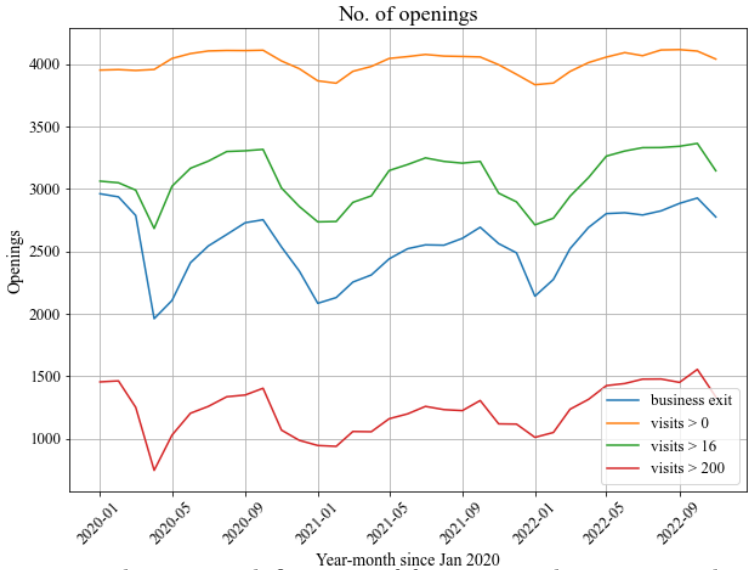
An alternative approach taken here is to infer the likelihood of temporary and permanent farmers market closures by analyzing patterns in visitor activity using Advan data. Following the method by Crane et al. (2022), we set a threshold of a 65 percent year-over-year decline in visits (using a 3-month moving average), a lower bound of 16 visits, and an upper bound of 200 visits. For a formal definition of temporary closure, a farmers market i is temporarily closed in month n if:

$$\tilde{v}_{i,n}^{t} = \begin{cases} 1 & \text{if} \quad \frac{1}{3}\sum_{j=n-1}^{n+1}\left(\frac{v_{i,j}-v_{i,j-52}}{v_{i,j-52}}\right) < -0.65 \quad \text{and} \quad v_{i,n} < 200 \\ 1 & \text{if} \quad v_{i,n} \leq 16 \\ 0 & \text{if} \quad \frac{1}{3}\sum_{j=n-1}^{n+1}\left(\frac{v_{i,j}-v_{i,j-52}}{v_{i,j-52}}\right) > -0.65 \quad \text{and} \quad v_{i,n} > 16 \\ 0 & \text{if} \quad v_{i,n} \geq 200 \end{cases} \tag{1}$$

To account for uncertainty in determining whether a farmers market is operational, we compare

several methods for defining market "open" status using Advan mobility data and external business registry information. Figure B1 presents trends in the number of open markets over time using four thresholds: any visit activity (visits > 0), moderate visit volume (visits > 16), high-volume markets (visits > 200), and administrative closure status from Crane et al. (2022). These distinctions help identify which markets are meaningfully operational versus potentially inactive or misclassified. Table B1 shows that our main demand estimates are robust to these alternative definitions of market open status. Across all specifications, travel cost, racial/ethnic distance, and income mismatch remain strong and statistically significant predictors of market visitation, suggesting that our key findings are not sensitive to how market openness is defined.

Figure B1: Number of Opened Farmers Markets using Different Methods



Note: This figure compares alternative definitions of farmers market openings based on mobility-derived visitation thresholds. Each line reflects a different method for identifying open farmers markets. "Visits > 0" includes any market with at least one recorded visit, capturing all activity but prone to noise. "Visits > 16" filters out incidental or non-customer visits and aligns with the lower bound used for identifying temporary closures. "Visits > 200" focuses on high-traffic markets likely to be fully operational. The "business exit" line reflects open status based on the approach by Crane et al. (2022).

Table B1: Logit IV Regression Results: Alternative Open Status

	(1)	(2)	(3)	(4)
Travel Cost (2019$)	-0.154***	-0.154***	-0.157***	-0.155***
	(0.000)	(0.000)	(0.000)	(0.000)
Euclidean racial-ethnic distance	-0.009***	-0.009***	-0.009***	-0.009***
	(0.000)	(0.000)	(0.000)	(0.000)
$\lvert Home_{Income} - Market_{Income} \rvert$	-0.002***	-0.002***	-0.002***	-0.002***
	(0.000)	(0.000)	(0.000)	(0.000)
Observations	14,378,876	14,371,712	14,035,663	14,321,117
Closure Status	>0 visits	business exit	>16 visits	>200 visits

Notes: Table B1 shows the results of running the demand model without visitor taste heterogeneity on travel distance and demographic distance using alternative open status definitions. All columns include farmers market fixed effects, year-quarter fixed effects, CBG fixed effects, and weather controls. Robust standard errors are in parentheses. ***,**,* denotes statistical significance at the 1%, 5%, and 10% levels, respectively. For additional details, see Section 4.

Online Appendix C Robustness Checks and Additional Findings

Online Appendix C.1 Robustness Checks

Table C1: Logit IV Regression Results with Alternative Demographic Distance Measures

	(1)	(2)	(3)	(4)
Travel Cost (2019$)	-0.154***	-0.154***	-0.157***	-0.154***
	(0.000)	(0.000)	(0.000)	(0.000)
Euclidean racial-ethnic distance	-0.009***			
	(0.000)			
$\lvert Home_{Income} - Market_{Income} \rvert$	-0.002***	-0.002***		
	(0.000)	(0.000)		
$\lvert Home_{Black} - Market_{Black} \rvert$		-0.009***		
		(0.000)		
$\lvert Home_{Hispanic} - Market_{Hispanic} \rvert$		-0.006***		
		(0.000)		
$I(Home_{Black} - Market_{Black})$			-0.110***	
			(0.003)	
$I(Home_{Hispanic} - Market_{Hispanic})$			-0.095***	
			(0.003)	
$I(Home_{Income} - Market_{Income})$			-0.104***	
			(0.003)	
$max(Home_{Black} - Market_{Black}, 0)$				-0.018***
				(0.000)
$max(Home_{Hispanic} - Market_{Hispanic}, 0)$				-0.012***
				(0.000)
$max(Home_{Income} - Market_{Income}, 0)$				-0.004***
				(0.000)
Observations	14,378,876	14,378,876	14,378,876	14,378,876

Notes: Table C1 shows the results of running the demand model without visitor taste heterogeneity on travel distance and demographic distance. All columns include farmers market fixed effects, year-quarter fixed effects, CBG fixed effects, and weather controls. Robust standard errors are in parentheses. Robust standard errors are in parentheses. ***,**,* denotes statistical significance at the 1%, 5%, and 10% levels, respectively. For additional details, see Section 4.

Table C2: Logit IV Regression Results: Alternative Travel Distance Cutoffs

	(1)	(2)	(3)	(4)	(5)
Travel Cost (2019$)	-0.154***	-0.154***	-0.154***	-0.157***	-0.147***
	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)
Euclidean racial-ethnic distance	-0.009***	-0.009***	-0.009***	-0.011***	-0.012***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$\lvert Home_{Income} - Market_{Income} \rvert$	-0.002***	-0.002***	-0.002***	-0.002***	-0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	14,378,876	14,256,906	14,042,749	13,704,459	13,111,181
Distance Cutoff	30 miles	25 miles	20 miles	15 miles	10 miles

Notes: Table C2 shows the results of running the demand model without visitor taste heterogeneity on travel distance and demographic distance. Each column corresponds to a different distance cutoff, restricting which markets are considered available to a consumer. Column (1) uses a 30-mile cutoff, which serves as our baseline specification. Columns (2)-(5) tighten this threshold to 25, 20, 15, and 10 miles, respectively, reflecting more restrictive assumptions about how far individuals are willing or able to travel for market access. All columns include farmers market fixed effects, year-quarter fixed effects, CBG fixed effects, and weather controls. Robust standard errors are in parentheses. Robust standard errors are in parentheses. ***,**,* denotes statistical significance at the 1%, 5%, and 10% levels, respectively. For additional details, see Section 4.

Table C3: Logit IV Regression Results: Alternative Market Sizes

	(1)	(2)	(3)	(4)	(5)
Travel Cost (2019$)	-0.154***	-0.154***	-0.154***	-0.154***	-0.154***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Euclidean racial-ethnic distance	-0.009***	-0.009***	-0.009***	-0.009***	-0.009***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$\lvert Home_{Income} - Market_{Income} \rvert$	-0.002***	-0.002***	-0.002***	-0.002***	-0.002***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	14,378,876	14,378,876	14,378,876	14,378,876	14,378,876
No. of Occasions per quarter	26	13	20	32	39

Notes: Table C3 examines the robustness of our logit IV regression results to alternative assumptions about market size, defined as the number of times an individual makes a farmers market choice per quarter. Each column represents a different value for this assumed frequency: Column (1) uses 26 occasions (our baseline), while Columns (2) through (5) test values ranging from 13 to 39. These adjustments influence the scale of market shares and choice probabilities but not the relative preference structure. All columns include farmers market fixed effects, year-quarter fixed effects, CBG fixed effects, and weather controls. Robust standard errors are in parentheses. Robust standard errors are in parentheses. ***,**,* denotes statistical significance at the 1%, 5%, and 10% levels, respectively. For additional details, see Section 4.

Online Appendix C.2 Sampling Weights

The non-uniform spatial distribution in our device sampling could skew results if left uncorrected. To mitigate this, we apply sample weights that are calibrated using the presumed home locations of the devices. We determine these sample weights by comparing the number of devices residing in a given area to the population in the corresponding CBG/county/state. The results in Appendix Table C4 indicate that when using CBG/county/state-level sampling weights, the coefficients for travel costs are slightly reduced.

Table C4: Logit IV Regression Results: Sampling Weights

	(1)	(2)	(3)	(4)
Travel Cost (2019$)	-0.150***	-0.154***	-0.156***	-0.152***
	(0.000)	(0.000)	(0.000)	(0.000)
Euclidean racial-ethnic distance	-0.009***	-0.009***	-0.009***	-0.009***
	(0.000)	(0.000)	(0.000)	(0.000)
$\lvert Home_{Income} - Market_{Income} \rvert$	-0.002***	-0.002***	-0.002***	-0.002***
	(0.000)	(0.000)	(0.000)	(0.000)
Observations	14,389,439	14,378,876	14,376,105	14,376,105
Sampling Weights	No	CBG	County	State

Notes: Table C4 reports results from our logit IV demand model under different sampling weight schemes designed to adjust for differences in device coverage across geographies. Column (1) shows the baseline specification with no weights. Columns (2)-(4) apply post-stratification weights based on the population-to-device ratio at the CBG, county, and state levels, respectively. These weights correct for the fact that mobile device data may not represent all areas equally, particularly in rural or low-income communities. All columns include farmers market fixed effects, year-quarter fixed effects, CBG fixed effects, and weather controls. Robust standard errors are in parentheses. Robust standard errors are in parentheses. ***,**,* denotes statistical significance at the 1%, 5%, and 10% levels, respectively. For additional details, see Section 4.

Online Appendix C.3 Measurement Errors in SNAP

Table C5: 2nd Stage Regression Results: Alternative SNAP Matching Rules

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
SNAP Dummy	0.149***	0.128***	0.129***	0.132**	0.157***	0.165***	0.156***
	(0.044)	(0.045)	(0.048)	(0.052)	(0.045)	(0.046)	(0.048)
Weekend Dummy	0.038	0.037	0.026	0.009	0.034	0.030	0.050
	(0.049)	(0.050)	(0.052)	(0.054)	(0.050)	(0.050)	(0.051)
Night Dummy	0.088**	0.088*	0.094**	0.100**	0.083*	0.090**	0.099**
	(0.044)	(0.045)	(0.046)	(0.047)	(0.045)	(0.045)	(0.046)
Log(Size)	0.428***	0.427***	0.427***	0.421***	0.425***	0.421***	0.424***
	(0.015)	(0.016)	(0.016)	(0.017)	(0.015)	(0.015)	(0.015)
FD Dummy	-0.118	-0.116	-0.107	-0.098	-0.111	-0.107	-0.107
	(0.076)	(0.077)	(0.079)	(0.083)	(0.078)	(0.079)	(0.080)
Urban Share	0.415***	0.416***	0.408***	0.421***	0.409***	0.411***	0.427***
	(0.062)	(0.062)	(0.063)	(0.064)	(0.063)	(0.063)	(0.064)
Observations	3983	3867	3668	3425	3872	3749	3630
R-sq	.404	.401	.395	.39	.405	.403	.406
Matching Score	87	90	95	100			
Nearest Distance	100				65	38	20

Notes: This table reports second-stage regressions of market fixed effects on observable attributes under alternative SNAP matching rules. The dependent variable is the estimated market-level attractiveness $\hat{\eta}_j$. The key regressor is the SNAP Dummy, coded under different combinations of string-matching score thresholds and nearest-distance cutoffs. Columns (1)-(4) vary the minimum acceptable fuzzy-matching score (87, 90, 95, 100), while holding the distance cutoff at 100 meters. Columns (5)-(7) vary the maximum centroid distance allowed (65, 38, 20 meters), while holding the minimum acceptable fuzzy-matching score at 87. All regressions control for weekend operation, night operation, log size, food desert location, urban share, and county FEs. Robust standard errors are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. For additional details, see Section 4.

Table C6: 2nd Stage Regression Results: Alternative SNAP Status Definitions

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
SNAP Dummy	0.149***	0.152***	0.148***	0.135***	0.150***	0.171***	0.167***
	(0.044)	(0.044)	(0.046)	(0.049)	(0.045)	(0.047)	(0.049)
Weekend Dummy	0.038	0.036	0.042	0.037	0.037	0.040	0.049
	(0.049)	(0.049)	(0.050)	(0.051)	(0.050)	(0.051)	(0.052)
Night Dummy	0.088**	0.096**	0.097**	0.094**	0.092**	0.097**	0.096**
	(0.044)	(0.044)	(0.045)	(0.046)	(0.045)	(0.046)	(0.046)
Log(Size)	0.428***	0.426***	0.425***	0.423***	0.425***	0.426***	0.421***
	(0.015)	(0.015)	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)
FD Dummy	-0.118	-0.103	-0.098	-0.091	-0.107	-0.113	-0.104
	(0.076)	(0.075)	(0.077)	(0.081)	(0.076)	(0.078)	(0.080)
Urban Share	0.415***	0.414***	0.408***	0.414***	0.417***	0.398***	0.413***
	(0.062)	(0.062)	(0.063)	(0.064)	(0.062)	(0.063)	(0.064)
Observations	3983	3948	3854	3599	3911	3723	3558
R-sq	.404	.402	.401	.397	.403	.4	.402
Begin Year					2022	2021	2019
End Year		2022	2021	2019			

Notes: This table reports second-stage regressions of market fixed effects on observable attributes under alternative SNAP coding rules that exclude markets with time-varying SNAP participation. The dependent variable is the estimated market-level attractiveness $\hat{\eta}_j$. In each column, we exclude markets that (i) end SNAP participation after the year indicated in the "End Year" row, or (ii) begin SNAP participation after the year indicated in the "Begin Year" row. This ensures that SNAP status is stable over the analysis window. All regressions control for weekend operation, night operation, log size, food desert location, urban share, and county FEs. Robust standard errors are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively. For additional details, see Section 4.

Online Appendix D Matching Procedure

To construct a valid comparison group of non-FD communities, we implement a nearest-neighbor matching procedure at the CBG level. Specifically, each FD CBG is paired with a non-FD CBG that is most similar in terms of key socio-demographic characteristics drawn from the American Community Survey (ACS). The matching covariates include:

- Median household income (economic resources),
- Racial and ethnic composition (share of non-Hispanic White, Black, and Hispanic residents),
- Educational attainment (share of adults with a college degree), and
- Vehicle ownership (share of households without access to a vehicle).

All covariates are standardized to have a mean of zero and unit variance prior to matching. We compute the Mahalanobis distance across these standardized covariates and assign to each FD CBG i the nearest non-FD CBG $m(i)$. To prevent reuse of the same non-FD CBG, we impose a one-to-one matching constraint without replacement.

We verify the balance between FD and matched non-FD CBGs by comparing standardized mean differences before and after matching. Balance improves substantially: all standardized mean differences fall below 0.1 after matching, a commonly used threshold for acceptable covariate balance.

Table D1: Balance of Matching Covariates Before and After Matching

Panel A. Before Matching				
Covariate	FD Mean	non-FD Mean	Diff	t-stat
Population	1521.22	1595.19	-73.97	-9.08
Share White (%)	64.78	72.95	-8.17	-40.48
Share Black (%)	23.53	12.04	11.49	68.11
Share Asian (%)	2.54	5.90	-3.36	-41.87
Share Native (%)	0.87	0.58	0.29	13.64
Share Hispanic (%)	19.58	17.29	2.29	12.89
Median household income	46.68	76.84	-30.16	-99.46
Sample size	18,615	151,711		
Panel B. After Matching				
Covariate	FD Mean	non-FD Mean	Diff	t-stat
Population	1521.22	1515.87	5.35	0.52
Share White (%)	64.78	65.02	-0.24	-0.81
Share Black (%)	23.53	23.54	-0.01	-0.02
Share Asian (%)	2.54	2.50	0.03	0.59
Share Native (%)	0.87	0.81	0.06	1.37
Share Hispanic (%)	19.58	19.45	0.13	0.50
Median household income	46.68	46.83	-0.15	-0.79
Sample size	18,615	18,615		

Notes: FD represents food desert CBGs. Diff is FD minus non-FD. t-statistics are from two-sample equal-variance tests of mean differences. Variable-specific N may be slightly lower due to missing values (e.g., income).

Online Appendix E Monte Carlo Simulation for Zero Market Share Corrections

E.1. Simulation Design

To assess the statistical performance of alternative approaches to the zero-market-share problem, we conduct a controlled Monte Carlo (MC) experiment. The exercise follows the structure of recent robustness studies in structural demand estimation (Dubé, Hortaçsu, and Joo, 2021; Li, 2019) and aims to illustrate the small-sample and sparsity properties of our proposed empirical Bayes (EB) correction.

We simulate artificial markets with $C = 200$ consumer block groups (CBGs), $J = 25$ sites, and $T = 60$ weekly periods. In each replication, each consumer $i \in C$ chooses among the J sites or an outside option according to the following true data-generating process (DGP):

$$U_{icjt} = \alpha_{\text{true}} TC_{cjt} + \eta_j + \xi_{jt} + \varepsilon_{icjt}, \tag{2}$$

where TC_{cjt} is the travel cost, η_j is a site-specific constant, ξ_{jt} captures week-level fluctuations in site attractiveness, and ε_{icjt} follows an i.i.d. Type-I extreme value distribution. True travel costs are generated from a log-normal distance process scaled into monetary units:

$$TC_{cjt} = \exp(\mu_d + \sigma_d z_{cjt}) + \upsilon_{cjt}, \tag{3}$$

with $z_{cjt} \sim \mathcal{N}(0,1)$ and $\upsilon_{cjt} \sim \mathcal{N}(0, \sigma_\upsilon^2)$. Site attractiveness varies with an exogenous "quality signal" $q_{jt} \sim \mathcal{N}(0,1)$ that enters additively in ξ_{jt}. Market shares are computed from the logit probability system

$$s_{cjt} = \frac{\exp(U_{cjt})}{1 + \sum_{k=1}^{J} \exp(U_{ckt})}. \tag{4}$$

From these probabilities, we draw multinomial counts with $N_c = 4000$ trials per CBG-week.

The resulting observed market shares contain naturally occurring zeros in low-probability markets.

To study the role of sparsity, the outside option share is calibrated to generate two regimes:

- **Low-zeros:** approximately 20% of CBG-site-week cells record zero visits.
- **High-zeros:** approximately 80% zero cells, mimicking sparse mobility data.

Within each regime, we vary the true $\alpha_{\text{true}} \in \{-0.010, -0.005, -0.001\}$. Each configuration is replicated 100 times.

E.2. Estimation Procedures

For every simulated dataset, we estimate the travel-cost coefficient $\hat{\alpha}$ using GMM after residualizing TC_{cjt} and log-share differences by CBG, site, and week fixed effects. We benchmark four families of zero-share treatments:

(i) **GMM[drop]** - Excludes zero shares prior to taking log differences.

(ii) **Aggregation** - Coarsens markets by merging CBGs into pairs (*tract2*) or quads (*tract4*) and then applies GMM[drop].

(iii) **Epsilon-adjustment** - Adds a constant $\varepsilon \in \{10^{-6}, 10^{-5}\}$ to inside shares before normalizing.

(iv) **Empirical Bayes (EB)** - Replaces raw inside shares with posterior means from a Beta-Binomial pooling scheme:

$$\hat{s}_{jc} = \frac{\lambda^1_{jc} + K_{jc}}{\lambda^1_{jc} + \lambda^2_{jc} + N_c}, \tag{5}$$

where the prior hyperparameters $(\lambda^1_{jc}, \lambda^2_{jc})$ are estimated from "similar" markets $l \in P_c$.

Two pooling strategies are implemented:

- *Distance pooling (EB_{dist})* - borrows information across similar CBGs for a given site-week using symmetric windows of ±15, ±20, and ±25 ranks, denoted [30], [40], [50].
- *Time pooling (EB_{time})* - borrows across weeks for a given CBG-site pair using ±10, ±15, and ±20 weeks, denoted [20], [30], [40].

For each method, the outside share is recomputed to ensure consistent normalization.

Performance is evaluated using bias, root mean square error (RMSE), 95% coverage of the true parameter relative to a noise-free benchmark that uses the true latent probabilities.

E.3. Results

Table E1 reports the RMSE of the estimated travel-cost coefficient across methods and sparsity regimes. The evidence demonstrates clear and stable dominance of the EB_{dist} estimator in both regimes. In the **high-zeros** regime (≈80% zeros), $\text{EB}_{\text{dist},40}$ achieves the smallest RMSEs across all true α values (e.g., 0.0007 at $\alpha = -0.01$), outperforming aggregation and ε-adjustments by an order of magnitude. EB_{time} performs notably worse, indicating that spatial pooling across markets is more informative than temporal pooling when sparsity is severe.

Table E1: Monte Carlo Simulation Results: RMSE of Travel-Cost Estimates Across Zero-Share Correction Methods

			Aggregation		**eps**		**EB_{dist}**			**EB_{time}**		
Sample	α_{true}	[drop]	[tract2]	[tract4]	[+1e-6]	[+1e-5]	[30]	[40]	[50]	[20]	[30]	[40]
highzeros	-0.010	0.0092	0.0089	0.0079	0.0015	0.0013	**0.0009**	**0.0007**	0.0018	0.0077	0.0078	0.0079
highzeros	-0.005	0.0046	0.0043	0.0036	0.0024	0.0006	0.0007	**0.0001**	0.0006	0.0036	0.0036	0.0036
highzeros	-0.001	0.0009	0.0008	0.0006	0.0008	0.0004	0.0002	**0.0001**	**0.0001**	0.0007	0.0007	0.0007
lowzeros	-0.010	0.0042	0.0035	0.0034	0.0198	0.0137	**0.0002**	0.0009	0.0015	0.0068	0.0068	0.0069
lowzeros	-0.005	0.0020	0.0009	0.0009	0.0116	0.0083	**0.0001**	0.0004	0.0006	0.0030	0.0030	0.0030
lowzeros	-0.001	0.0003	**0.0000**	0.0001	0.0020	0.0015	**0.0000**	**0.0000**	0.0001	0.0005	0.0005	0.0005

Notes: This table reports root mean square errors (RMSE) of estimated travel-cost coefficients ($\hat{\alpha}$) across alternative treatments of zero-market-share observations in simulated random-coefficients logit models. Each panel corresponds to a different sample size (large, medium, small), with factorial variations in the true α, random-coefficient dispersion (rc_{sd}), and travel-cost noise ($noise_{sd}$). All results are averaged over 100 Monte Carlo replications.

In the **low-zeros** regime (≈20% zeros), EB_{dist} again outperforms all alternatives, with the optimal window slightly smaller (30-40). Aggregation yields moderate improvement over GMM[drop] but remains materially less efficient, while ε-adjustments become unstable, often inflating RMSEs when zeros are infrequent.

E.4. Discussion

There are two takeaways. First, EB_{dist} consistently achieves the best bias-efficiency trade-off across both sparsity regimes, but the *optimal pooling window is data-dependent.* In our Monte Carlo

experiments with 200 CBGs, moderate windows (30-40) strike the best balance between smoothing and local fidelity. Although the table does not directly test larger systems, the same logic suggests that when the number of CBGs exceeds 10,000, as in our empirical analysis, the optimal window would likely shift upward to capture comparable spatial neighborhoods. In such high-dimensional settings, slightly broader pooling (e.g., 40-50) can stabilize estimates without oversmoothing genuine cross-sectional variation. Second, methods that either delete zeros (GMM[drop]), coarsen the market (tract2/tract4), or apply ad-hoc smoothing (ε-add) either attenuate the travel-cost coefficient or inject instability, thereby overstating welfare in sparse settings or inflating variance in denser settings. In contrast, EB_{dist} preserves local cross-sectional structure while shrinking extreme cells toward an empirically relevant prior, yielding order-of-magnitude RMSE gains over common fixes. These findings confirm the empirical Bayes framework as a robust, theoretically coherent, and computationally practical solution to the zero-market-share problem.