Relocating within the Tompkins County Pantry Network: Estimating Demand for the new Enfield Food Pantry

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1. Introduction

Food pantries play a critical role in communities, especially those in rural locations with limited access to grocery stores and transportation methods. Most food insecure individuals and families do not solely rely on one pantry; rather, they rely on a pantry network, which is a set of distinctly operating food pantries within a shared geographic region. In Tompkins County, the Enfield Food Pantry is relocating and expanding, and local partners want to understand the implications of this move on food assistance within the county. Our research answers the question: How does relocating and expanding a food pantry affect estimated expected demand at the site? In this final report, we discuss the context of the question and our conducted literature review, outline data sources, then present our methodology and models in order to estimate expected demand. We conclude with the significance of this estimate for Tompkins County, as well as subsequent actions for next steps.

2. Background and Context

Tompkins County faces persistent food insecurity due to its high relative rurality and patterns of local poverty. Food insecurity is not only determined by poverty rates and income levels, but also by relative access to grocery stores and food resources.

The food pantry network in Tompkins County primarily consists of eight food pantries and food distribution centers: Tompkins Community Action, St. John's Community Services Pantry, Ithaca Kitchen Cupboard, Immaculate Conception Food Pantry, Salvation Army Saturday Pantry, Baptized Church of Jesus Christ, Ithaca Free Clinic, and the Enfield Food Pantry. These pantries are operated by community organizations, non-profit organizations, and churches, allowing them to reach a substantial amount of the Tompkins County population. However, this decentralized network makes it difficult to predict demand for food pantries due to a lack of standardized regulation for food supply and hours of operation.

'Access' to a food pantry can be determined by multiple factors such as eligibility, operating hours, and distance. In our research, we found that distance and transportation to a pantry was the largest indicator for accessibility. Especially in rural areas such as Tompkins County, low income households may have limited access to personal vehicles, and public transportation may not reach rural areas and may be unreliable. These constraints suggest that the physical location of a food pantry, and its specific position within the pantry network has direct implications for food pantry access.

There is limited quantitative evidence on one, expected demand at a food pantry, and two, how relocating a specific food pantry might affect future demand. Furthermore, there is sparse quantitative information on food pantry networks and how a small change in one pantry has implications for the network as a whole. This research project addresses a gap in this data.

Enfield Food Pantry's new location continues to be situated within Tompkins County, but also borders the nearby Schuyler County. Schuyler County is much smaller than Tompkins County, with roughly only 18 percent of the population of Tompkins. However, poverty rates and food insecurity in Schuyler County is comparable to Tompkins County. Households bordering both counties may utilize pantries in either county. In our analysis, we include nearby Schuyler pantries to account for the possible overlap in food distribution across both counties and for Enfield's new location.

3. Literature

Client Behavior: Frequency of Visits and Multi-Pantry Use

Patterns of Food Pantry Use and Client Mobility Research consistently shows that food pantry use is not occasional or limited to a single location. Instead, people facing food insecurity often depend on several pantries over long periods. Martin et al. (2010), in a study of 228 pantry users, found that most participants visited food pantries regularly. Sixty-three percent attended at least once per week, while 38 percent visited three or more pantries during the same timeframe. Similarly, Walch et al. (2021) reported that nearly three-quarters of surveyed pantry clients visited multiple pantries each month. National data from the Food Insecurity Survey Supplement supports these findings. It shows that pantry use stays steady for twelve months or longer, especially among households earning less than 185 percent of the federal poverty line (U.S. Census Bureau, 2014). Overall, this research indicates that pantry users actively navigate a network of food resources. They make decisions across different locations instead of seeing pantries as separate points of access.

Factors Affecting Food Pantry Access

Research papers identify travel distance as a primary determinant of food access. Studies on grocery store selection indicate that individuals are generally willing to travel greater distances for stores perceived as higher quality or more reliable. For instance, an analysis of nearly 12,000 food-related trips found that consumers traveled significantly farther to supermarkets than to smaller grocery stores, primarily due to greater product variety and a higher likelihood of finding desired items (Ver Ploeg et al., 2015). Nevertheless, travel cost remains a significant constraint. Fan, Guthrie, and Levinson (2016) demonstrate that although store attractiveness increases willingness to travel, reductions in travel cost exert a substantially larger influence on shopping behavior than comparable increases in store size or variety. When travel conditions are favorable, such as on weekends or during periods of reduced congestion, consumers are more likely to select higher-variety stores even if they are located farther away. Collectively, these findings indicate that while quality and variety are important, distance and travel burden ultimately constrain how far individuals are willing to travel for food.

Research on food pantries shows that their quality and environment are important for access. Ginsburg et al. (2019) studied food pantries in the Bronx and found that food quality, fresh options, and how food is distributed all shape client experiences. Pantries with refrigerated or frozen foods and client choice were seen as more valuable, while poor food quality, long waits, and strict rules made access harder. The study also found that pantries sometimes closed early due to food shortages, which mostly affected people who arrived later. These results show that a pantry's value depends on more than just location. Dignity, reliability, and flexibility in service also matter.

Research shows that how far people travel for food is not just about distance. Many people skip nearby stores to go to places they like better. For example, some shoppers live close to a supermarket but travel farther to shop at a preferred store, showing they weigh quality against distance (Handbury & Weinstein, 2015). Studies also find that some households care more about variety, while others value convenience (Briesch et al., 2009). People who want more variety and quality are willing to travel farther, while those who care less about variety prefer closer options. This means that people's willingness to travel depends on how they balance distance with what each food source offers.

Implications for Food Pantry Access Model

The research specifically helps build the structure for our model of demand. This literature finds travel distance to be the single most important predictor of the usage of the food pantries. This helps build the structure for our model of demand. Modeling the probability of visiting as a function that decreases with distance helps the model account for the behavior.

On the other hand, the fact that there is research predicting frequent use of multiple pantries implies that it is valid to spread the demand among several pantries using weighted probabilities rather than simply choosing the closest pantry exclusively. This avoids the possibility of placing the demand only in one pantry.

Additionally, the literature shows that food quality and variety are factors affecting the willingness to travel, although they cannot be measured easily. To address this challenge, the size of the pantry used as a proximity indicator to attractiveness and distance decay takes into account sensitivity analysis to ensure that attractiveness does not control the spatial effect in the negativity of demand.

At last, use of regional pantries provides evidence for including surrounding counties as variables to reduce boundary effects and make known patterns of access better.

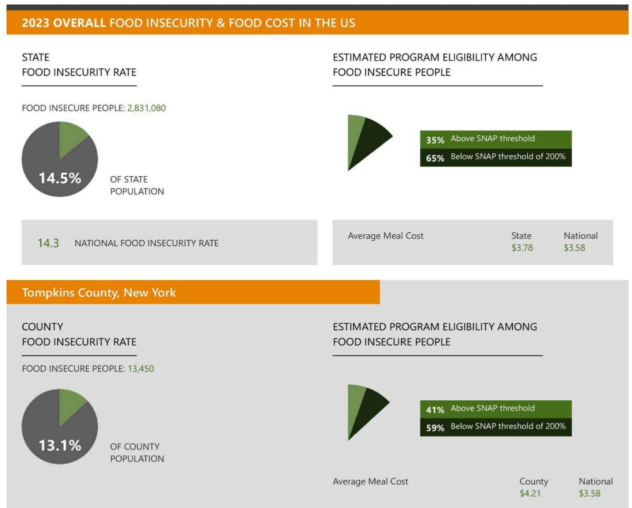

Figure 3.1: Food Insecurity and Cost Burdens in Tompkins County (2021–2023)

This figure summarizes findings from the Tompkins County Food System Baseline Assessment (2021) and the Food Insecurity Report (2023). It highlights the increase to 13,450 food-insecure individuals (13% of the county population), elevated meal costs, and the substantial proportion of residents above SNAP eligibility. These factors reinforce transportation and financial barriers to pantry access.

4. Methods and Data

This research evaluates how the relocation of a food pantry affects spatial access to food assistance across Tompkins County and neighboring regions. Using demographic, socioeconomic, and geographic data, the analysis identifies current areas of need, measures changes in access following the pantry relocation, and evaluates which populations may benefit or be disadvantaged as a result of the move.

4.1 Research Questions

This analysis is guided by three research questions:

1. **Where is there a current need for food pantries?**
   This question identifies geographic areas with higher socioeconomic vulnerability using normalized poverty and income indicators.
2. **How does access for individuals change after the pantry relocation?**
   This question measures how proximity to food pantries changes following the move and whether spatial access improves or worsens across census geographies.
3. **Who is positively or negatively impacted after the move?**
   This question combines need and access measures to identify areas that benefit from improved access and areas that remain underserved.

Together, these questions evaluate whether the relocation aligns pantry accessibility more closely with areas of highest need.

4.2 Data Sources

Multiple public and local datasets were integrated to support this analysis:

- **American Community Survey (ACS)**: Used to obtain income and poverty estimates at the census tract level.
- **2020 U.S. Census:** Provided population counts and geographic boundaries for spatial analysis.
- **Tompkins County Open Data Portal:** Supplied county-specific geographic data, including administrative boundaries and transportation layers.
- **Pantry Network Data:** Included the locations and acreage of all food pantries in the regional pantry network.
- **Find My Pantry Tool:** Used to validate pantry locations and confirm service information where available.

In addition to Tompkins County, Schuyler County was included to account for cross-county access patterns and regional spillover effects. All variables were aligned to consistent census geographies before analysis.

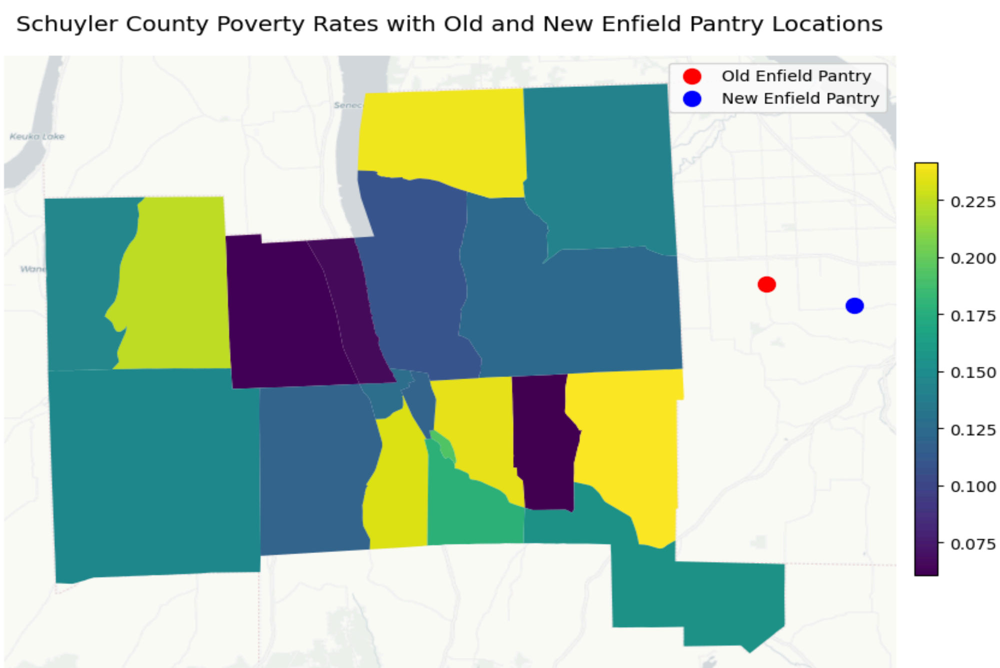

Figure 4.1: Census-tract poverty rates in Schuyler County with old and new Enfield pantry locations overlaid.

4.3 Measuring Need

To quantify food assistance need across the study area, a Need Score was constructed using poverty and income indicators derived from ACS data. Poverty rate and median household income were normalized to a scale from 0 to 1, where higher values indicate greater relative need. Normalization allows for consistent comparison across census tracts with differing population sizes. This composite measure captures economic vulnerability while avoiding reliance on a single indicator. The Need Score is used as an input into later access and demand modeling, but is not itself a prediction of pantry usage

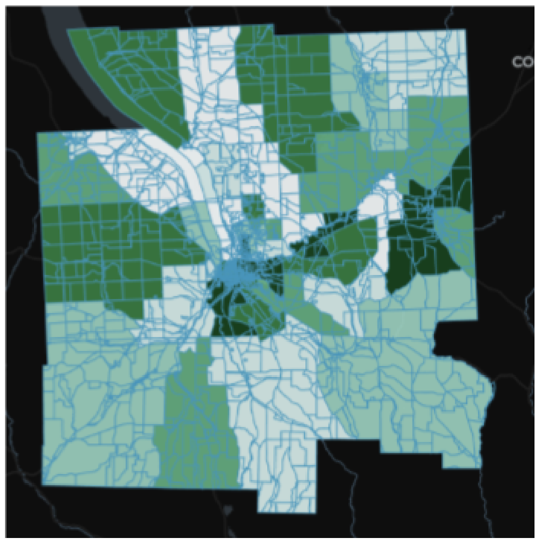

Figure 4.2: Need Score by census block (light to dark, 0-1 scale). The score combines normalized poverty and income indicators and represents underlying food assistance need independent of pantry relocation.

4.4 Measuring Access and Access Change

Access to food pantries is modeled using distance-based proximity, where distance is treated as a proxy for ease of access.

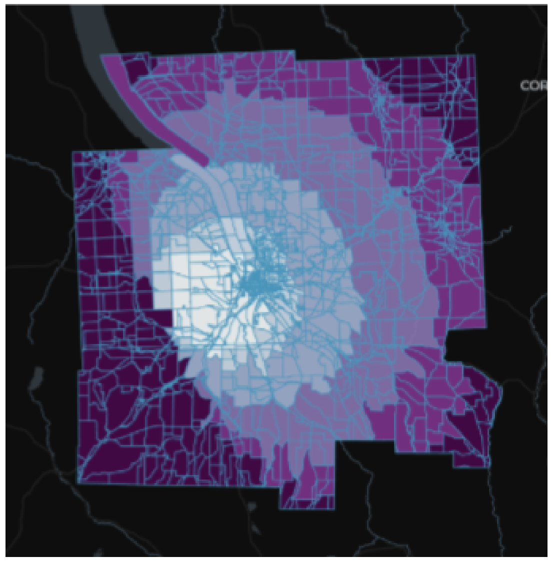

Figure 4.3: Change in access following pantry relocation (light to dark). Positive values indicate improved access and negative values indicate worsened access relative to the pre-relocation location.

Access Before and After Relocation

For each census tract, the distance to the nearest pantry was calculated before and after the relocation. Changes in distance were used to define Access Change, where negative values indicate improved access and positive values indicate worsened access. This approach allows for a direct comparison of spatial accessibility outcomes attributable solely to the relocation

4.5 Priority After the Move

To identify areas that remain underserved after relocation, a Priority After Move metric was developed. This metric highlights census tracts that have high Need Scores, and experience poor or worsening access following the relocation. These areas represent locations where food insecurity remains high despite the pantry move and may warrant further intervention for future expansion. This metric is intended as a diagnostic tool rather than a direct prediction of usage. Together, the Need Score, Access Change, and Priority After Move metrics provide a structured framework for evaluating how relocation redistributes accessibility relative to underlying demand

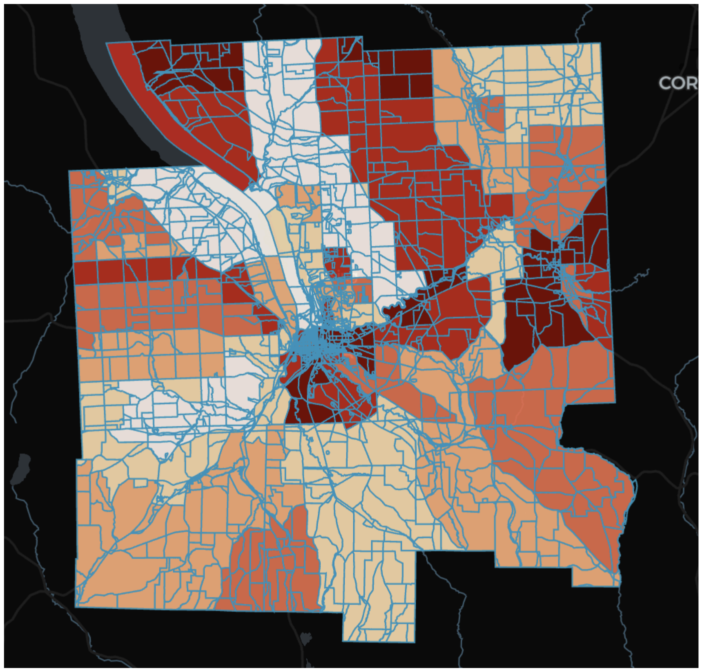

Figure 4.4: Priority After Move index (light to dark). Darker values identify areas with high underlying need and poor access after relocation, representing the greatest concern for outreach or additional support.

4.6 Probabilistic Overlay of Pantry Use

Beyond simple distance measures, the analysis incorporates a probabilistic overlay estimating the likelihood that individuals visit a pantry as a function of distance from the new Enfield location. The probability of visitation decreases as distance increases. This overlay provides a more realistic representation of behavioral access patterns without introducing complex travel models.

4.7 Assumptions and Limitations

Several assumptions were necessary to scope the analysis. The study focuses exclusively on pantry relocation, not capacity expansion or service changes. Distance is used as a proxy for access without explicitly modeling transportation barriers such as car ownership, public transit availability, mobility limitations, or travel time. Pantry demand is assumed to respond smoothly to distance rather than through abrupt thresholds.

While these assumptions simplify reality, they allow for a focused evaluation of spatial access changes attributable to relocation alone. Data availability varied across counties, leading to differences in spatial resolution between Tompkins and Schuyler County.

4.8 Use of AI in Research

Artificial intelligence tools were used in a supportive role throughout this research process. AI assisted with reviewing relevant literature and clarifying definitions, supporting exploratory data analysis and code debugging, and improving clarity and structure in written sections.

5. Models

Over the course of this project we built a predictive model for food pantry demands. We were able to use this model to compare how relocating the Enfield food pantry affected their demand to their current demand. We started with very simple assumptions based on the literature review we had conducted and each iteration added a little more complexity to try and give the most complete picture possible.

5.1 Mapping Probabilities

Our initial model was more of a proof of concept than anything else. We collected the geographical coordinates of each of the pantries in Ithaca and plotted them on a graph using the geopandas library in python. From the literature mentioned above, we found that there was about a 23.5% decrease in the chance of someone visiting a pantry for every one euclidean mile of distance they were away from the given pantry. We also found that people don't generally visit pantries and supermarkets if they are further than six miles away from their home. Using these two pieces of information we constructed a model that creates a buffer of six miles surrounding each pantry and within the buffer there exists a probability gradient. The probability was calculated by $p(x) = 0.765^x$ where x is the distance in miles from the given pantry. An example of this can be seen in the following figure.

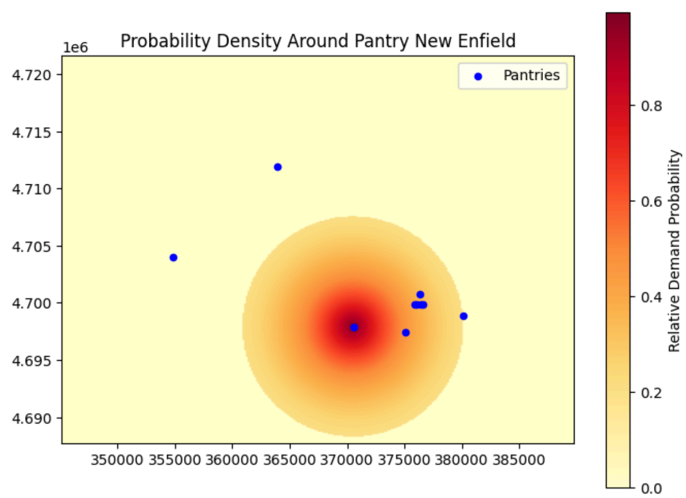

Figure 5.1: Distance weighted exponential decay model. Using statistics from the literature we chose a decay rate and fit an exponential model to estimate the probability an individual visits a pantry at a given radius.

From this model we knew that if we overlaid the population we could get a fairly naive but decently useful predictive model.

5.2 Integrating Population Data and Adding Complexity

The next iterations of our model involved integrating population data and complicating our model with “attractiveness scores”. We were able to gain access to a dataset that contains poverty rate by block (think city block in size) in Ithaca and then join it with a NHGIS dataset that contains the population of each block.

At the same time, we made our model more nuanced as we know that distance isn’t the be all end all of which pantry to choose. We wanted to add some kind of quality factor to the pantries to help differentiate them so we chose to use building size as a proxy for quality under the assumption that bigger pantries will have more stock and thus better options to choose from. We first normalized all the pantry sizes against the mean pantry size so that they could be compared easier. Then we created an attractiveness score per pantry which combines the previous decay rate numbers with the normalized pantry size. Both decay and size are weighted with tunable parameters α and β respectively. We then normalized the attractiveness scores to make them a legit probability. A more in-depth look at the math:

d_{ij} = distance in miles from block i to pantry j

ℓ_j = lot size in acres for pantry j

Weight parameters: α, β

Distance decay: $D_{ij} = 0.765^{d_{ij}}$

Normalized Lot sizes: $L_j = \ell_j$ / mean(all ℓ_j’s)

Attractiveness score: $A_{ij} = (D_{ij})^{\alpha} \times (L_j)^{\beta}$

For each block i we normalize across pantries j: $P_{ij} = A_{ij} / \sum_j A_{ij}$

Expected demand (for now): $demand_{ij} = poverty\_rate_i \times P_{ij}$

Total demand for pantry j: $Demand_j = \sum_i demand_{ij}$

The only parts of this model that are still relatively unknown are the weight parameters α and β. To understand how adjusting them affected our model, we conducted a sensitivity analysis on β while keeping α constant. This enabled us to see how heavily we should weigh the size component. Figures 5.2 below show the results of the analysis taking into consideration both Enfield’s old and new location.

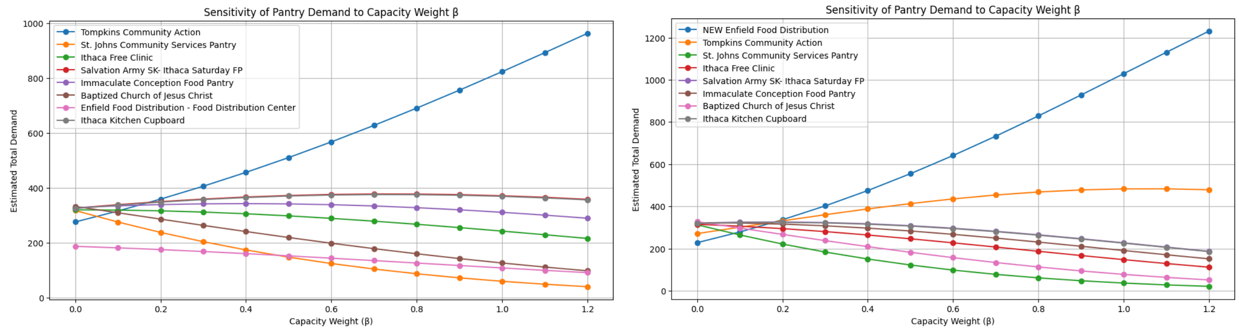

Figure 5.2: Estimated total demand per pantry vs Beta value considering only the old Enfield pantry location (Left) and only the new pantry location (Right).

From this analysis we found that $\beta = 0.4$ was a reasonable choice as it encodes the idea that larger pantries attract more demand but it avoids concentrating nearly all demand into the largest pantry.

5.3 Final Model

To complete our model we calculated the estimated demand each block would provide each pantry. We also added the neighboring county of Schuyler County to help give a fuller picture of potential incoming demand. Lastly, we recognized that people sometimes visit multiple pantries and from our literature review we found that 40% of people visit two pantries and 20% visit three pantries. So we calculated the demand from block i to pantry j as:

$$demand_{ij} = population_i \times poverty\_rate_i \times (P_{ij}^{(1)} + 0.4P_{ij}^{(2)} + 0.2P_{ij}^{(3)}).$$

We did not have as granular data for Schuyler County as we did for Tompkins County so we uniformly distributed their county wide known poverty rate over their population blocks. While this isn't as ideal as the Tompkins data, we felt like it was still a valuable asset to aid in our understanding of how demand will change due to the relocation.

With the relocation in mind we were able to use the model to produce side by side maps that show which blocks favor which pantry and how they change when Enfield relocates (Figures 5.3 and 5.4). The last thing our model produces is a side by side bar chart that shows the demand for each pantry before and after relocation (Figures 5.5 and 5.6).

Figure 5.4: *Top;* Map of pantry coverage area in Schuyler and Tompkins counties for the Enfield Pantry's old location (Left) and new Location (Right). *Bottom;* Estimated demand in terms of monthly visitors for the old (Left) and new (Right) locations of Enfield pantry.

6. Findings

From the graphs and charts produced by our model, we expect to see about a four times increase in demand. In the graphs, we can see that prior to the move, Enfield is the top choice for a decent number of people but the bar chart shows us that the area it is attracting from is fairly sparse in terms of population. However, after the move, it attracts a much larger portion of the area and the bar chart confirms our understanding of the graph as it shows a significant increase in demand.

From our analysis, if we assume the average person visits once a month, we predict that there will be approximately 994 visitors per month compared to the current 247 visitors. However, if that assumption is incorrect, these numbers should still hold for a more accurate frequency of visitation.

In the block figures above, there are several food distribution centers that seem to dominate demand for the two counties. This is due to the increased lot size and advantageous distance of these pantries allowing them to maintain a priority. While there are still smaller food pantries that might be the primary source for smaller neighborhoods, this model captures the overarching reach of the largest and most capable food pantries. We see that the movement of the Enfield food pantry will cause less competition for the Schuyler County customers, and take more area from the Tompkins Community Action Pantry. Additionally, the coverage of Tompkins Community Action Pantry (colored in light blue on the top left graph) loses a large portion of area as the New Enfield Food Distribution Center moves to the right and scales up. We notice that the left border of the old and new Enfield Food Distribution Centers are roughly in the same area. This happens in our model because although the pantry is moving to the right, they are scaling up a considerable portion which will likely draw customers from farther areas. This also makes intuitive sense, as previous customers will likely still be willing to travel the extra distance after the move, because of the added size and variety now offered.

It is also important to note that these findings come with additional limitations. While we are confident in the sizable relative increase, we acknowledge that these population metrics and general statistics may not be completely accurate, either being outdated or broad in application. However, since we keep our model as a simple largely distance based decay weighting, we can be confident that our results best represent the general population behavior found in our background research. Model parameters like beta and distance decay rate were either chosen on statistical evidence in the literature or as a reasonable choice after analysis. One of the most important setbacks that deserves discussion is the census data, which was provided from 2020. We believe this may be the reason for our overinflated final demand numbers, as census statistics for percent of individuals above and below the poverty line requesting food aid was most likely higher than in more recent years.

7. Conclusion

This project estimated how relocating the Enfield Food Pantry within the Tompkins County pantry network may change expected demand at the new site. Using demographic and poverty data, distance-based access measures, and a network-based demand allocation model that accounts for travel burden and pantry attractiveness, we compared predicted demand at Enfield's current location to predicted demand after relocation.

Across model iterations, the relocation consistently increased predicted demand at the Enfield site. Under the final model, we estimate a substantial increase in expected visits compared to current demand. While the exact magnitude depends on modeling assumptions, the direction of change is robust. The new location is positioned to draw demand from additional high-need areas and may also attract cross-county usage, particularly from nearby Schuyler County.

These results have direct operational implications. A substantial increase in demand would require planning for staffing, volunteer capacity, storage and distribution space, scheduling, and supply coordination with partner organizations. It may also require redesigning intake and distribution workflows to avoid longer wait times and maintain consistent service quality as utilization increases. More broadly, the analysis highlights that pantry relocation is not simply a local change. Because households often use multiple pantries, changing one site's location can shift demand patterns across the network

This work has several limitations. The model uses distance as a proxy for access and does not explicitly incorporate transportation barriers such as vehicle ownership, transit availability, mobility constraints, or travel time. Pantry attractiveness was approximated using lot size or facility size rather than direct measures of food variety, hours, client choice, reliability, or capacity. Additionally, some inputs, especially for Schuyler County, were available at a coarser resolution than for Tompkins County. For these reasons, the estimates should be interpreted as decision-support projections rather than precise forecasts.

Despite these limitations, the model provides a transparent and reproducible framework to help local partners anticipate changes in demand and to guide planning for the transition. The results suggest that Enfield's relocation is likely to increase usage substantially and that the pantry network should treat the move as a system-level change that may require coordination across multiple sites.

7.1 Recommendations and Next Steps

1. **Operational planning at Enfield**
    a. Use the predicted increase to plan staffing, volunteer shifts, storage capacity, distribution hours, and supply needs. Consider scenario planning using low, medium, and high demand cases to account for uncertainty
2. **Network coordination**
    a. Communicate projected demand shifts with other pantries in the Tompkins network. If Enfield draws additional demand, other sites may experience offsetting changes that affect their own staffing and inventory planning.
3. **Improve access modeling with travel time and transportation constraints**
    a. Replace Euclidean distance with estimated travel time and incorporate car ownership rates or transit access if data are available. This would better represent rural access barriers
4. **Validate predictions after relocation**
    a. Compare predicted demand to actual post-move visitor counts over the first 3–6 months. Use observed usage to recalibrate parameters, including distance decay, attractiveness weighting, and multi-pantry behavior rates.
5. **Add pantry-level service quality measures**
    a. If feasible, incorporate pantry hours, frequency of distribution, client choice availability, reliability, and capacity constraints.

By combining these next steps with ongoing data collection, Tompkins County partners can strengthen planning around the move and improve the long-term accuracy and usefulness of demand forecasting for the pantry network.

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9. Drive And Github

- Drive: Food Pantry Team
- Github: https://github.com/Logan-Abramowitz/Food-Pantry
- Final Slideshow: Food Pantry Team - Final Slides (30 minutes)