Three Essays on Food Insecurity and Economics

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(ABSTRACT)

This dissertation is composed of three manuscripts focusing on food insecurity and food economics in the United States. The first manuscript titled "Differences in Food Insecurity Across the Rural/Urban Spectrum - The Role of Trade Flows" uses county food trade data to examine its correlation with food insecurity rates based on a county's rural-urban continuum code. In addition, an Oaxaca-Blinder decomposition is employed to determine the causes of food insecurity rate differences between county's based on their rural-urban continuum codes.

The second manuscript titled "The Role of Infrastructure on Food Flows in the United States" uses county food trade data to examine the relationship between county infrastructure important to the food supply chain, such as roadways, ports, food processing and manufacturing plants, grocery stores, supercenters, and restaurants, and the impact on food trade between counties. Specifically, two types of food trade from two Standard Classification of Transported Goods categories are analyzed: agricultural products, and other food stuffs. A Poisson pseudo-maximum likelihood model is employed to account for the zero-trade flows observed between counties. The analysis determines that certain infrastructure has an important impact, and the impact can differ depending on the type of goods category. The third manuscript, "Reactions to Food Safety Recalls Among Food Insecure and Food Secure Households" examines the behavioral responses of food secure and food insecure persons to a hypothetical food safety recall using a vignette approach. The analysis finds that reactions can differ across demographics, including those of food insecure individuals.

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(GENERAL AUDIENCE ABSTRACT)

This dissertation focuses on two areas in agricultural and applied economics: food insecurity and food economics. In the first manuscript, I examine how certain types of food trade among counties in the United States impacts a county's food insecurity rate. I also determine how this impact changes based on a county's rural/urban status. Depending on the type of food that is traded, I find that food trade can have an impact on county food insecurity rates. Additionally, the impact of food trade on food insecurity rates differs depending on the rural/urban status of a county.

In the second manuscript, I use county food trade data to analyze the drivers of food trade between counties in the United States. Specifically, I examine how a county's infrastructure encourages or discourages the trade of agricultural products and other foodstuffs. I find that infrastructure like roadways, food processing and manufacturing plants, and ports are important drivers of food trade between counties.

Lastly, in the third manuscript, I study how food insecure and food secure persons might react differently to a food safety recall of eggs or romaine lettuce. Specifically, I determine how attributes such as price, travel time to a store, and risk of illness from consumption of a recalled food affect a person's decision to throw away, consume, or refund a recalled food. I find that price and travel time to a store impacts this decision. Additionally, I find that demographics such as a person's food insecurity status, race, age, and gender can influence their reaction to a food safety recall in some cases.

Dedication

I would like to dedicate this dissertation to my husband, Josh, and our son.

Acknowledgments

I would like to thank my advisor and mentor, Clinton Neill. Additionally, I would like to thank Kimberly Morgan. Thank you both for seeing potential in me, and encouraging me to pursue my dreams and helping them become reality. I would not have had the confidence to pursue a PhD had it not been for you. Thank you for all the time you spent with me shaping my research ideas, and helping this dissertation come to fruition. Thank you to my committee members Ford Ramsey and Klaus Moeltner for your help and guidance during my time at Virginia Tech. I would also like to thank my husband for pursuing this journey with me. Thank you for supporting my dreams. These past five years have been some of the hardest and most challenging years we have had, and I could not have accomplished any of it without your constant love and encouragement.

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List of Abbreviations

NMNR Non-metropolitan, Non-rural

PPML Poisson pseudo-maximum likelihood

RUCC Rural Urban Continuum Code

SCTG Standard Classification of Transported Goods

NMNR is a designation used in Chapter 2 to signify a county belongs to RUCCs 4, 5, 6, or 7. Using this definition, a county is neither metropolitan or rural.

PPML is a type of modeling used in trade literature that accounts for the heteroskedasticity of error terms, as well as the observed zero-trade flows among trade partners.

RUCCs are used by the USDA to differentiate county's based on population size and location to a metropolitan area. Counties are sorted into one of nine designations.

SCTG is a product classification system used by the Bureau of Transportation Statistics to categorize and track traded goods in the United States.

Chapter 1

Dissertation Overview

This dissertation examines three areas within the field of Agricultural and Applied Economics: (i) food insecurity, (ii) food trade, and (iii) food safety. In Chapter 2, the focus is on the intersection between food insecurity and food trade between counties in the United States. In Chapter 3, we emphasize the importance of county infrastructure to county food trade. Both of these manuscripts utilize new data on food trade at the county level from Lin et al. (2019). Finally, in Chapter 4, the focus is on the intersection between food insecurity and food safety. This chapter analyzes the behavioral differences across food secure and food insecure persons when faced with a food safety recall.

Chapter 2, titled "Differences in Food Insecurity Across the Rural/Urban Spectrum - The Role of Trade Flows," uses county rural-urban continuum codes, combined with the new county trade data and county food insecurity rates, to determine the correlation between county food trade and food insecurity rates, and how this differs across the rural/urban divide. These results indicate food trade has a heterogeneous impact on food insecurity, depending on the county's rural/urban status. In addition, an Oaxaca-Blinder decomposition determines how much county food trade explains differences between rural, metropolitan, and non-metropolitan non-rural counties. We also find heterogeneous differences in how much food trade explains differences in county food insecurity rates. Using these results, it is recommended that policy makers use a more nuanced approach in improving food insecurity measures. For example, promotion of certain food trade categories based on a county's rural/urban status is recommended over the current "one-size fits all" approach of some food assistance programs.

The next manuscript, "The Role of Infrastructure on Food Flows in the United States," uses the trade data utilized in Chapter 2 to examine drivers of food trade between counties in the United States. Specifically, we analyze county trade of two food categories: (i) agricultural products and (ii) other foodstuffs. Literature shows that infrastructure is one important driver of food trade at the international level, yet this has been little studied across smaller spatial scales, like county trade in the United States. We use both a traditional gravity model and a Poisson pseudo-maximum likelihood model to determine if food supply chain infrastructure such as roadways, ports, food processing and manufacturing plants, grocery stores, and restaurants impact a county's propensity to engage in food trade. The Poisson pseudo-maximum likelihood results indicate that infrastructure plays an important role in county food trade. Given these results, policy that promotes flexibility in the U.S. supply chain and investment in quality infrastructure is suggested.

Lastly, the third manuscript given in Chapter 4, "Reactions to Food Safety Recalls Among Food Insecure and Food Secure Households," is presented. In this manuscript, we use a vignette method to examine the reactions of food secure and food insecure individuals to food safety recalls of both shell eggs and romaine lettuce. We determine how these reactions vary based on other demographics such as age, gender, education, race, whether the person is a SNAP benefit recipient, personal risk preference, and patience measures. Additionally, we examine how attributes of a food item facing a food safety recall, such as price, travel time to a store, and risk of illness from consuming the food item, impact a person's decision

to throw away, consume, or seek a refund. Results indicate reactions are heterogenous across demographics of respondents, including food insecure and food secure persons. Governmental policy measures and private sectors should use multiple avenues to target these groups of respondents and promote information regarding food safety and food safety recalls.

Chapter 2

Manuscript 1: Differences in Food Insecurity Across the Rural/Urban Spectrum - The Role of Trade Flows

2.1 Abstract

[1]

Food insecurity and its determinants has been studied extensively in the United States. However, there has been little work relating food flows with food insecurity, and how such inter-county trading can drive differences in food insecurity across the rural/urban divide. We use county rural-urban continuum codes in combination with a new data set on food flows at the county level to examine the correlation between food insecurity and trade. Further, we use decomposition methods to identify differences in food insecurity rates across different county types to provide better policy prescriptions. Results indicate heterogeneous impacts of food trade flows and county types on food insecurity rates. From Oaxaca-Blinder decompositions we find that differences between rural and metropolitan counties are largely due to explained factors, but differences between non-metropolitan, non-rural counties and

[1]A version of this manuscript has been published in *Journal of the Agricultural and Applied Economics Association*. See Beverly and Neill (2022).

the other county types are due to unexplained factors. We argue for a more nuanced policy approach to improving food insecurity measures – such as promoting food trade of certain trade categories based on a county's rural/urban status – rather than a "one-size fits all" approach taken by some existing food assistance programs.

2.2 Introduction

The United States is one of the world's wealthiest nations, yet food insecurity still plagues the populous. In 2018, more than 26 million adults and over 11 million children lived in a food-insecure household (Coleman-Jensen et al., 2019). While the United States is considered self-sufficient in terms of food production (D'Odorico et al., 2014; Beltran-Peña, Rosa, and D'Odorico, 2020) this is not an adequate condition to ensure against food insecurity (Barrett, 2010). Food insecurity is a bigger threat in some communities than others partly due to food availability. Rural communities are at increased risk for food insecurity due to it's correlation with higher poverty rates, lower rates of labor force participation, a less educated population, and lower real personal income (Halverson et al., 2011; Economic Research Service, 2020; Pender, 2019; Powell et al., 2007).

Several studies have explained some of the disparity in food insecurity across communities, both globally and domestically. From an income perspective, higher food prices significantly contribute to incidences of food insecurity both at an international level (Fyles and Madramootoo, 2016; Warr, 2014) and for low income households in the United States (Gregory and Coleman-Jensen, 2013). Besides income, geography can play an important role in food insecurity rates. Gundersen and Ziliak (2018), Gundersen et al. (2017), and Halverson et al. (2011) show that food insecurity varies across regions in the United States. Specifically, Appalachia and the Mississippi Delta exhibit higher rates of food insecurity, while the

Northeast and Midwest experience lower rates as compared to the rest of the United States. Households in areas with lower food prices and lower heating costs are also less likely to be food insecure (Gregory and Coleman-Jensen, 2013; Nord and Kantor, 2006).

As such, food trade can impact the well-being of a county's residents. Studies have shown a multitude of benefits to trade at the international level. Trade liberalization has been linked to positive health outcomes, such as increased life expectancy and lower rates of infant mortality (Herzer, 2017; Owen and Wu, 2007). Trade has also been linked to job creation. For example, exports from the European Union supported a total of 50.3 million jobs across the world in 2011 (Arto et al., 2015). In addition, trade has caused inflation and prices of goods to fall which allows workers more buying power for consumers (Rogoff, 2003, 2004). Given these potentially positive outcomes from trade, encouraging poorer regions to participate in trade to enhance the well-being of its people is a key aspect to alleviating food insecurity. While a vast amount of literature examines international trade between multiple countries, including the United States, few studies have examined intra-country trade – especially at the county level. This has largely been due to a lack of data. If global trade observations are any indication of what is happening at a sub-national level, one would expect balanced trade flows between counties to increase the well-being of its residents (Boudreaux and Ghei, 2017).

In the United States, food moves from field to fork through many channels, including: producers, first-line handlers/manufacturers, wholesale/logistics, retail food/food service sector, and the consumer [2]. Food is occasionally sold directly from producers to consumers, but a majority of food travels through the other channels previously mentioned before reaching the consumer. Most producers sell their product to first-line handlers where food can be collected, stored, and initially processed before being sold to either a manufacturer or

[2]For more details regarding the U.S. food supply, see National Research Council (2015).

wholesaler. Additionally, first-line handlers may also prepare raw materials for use in manufacturing/processing of finished food products, as well as wax, wrap, and package fresh produce. Manufacturers and processors include meat packers, bakeries, and consumer product companies that are part of the value-added food supply. Wholesalers collect food from first-line handlers and the processing and manufacturing companies to be distributed to retail outlets, while logistics companies provide distribution and inventory coordination to the retail/food service sector. The retail sector is where the bulk of American consumers purchase their food. This sector includes grocery stores and restaurants. The food service sector includes restaurants and fast-food outlets. Finally, the consumer purchases food to be eaten at home, or purchases food to be eaten in a food service establishment.

While the United States has many programs at the state and federal levels to alleviate food insecurity (such as the Supplemental Nutrition Assistance Program, Temporary Emergency Food Assistance Program, Special Supplemental Nutrition Program for Women, Infants, and Children, etc.), these policies are typically a "one-size fits all" approach, meaning that counties are treated equally, regardless of their rural/urban classification or trade flows. In order to combat this problem and give policy makers a new angle with which to alleviate food insecurity, we analyze how a county's trade flows and rural/urban status impact food insecurity, and examine drivers of differences in food insecurity across the rural/urban divide. We find that processing facilities for cereal grains, agricultural products, meat, and milled grain products may reduce food insecurity. As such, policies promoting trade of cereal grains could reduce food insecurity in some rural counties. More generally, we believe our results provide an opportunity for law makers to create regulations targeting specific county types and food categories to improve food insecurity rates. This approach follows the well established work of previous literature such as Gundersen, Engelhard, and Waxman (2014); Gundersen, Kreider, and Pepper (2011); Gundersen and Ziliak (2018); Halverson et al. (2011), and Stephens and Deskins (2018) in examining food insecurity and differences across the rural-urban divide. Further, we find that the addition of food trade aids in explaining the difference in food security between rural and urban counties via Oaxaca-Blinder decompositions (up to 55%), while also highlighting a lack of knowledge on what drives the difference between counties in the middle of the rural-urban spectrum and those on the extremes. From these results we suggest a more nuanced approach to policy interventions in order to create a more effective response to reducing food insecurity.

This work offers several expansions to the existing U.S. food insecurity literature. First, we use a novel data set from Lin et al. (2019) that maps inter-county food trade flows and combine that information with counties' rural/urban status to examine which trade categories play critical roles in decreasing (increasing) food insecurity. Our analysis adds to previous literature examining food insecurity across the rural-urban divide by pinpointing more specific policies suggested by Halverson et al. (2011); Gundersen, Engelhard, and Waxman (2014). Our analysis provides insight on which foods to increase availability and access of via increased trade to potentially alleviate food insecurity rates in rural populations. In addition, our study offers organizations responsible for directing resources for food programs an idea on which food resources are most correlated with alleviating food insecurity rates. Finally, while others have determined there are differences in food insecurity rates across different rural/urban counties (Gundersen, Engelhard, and Waxman, 2014; Halverson et al., 2011), we add to this body of literature by examining drivers of differences (rather than whether differences exist) across county types via Oaxaca-Blinder decompositions.

The remainder of this article presents a discussion of the trade and rural/urban data, an overview of the food insecurity data, the empirical model of food insecurity, the decomposition to explain differences across the urban-rural spectrum, corresponding results, a discussion of policy implications and solutions, and concluding remarks about our approach and areas for future work.

2.3 Data

This study expands on the work of Gundersen, Engelhard, and Waxman (2014) and Gundersen, Kreider, and Pepper (2011) by adding new determinants to the food insecurity model. As previously mentioned, this study also uses a novel data set from Lin et al. (2019) that captures inter-county food flows within the food insecurity model. In addition to trade, we use decomposition methods to argue the importance of rural/urban classification at the county level in order to analyze food insecurity from a more disaggregated viewpoint.

2.3.1 Rural-Urban Classification, Trade, and Food Insecurity

Rural-urban classification and food trade should be considered when analyzing food insecurity, because of the variation across rural/urban communities and the benefit food trade can have on food security. The risk of food insecurity increases as counties become more rural along the rural-urban continuum (Halverson et al., 2011). Gundersen et al. (2017) established that food insecurity rates differ across the rural-urban divide and regions. Given the differences in demographic/socioeconomic traits and food insecurity across a county's rural/urban status, we use the 2003 Rural-Urban Continuum Codes (RUCCs) to provide a more granular view of food insecurity rates. The USDA uses RUCC status to distinguish between metropolitan and non-metropolitan counties. There are a total of nine subcategories based on the degree of urbanization and proximity to a metropolitan area. Each county is sorted into one of three metropolitan subcategories or six non-metropolitan categories. Explanation of the breakdown of RUCC categories can be found in Table 2.1. We use the

RUCC status to group counties into one of three groups: rural (RUCC 8 and 9), metropolitan (RUCC 1, 2, and 3) and non-metropolitan, non-rural (abbreviated NMNR; RUCC 4, 5, 6, and 7).

Table 2.1: Rural-Urban Continuum Code Descriptions

	Rural-Urban Continuum Code Descriptions
Code	**Description**
1	Counties in metro areas of 1 million population or more
2	Counties in metro areas of 250,000 to 1 million population
3	Counties in metro areas of fewer than 250,000 population
4	Urban population of 20,000 or more, adjacent to a metro area
5	Urban population of 20,000 or more, not adjacent to a metro area
6	Urban population of 2,500 to 19,999, adjacent to a metro area
7	Urban population of 2,500 to 19,999, not adjacent to a metro area
8	Completely rural or less than 2,500 urban population, adjacent to a metro area
9	Completely rural or less than 2,500 urban population, not adjacent to a metro area

Note: We use the 2003 RUCC designations in this analysis.

Food insecurity estimates are based on the Core Food Security Module found in the Current Population Survey. A household is considered to be food insecure if the respondent answers affirmatively to three or more questions in the Core Food Security Module. Summary statistics on food insecurity rates for each group are presented in Table 2.2. One can see that food insecurity rates vary within and across these groups. Rural counties have the lowest mean rate of food insecurity, while NMNR counties have the highest mean rates of food insecurity at over 15%. While literature indicates rural areas are more at risk for food insecurity, rates of food insecurity in rural areas may be lower compared to NMNR counties because rural areas have the greatest coverage of charitable food providers such as food bank programs, and also have the highest reliance on Supplemental Nutrition Assistance Program benefits (Gundersen et al., 2017; Bailey, 2014).

Table 2.2: Summary Statistics for Food Insecurity Rates by Rural/Metropolitan Status

	Observations	Mean	Standard Deviation	Minimum	Maximum
Rural	671	14.115	4.076	3.900	29.500
Non-metropolitan, Non-rural	1,382	15.447	3.916	4.800	32.800
Metropolitan	1,090	14.224	3.490	5.200	31.200
Metro-adjacent	1,061	15.444	3.783	4.800	32.700
Non-metropolitan, Non-adjacent	992	14.549	4.206	3.900	32.800
Pooled	3,143	14.738	3.860	3.900	32.800

To further examine differences in the three county groups (rural, NMNR, and metropolitan), Figure 2.1 shows where each county group exported their food. Graphical examination of the trade data supports the idea that trade flows matter to food insecurity. For example, metropolitan counties exported over 70% of their total food exports to other metropolitan counties, and sent the least amount of food to rural counties. NMNR counties exported most to other NMNR counties, and traded least with rural counties. On the other hand, when examining rural counties, exports are more evenly split across all three county groups. It is interesting to note that NMNR counties are the most popular destination for exports for two of the three groups, yet have the highest rates of food insecurity. This phenomenon further motivates our hypothesis that trade flows and rural/urban status are important to consider for accurate understanding of food insecurity rates.

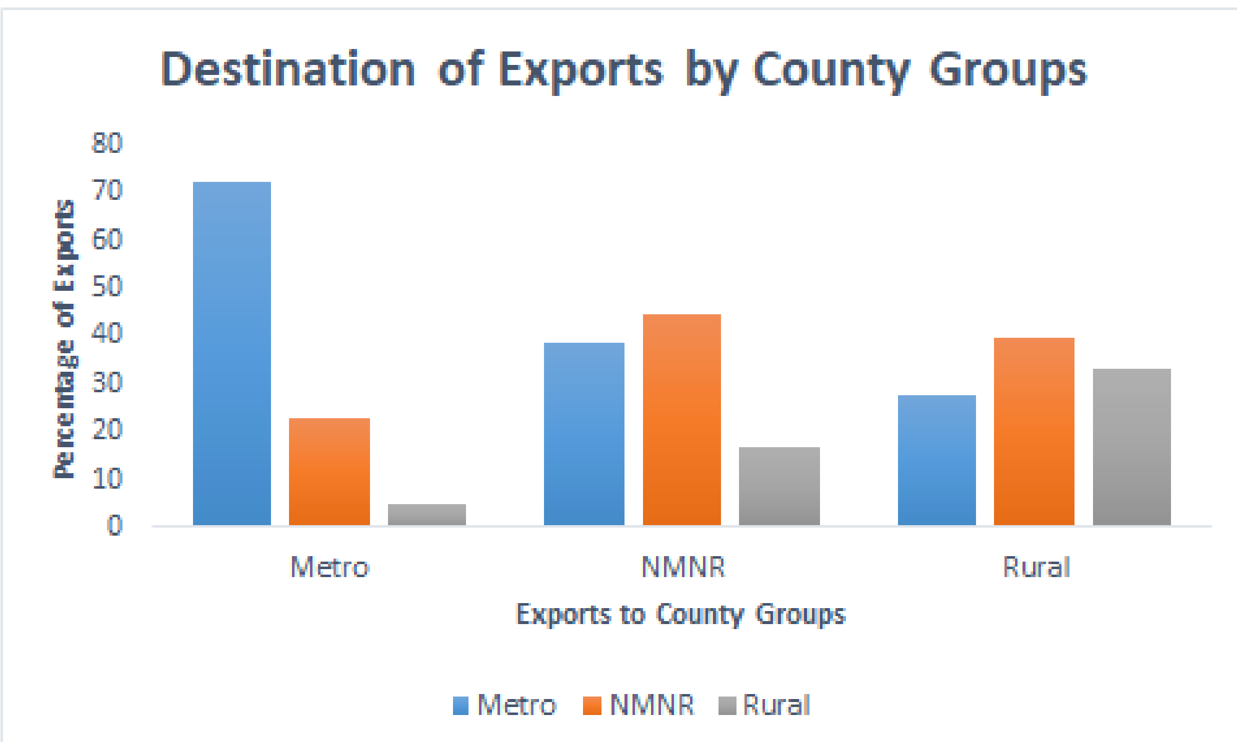


Figure 2.1: Destination of Exports by County Type

2.3.2 Data and Descriptive Statistics

Map the Meal Gap, a project headed by Feeding America, has determined food insecurity rates at the county level since 2009 (Gundersen et al., 2014a). However, this study focuses on the food insecurity rates only from 2012 to remain consistent with available food trade flow data. Gundersen et al. (2014b) explains in detail how the food insecurity estimates used in our study are created. In summary, the authors used a two-step process to arrive at the estimates. First, state level data on unemployment rate, poverty rate, median income, percent Hispanic, percent African-American, and home ownership rate was regressed against state-level food insecurity rates. In the second step, the coefficient estimates from the state model, plus information on the same variables at the county level were then used to generate food insecurity rates at the county level. We use the county estimates as our dependent variable of interest. Due to the use of demographic information like poverty rate, unemployment rate, median income, etc. in the creation of the food insecurity estimates, we do not use these measures in our main model as they are highly collinear with the food insecurity estimates due to its construction[3].

[3] However, at the suggestion of one reviewer, we do include these variables in a separate regression, presented in Table 2.13. Differences in these estimates are discussed in Appendix C.

To obtain food trade flow estimates for counties we use a novel data set from Lin et al. (2019). Lin et al. (2019) used a computational algorithm that integrated machine learning, linear programming, network constraints,and mass balance in order to create a food flow model to estimate the county food flow data. Using the Freight Analysis Framework regions, the authors down-scaled the information to the counties and county equivalents in the United States via network and transportation analysis. Food flow estimates are then broken down by standard classification of transported goods (SCTG) categories. Specifically, the first seven categories pertaining to food are examined. Table 2.3 describes classification of each category. To construct exports for each county, every SCTG category was totaled by origin, excluding flows that shared the same origin and destination. Imports for each SCTG category is constructed similarly by totaling destination of the food flows, excluding flows that shared the same origin and destination. Net trade flows for each county are then calculated by subtracting imports from exports.

Table 2.3: List of Standard Classification of Transported Goods (SCTG) food categories included in Food Flows

Category	Description
SCTG 1	Animals and fish (live)
SCTG 2	Cereal grains (includes seed)
SCTG 3	Agricultural products (excludes animal feed, cereal grains, and forage products)
SCTG 4	Animal feed, eggs, honey, and other products of animal origin
SCTG 5	Meat, poultry, fish, seafood, and their preparations
SCTG 6	Milled grain products and preparations, and bakery products
SCTG 7	Other prepared foodstuffs, fats, and oils

Gross domestic product was collected for each county from the Bureau of Economic Analysis

(Bureau of Economic Analysis, 2020).[4] In addition, population estimates were collected from the U.S. Census Bureau (United States Census Bureau, 2020). GDP per capita estimates are constructed from these two data sets. Information on the number of food processing and manufacturing facilities in each county was gathered from the U.S. Cluster Mapping Project (U.S. Cluster Mapping Project, Institute for Strategy and Competitiveness, Harvard Business School, 2021). Note that all data is for the year 2012 in order to reconcile with the year the trade data represents. Table 2.4 summarizes the variables used in the analysis, their descriptions, and their summary statistics.

[4] Some Virginia GDP measures consist of one or two independent cities. Those with populations less than 100,000 are combined with an adjacent county. Separate estimates for the jurisdictions making up the combination area are not available.

Table 2.4: Variable Descriptions and Summary Statistics

Variable	Description	Mean	Std. Dev.
Food insecurity rate	The percentage of the population in a county that experienced food insecurity at some point during the year	14.74	3.86
GDP per Capita	Gross domestic product per capita (in thousands of 2012 chained dollars)	49.21	176.77
Rural	Dummy for whether the county is rural	0.21	0.41
NMNR	Dummy for whether the county is non-metropolitan & nonrural	0.44	0.50
Metro	Dummy for whether the county is metropolitan	0.35	0.48
Net Trade SCTG 1	Net trade of live animals and fish (millions kgs)	0.002	81.60
Net Trade SCTG 2	Net trade of cereal grains (millions kgs)	-0.018	375.00
Net Trade SCTG 3	Net trade of agricultural products (millions kgs)	0.037	293.00
Net Trade SCTG 4	Net trade of animal feed, eggs, honey, etc. (millions kgs)	-0.005	132.00
Net Trade SCTG 5	Net trade of meat, poultry, fish, etc. (millions kgs)	0.0003	61.80
Net Trade SCTG 6	Net trade of milled grain products, etc. (millions kgs)	-0.031	78.00
Net Trade SCTG 7	Net trade of other prepared foodstuffs (millions kgs)	0.033	303.00
Establishments	The number of food processing and manufacturing establishments in the county	13.84	98.68
New England	Dummy for county location in New England region	0.02	0.13
Mideast	Dummy for county location in Mideast	0.06	0.23
Great Lakes	Dummy for county location in Great Lakes region	0.14	0.35
Plains	Dummy for county location in Plains region	0.20	0.40
Southeast	Dummy for county location in Southeast	0.34	0.47
Southwest	Dummy for county location in Southwest	0.12	0.33
Rocky Mountain	Dummy for county location in Rocky Mountain region	0.07	0.25
Far West	Dummy for whether the county is in the Far West	0.06	0.23

2.4 Methods

As the literature has established, trade generally improves food insecurity (Maasdorp, 1998; Dorosh, 2001; D'Odorico et al., 2014). However, a gap in the research exists due to a lack of data for intra-national trade within the United States. With the advent of new data from Lin et al. (2019), we can directly account for the effect of food flows on county level food insecurity in the United States.

Most econometric models, if any, related to county-level food insecurity literature do not currently include gross domestic product (GDP). This is due to official county GDP measurements being unavailable until December 2019. It has long been established in the trade literature that GDP and equivalent measures are determinants of trade flow between two trading entities (Anderson, 2011). Given the link between trade flows and GDP, the county measures for GDP per capita are included in the model.

In order to account for the impact of food trade flows and RUCC status in a county's food insecurity estimate, we propose the following model to be estimated via maximum likelihood estimation:

$$FI_c = \beta_0 + \sum_{k=1}^{3} \beta_k T_{ck} + \beta_4 G_c + \beta_5 E_c + \sum_{k=1}^{7} \eta_k x_{ck} + \sum_{k=1}^{8} \rho_k R_{ck} + \varepsilon_c \tag{2.1}$$

where FI is the food insecurity rate for county c, T is an indicator for the county type (either metropolitan, NMNR, and rural), G is the GDP per capita, E is the number of food processing and manufacturing facilities within the county, x is the net trade (exports minus imports) from SCTG category k, R is an indicator variable for the eight regions r defined by the Bureau of Economic Analysis, and ε is the normally distributed error term.

We use the above equation to further examine county food insecurity rates by county group (metropolitan, NMNR, and rural), for a total of four estimated equations. In addition, we use Equation 2.1 to examine the food insecurity rate of each individual RUCC type. To explore the heterogenous effects across county types, the results for each individual RUCC (a total of nine regressions) are presented in Appendix A.

To examine unexplained differences arising from rural/urban classifications, an Oaxaca-Blinder decomposition is employed (Oaxaca, 1973; Blinder, 1973). This method is used to determine how much of a mean outcome difference between two groups is accounted for by group differences in the predictors.

The methods of the Oaxaca-Blinder decomposition are explained in detail in Jann (2008), but are summarized here. For illustration, suppose metropolitan counties are group A and NMNR counties are group B. The mean outcome difference between the two groups in our study can be written as:

$$R = E(FI_A) - E(FI_B) \tag{2.2}$$

and expanded as:

$$R = \{E(X_A) - E(X_B)\}'\beta^* + \{E(X_A)'(\beta_A - \beta^*) + E(X_B)'(\beta^* - \beta_B)\} \tag{2.3}$$

where X is a vector containing the predictors and a constant and β contains the slope parameters and intercept. β^* is estimated by using the coefficients from a pooled regression over groups A and B. The first component on the right-hand side of the equation is considered the outcome differential that is explained by group differences in the predictors. The last component is the unexplained portion. The unexplained portion captures all potential effects of differences in unobserved variables. In total, we conduct four separate Oaxaca-Blinder decompositions using county groups: (1) metropolitan counties versus non-metropolitan, non-rural (NMNR) counties; (2) NMNR versus rural counties; (3) metropolitan versus rural counties; and (4) metropolitan versus non-metropolitan counties (RUCC 4-9) as a robustness check.

One limitation of our study is the potential for endogeneity. It is possible that government assistance programs for low-income families (such as the Supplemental Nutrition Assistance Program, or SNAP) impacts both food insecurity rates and trade flows, leading to potentially biased estimates. However, county SNAP participation rates were not included because that data is not publicly available for all counties in our study. Further, agricultural subsidies may impact both trade and food insecurity. Unfortunately, county subsidy data is not publicly available. In addition, the earliest trade data available by county is for the year 2012. This adds another limitation to our study, as trade patterns and their impact on food insecurity could have changed since that time. Despite the potential for endogeneity, we believe our results provide valuable insights on how food trade can impact food insecurity, and how policy interventions surrounding food trade can improve food insecurity rates.

2.5 Results

The results for the pooled regression and regressions for rural, NMNR, and metropolitan groups are presented in Table 2.5. GDP per capita is only statistically significant for NMNR counties, and correlates with lower food insecurity rates. This is consistent with previous literature in an international context which concludes higher GDP growth or GDP per capita is associated with lower incidences of food insecurity (Warr, 2014; FAO, WFP, and IFAD, 2012; Smith, Kassa, and Winters, 2017; Smith, Rabbitt, and Coleman-Jensen, 2017).

Table 2.5: Results from Pooled and County Group Regressions

	Pooled		Rural		NMNR		Metro	
Observations	3,104		666		1,368		1,070	
Variables	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.
GDP per capita	-0.001	(0.001)	-0.000	(0.000)	-0.008*	(0.005)	-0.001	(0.004)
Rural	0.645***	(0.167)						
NMNR	1.445***	(0.133)						
Net SCTG 1	-0.327	(0.507)	-0.592	(1.917)	-1.507	(1.072)	0.447	(0.587)
Net SCTG 2	0.018	(0.120)	-0.432*	(0.250)	0.244	(0.185)	0.223	(0.180)
Net SCTG 3	-0.211	(0.317)	-1.093**	(0.535)	-0.305	(0.549)	0.022	(0.436)
Net SCTG 4	-0.562	(0.397)	-0.727	(0.798)	-0.163	(0.550)	-0.677	(0.732)
Net SCTG 5	1.426*	(0.832)	2.526	(2.990)	-2.013	(1.450)	2.920***	(1.024)
Net SCTG 6	0.849	(0.651)	0.904	(3.028)	-0.845	(1.329)	1.285*	(0.752)
Net SCTG 7	-0.042	(0.176)	-0.131	(1.250)	-0.584	(0.370)	-0.004	(0.195)
Establishments	0.002***	(0.001)	-0.084***	(0.021)	0.004	(0.004)	0.002***	(0.001)
Mideast	-0.205	(0.346)	-0.824	(1.115)	-0.841*	(0.505)	0.052	(0.487)
Great Lakes	0.796**	(0.310)	0.675	(0.922)	0.526	(0.494)	1.096**	(0.440)
Plains	-0.728**	(0.318)	-1.236	(0.895)	-0.561	(0.501)	0.071	(0.485)
Southeast	4.382***	(0.316)	4.649***	(0.914)	5.326***	(0.520)	3.070***	(0.435)
Southwest	3.526***	(0.319)	2.449***	(0.918)	3.540***	(0.511)	4.361***	(0.450)
Rocky Mountains	1.245***	(0.326)	0.468	(0.902)	1.434***	(0.519)	1.804***	(0.465)
Far West	2.733***	(0.337)	2.574***	(0.943)	2.740***	(0.555)	2.913***	(0.469)
Constant	11.875***	(0.297)	13.041***	(0.870)	13.378***	(0.521)	12.147***	(0.428)

Note: Cluster robust standard errors are presented in parentheses.Errors are clustered at the county level.
Note: *** p>0.01, ** p>0.05, * p>0.1

We find in the pooled regression that county type indicators for rural and NMNR counties are statistically significant, when compared to the base of metropolitan counties. All else equal, rural counties correlate with higher food insecurity rates of 0.65% compared to metroplitan counties, while NMNR counties correlate with higher food insecurity rates of 1.45% compared to metropolitan counties. This is consistent with the findings of Halverson et al. (2011), which conclude that the risk of food insecurity increases as RUCC increases (both rural and NMNR counties have higher RUCCs than the base of metropolitan counties). However, we did not find that net trade significantly impacted food insecurity rates for NMNR counties for any food category.

Net trade by SCTG types impact each group differently. The only SCTG categories for which net trade is significant include cereal grains (SCTG 2), agricultural products (SCTG 3), meat (SCTG 5), and milled grain products (SCTG 6). A table detailing the significant impacts of net trade by SCTG type on each county type, as well as the pooled regression, is given in Table 2.5.

For rural counties, net trade of cereal grains (SCTG 2) is correlated with a 0.432% reduction in food insecurity rates per billion kilograms of cereal grains traded. Cereal grains include wheat, corn (excluding sweet corn), rye, barley, oats, etc. As net trade of this category grows, it may be a signal that households are no longer as concerned about maintaining caloric intake by consuming energy dense foods (like cereal grains), and rather are trading energy dense foods for higher-quality foods (like produce, lean protein, etc.) (Seligman and Schillinger, 2010). Some studies have linked food insecurity with lower intake of fresh fruit and/or vegetables (Dharod, Croom, and Sady, 2013; Robaina and Martin, 2013), which explains how this trade-off could decrease food insecurity rates.

Net trade of agricultural products (SCTG 3) is also significant for rural counties. Net trade of this category correlates to a decrease in food insecurity in rural counties by 1.093% per billion kilograms of agricultural products traded. The SCTG category of agricultural products encompasses many items, from fresh fruits and vegetables, nuts, soy beans, cotton seeds, fresh cut flowers, raw cotton, tobacco, and sugar beets/cane. It may be the case that exported cash crops such as tobacco, sugar, soybeans, and cotton are contributing to better economies in rural counties, thus leading to lower food insecurity rates.

Net trade of SCTG 5 foods, which include meat, poultry, fish, seafood, and their preparations correspond with increases in food insecurity rates for the pooled sample and metropolitan counties by approximately 1.43% and 2.92% per billion kilograms of net trade increase, respectively. One study among adolescents linked food insecurity with lower intake of animal source and protein rich foods, which could explain why net trade increases of SCTG 5 foods can increase food insecurity rates (Belachew et al., 2013). As net trade grows, meat and their preparations could become less available in a county, leading to increased food insecurity rates.

Milled grain products and preparations, and bakery products (SCTG 6) encompasses many items. This SCTG category includes wheat flour, instant rice, corn meal, pasta, breakfast cereals, mixes and dough for the preparation of bakery products, baked products like bread, and baked snack foods. Net trade of milled grains and other products is significant and correlates with an increase in food insecurity rates by 1.285% per billion kilograms of net trade increases for metropolitan counties, respectively. Individuals that are food insecure may be forced to concentrate their efforts on securing food that is low-cost and energy dense (such as refined carbohydrates like pasta, bread, etc.) or foods with added sugars, fats, and sodium (such as snack foods, baked products, etc.) (Seligman and Schillinger, 2010). When counties export these type of items (i.e. net trade grows due to increased exports), they may be less available to individuals within the county that are food insecure, thus exasperating food insecurity rates. On the other hand, if imports increase (i.e. net trade decreases due to increased imports), it may be that the increase in fiber intake with items like instant rice, bread, and pasta are contributing to lower food insecurity rates. Lower fiber intake has been associated with incidences of food insecurity (Robaina and Martin, 2013).

In addition to net trade, the number of food processing and manufacturing facilities in each county was statistically significant for the pooled sample, rural counties, and metropolitan counties. For the pooled sample and metropolitan counties, the number of food processing and manufacturing establishments is correlated with increases in food insecurity rates. However, the increases in food insecurity rates for these samples are almost negligible, at 0.002% for both the pooled sample and metropolitan counties. We find that the number of establishments in rural counties is correlated with a 0.084% decrease in food insecurity. It is likely that the number of food processing and manufacturing establishments in rural counties significantly contribute to the economies and well-being of individuals in rural counties, thus leading to decreased food insecurity rates.

When comparing the regional location of counties, the impact on food insecurity rates varies by county type and region, which is consistent with the findings of Gundersen et al. (2017). Our analysis divides counties into one of eight regions, while Gundersen et al. (2017) divides counties into four regions (South, West, Midwest, and Northeast). Note, all samples use counties located in the New England region as the base. For the pooled sample, all regions except the Mideast are significant. For the pooled sample, we find that all statistically significant regions result have higher food insecurity rates compared to the base, except for the Plains region, which has lower food insecurity rates compared to the base. For rural counties, significant regions include the Southeast, Southwest, and Far West, and are correlated with higher food insecurity rates compared to counties in the New England region. NMNR counties in the Southeast, Southwest, Rocky Mountains, and Far West correspond with higher rates of food insecurity compared to NMNR counties in the New England region. NMNR counties in the Mideast region correspond with lower food insecurity rates compared to counties in the New England region. Metropolitan counties located in the Great Lakes, Southeast, Southwest, Rocky Mountains, and Far West regions are correlated with higher rates of food insecurity compared to metropolitan counties in the New England region.

2.6 Policy Analysis and Implications

Utilizing an Oaxaca-Blinder decomposition can be immensely useful for policy analysis, in that it pinpoints what significant differences (if any) in food insecurity rates across county types are explained by known factors. In this way, policy makers are able to form regulations that can close the food insecurity gap by focusing interventions around factors known to significantly impact food insecurity. At a state level, this can be extremely helpful, as law makers can tailor policy to specific county types (such as rural, NMNR, or metropolitan). This could be more effective than a "one size fits all" approach.

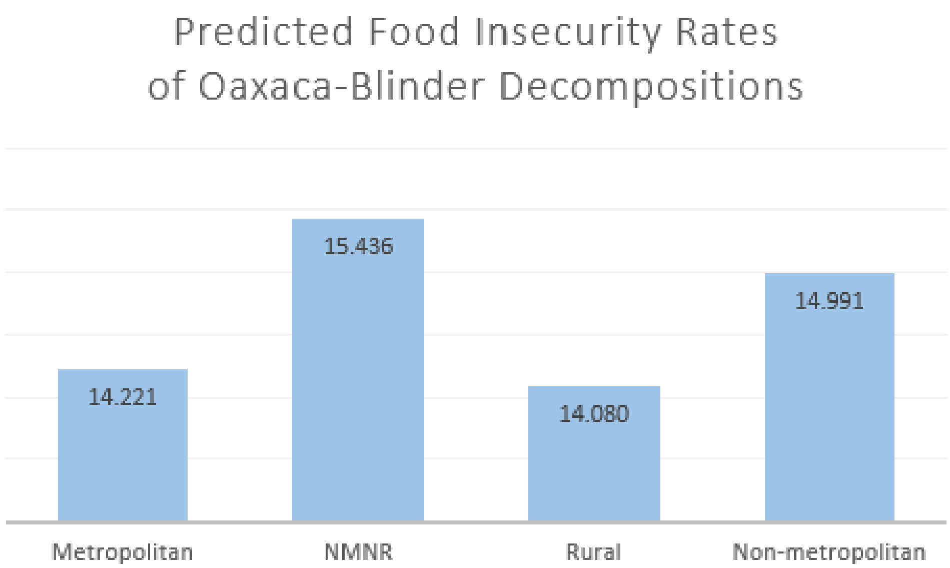
From the Oaxaca-Blinder decomposition, we find statistically significant predicted group differences for all but one comparison. Figure 2.2a displays the predicted food insecurity rates of each decomposition, while Figure 2.2b shows how much of the difference in predicted food insecurity rates are attributed to explained or unexplained factors. In Appendix B, we also include a more detailed summary of the explained and unexplained portions of the Oaxaca-Blinder decomposition. The "explained" portion gives the detailed contributions of each predictor in our regression, as well as the total contribution of all predictors (found in the row labeled "total"). The "unexplained" row gives the portion of the differences not explained by predictors. It is noted that results for categorical predictors (such as indicator variables for region in our analysis) depend on the choice of base category. To account for this, we transform the coefficient vectors so that deviations from the grand mean are expressed and the redundant coefficient for the base category is added. In this way, the results of the Oaxaca-Blinder decomposition are independent of the choice of base category. For a detailed summary of this method see Jann (2008).

In the case of the NMNR vs. metropolitan decomposition, we find that NMNR counties have higher predicted rates of food insecurity than metropolitan counties. The differences in the predictors account for approximately 12% of the difference in food insecurity rates among metropolitan and non-metropolitan counties, leaving 88% of the difference in food insecurity rates to unexplained factors, as shown in Figure 2.2b.

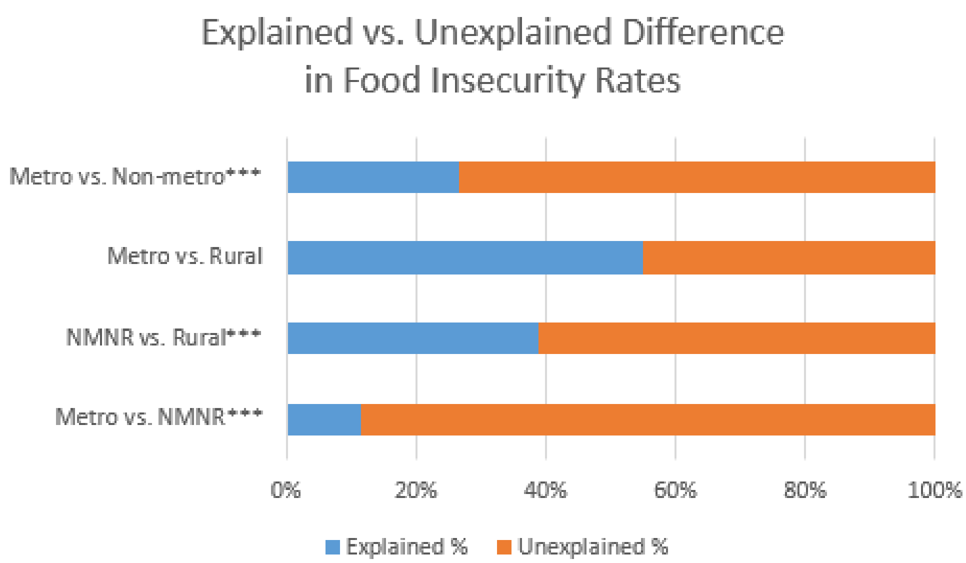
For the decomposition involving NMNR (RUCC 4-7) and rural (RUCC 8-9) counties (shown in Figure 2.2a), we find that NMNR counties are predicted to have higher rates of food insecurity than rural counties. Like the case of metropolitan and non-metropolitan counties, this difference is primarily driven by unexplained factors. The explained portion of the decomposition accounts for only 39% of the difference in food insecurity rates in these two groups. The remainder is driven by unexplained differences.

The metropolitan and rural county decomposition in Figure 2.2a shows that metropolitan counties have higher predicted rates of food insecurity than rural counties. The difference between the two predictions is not statistically significant. The explained portion makes up approximately 55% of the difference between the two groups. The remainder of the difference is due to unexplained factors.

As a robustness check, we also utilize an Oaxaca-Blinder decomposition for metropolitan counties and non-metropolitan counties. This decomposition uses all counties in the United States, as all RUCC categories are utilized. Metropolitan counties include RUCCs 1-3, and non-metropolitan



(a) Predicted Food Insecurity Rates
of Oaxaca-Blinder Decompositions



(b) Explained vs. Unexplained Differences
of Oaxaca Blinder Decompositions

Note: Cluster robust standard errors are presented. Errors are clustered at the county level.
Note: *** p>0.01, ** p>0.05, * p>0.1

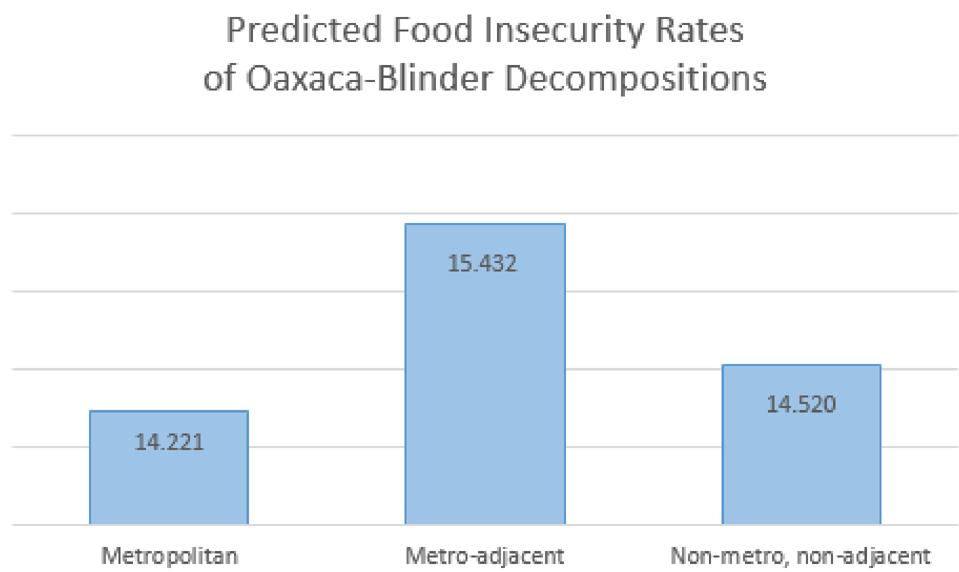
Figure 2.2: Oaxaca-Blinder Decomposition Results

counties include RUCCs 4-9. The decomposition shows that non-metropolitan counties have higher predicted rates of food insecurity compared to metropolitan counties, and the difference in food insecurity rates between these two groups is statistically significant. We also find that the predictors in our model account for 27% of this difference, while the remainder of the difference is due to unexplained factors.

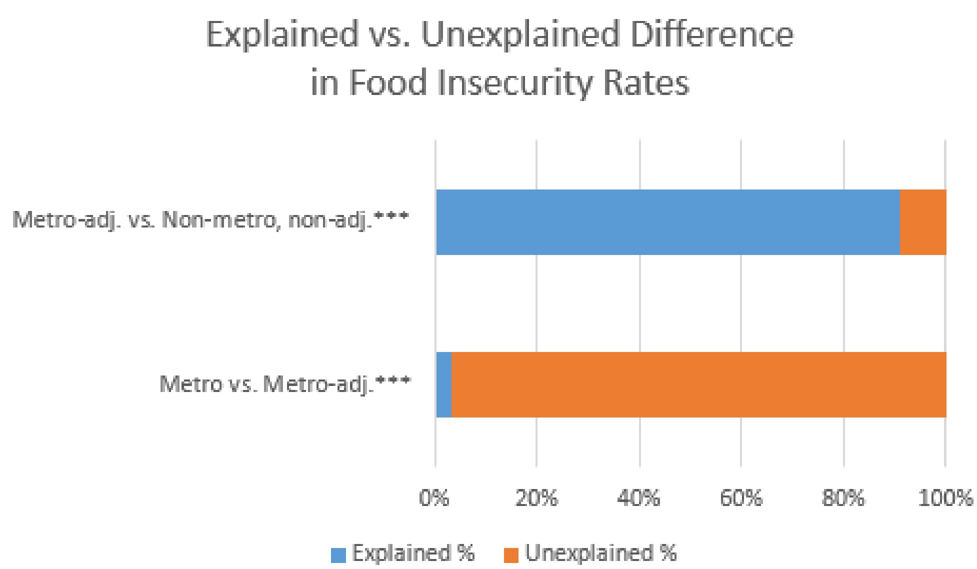
As an additional robustness check, we also compared metropolitan adjacent counties (RUCC 4, 6, 8) with metropolitan counties and with non-metropolitan, non-metropolitan adjacent counties (RUCC 5, 7, 9). One argument is that metro-adjacent areas may have lower levels of food insecurity due to their proximity to metropolitan areas. The results of these comparisons are shown in Figure 2.3a and Figure 2.3b. The Oaxaca-Blinder results between metropolitan and metropolitan adjacent (labeled metro-adj. in the figure) show that differences in food insecurity are largely unexplained by the predictors in our model. This contrasts with the Oaxaca-Blinder results comparing metropolitan adjacent counties and non-metropolitan, non-metropolitan adjacent (labeled non-metro, non-adj. in the figure), which concludes that the differences in food insecurity rates between these county types are overwhelmingly explained by the predictors in our model.

At a federal level, it may be beneficial to consider policies surrounding regional food trade and food systems to improve food insecurity. Policies promoting regional food systems can increase economic development, and provide necessary products to these different regions (Clancy and Ruhf, 2010). Therefore, policies that support processing facilities for meat, poultry, fish, seafood, and their preparations (SCTG 5), and milled grain products and preparations (SCTG 6) could reduce food insecurity for metropolitan counties by balancing net trade flows.

For rural counties, we find that policies promoting net trade of cereal grains (SCTG 2) and agricultural products (SCTG 3) potentially reduce food insecurity rates. In addition, we also find that food processing and manufacturing establishments in rural counties contribute to lower food insecurity rates. Policies that increase establishments in rural counties while also promoting net trade of cereal grains and agricultural products could improve food insecurity rates for these counties.



(a) Predicted Food Insecurity Rates
of Oaxaca-Blinder Decompositions: Robustness Check



(b) Explained vs. Unexplained Differences
of Oaxaca Blinder Decompositions: Robustness Check

Note: Cluster robust standard errors are presented. Errors are clustered at the county level.
Note: *** p>0.01, ** p>0.05, * p>0.1

Figure 2.3: Oaxaca-Blinder Decomposition Results with Metro-adjacent and Non-metro, non-adjacent Comparisons

In general, liberal trade policies in food and agricultural sectors on an international level have been found to increase food imports, lower food prices, improve volatility in the domestic food supply, and expand food production domestically, which help alleviate food insecurity (Barlow et al., 2020; Burgess and Donaldson, 2010; Ravallion, 1987; McCorriston et al., 2013). Though the individual states within the U.S. cannot legally impose import taxes on interstate traded goods, they can impose other state protectionist policies such as licensing, administrative restriction, or performance criteria (Craig and Sailors, 1987). In addition, policies promoting trade may lead to job creation in the United States, as they have for exports in the European Union (Arto et al., 2015). Given the benefits to free trade at the international level, the United States may also see benefits to food insecurity from states decreasing trade barriers within its own borders.

Our results show that food trade flows impact county types differently, and therefore a single approach for policies aimed at reducing food insecurity may not always be the most effective. The Oaxaca-Blinder decompositions further highlight the differences in food insecurity rates across county types, and supports our theory that determinants of food insecurity can differ at the county level and by food trade categories.

2.7 Summary and Conclusions

We distinguish between the rural/metropolitan status of a county to better discern unobserved rural/metropolitan nuances that contribute to food insecurity by incorporating the RUCC type of each county into our analysis. With a novel data set from Lin et al. (2019), we are able to contribute a new element to the food insecurity literature by including food trade flows from seven SCTG categories - many of which are correlated with food insecurity. We show that the type of food traded impacts food insecurity differently. In addition, food trade is significant for some county types and not others. While our results are not causal, we believe they provide valuable insight on the role of food trade in food insecurity rates.

When comparing metropolitan and NMNR counties, differences in food insecurity are largely driven by unexplained factors in our model. This is also the case when comparing NMNR and rural counties, as well as comparing metropolitan and non-metropolitan counties. However, nearly half of the difference in food insecurity rates between metropolitan and rural counties are due to predictors in our model. It is likely the difference is driven by factors we excluded from the model to reduce the potential for endogeneity, like unemployment rate and median income. This is shown in Figure 2.4b where endogenous variables median income, unemployment rate, poverty rate, percent black, percent Hispanic, and home ownership rate are included in the model. In this case, most of the differences between county groups are largely explained by predictors included in the model. Future work is needed to determine the drivers of differences in food insecurity between these groups while avoiding endogeneity.

Policy implications include federal policies supporting balanced trade flows of SCTG 5 and 6, particularly for metropolitan counties. In addition, promoting processing facilities for agricultural products and cereal grains can improve food insecurity rates for rural counties. Overall, liberal trade policies have been found to improve food insecurity at an international level (Barlow et al., 2020). Therefore, policies that promote lower costs to interstate trade should also be pursued.

This study lays the foundation for further work regarding food trade flows and food insecurity. With the new food flow data, supply chain shocks in the food system and its impact on food insecurity can be examined. Regional analyses on food supply systems and food insecurity within the United States is an area for further exploration. Such research would not only contribute to the general understanding of food insecurity, but would also provide policy makers with a better understanding of how to respond to supply chain shocks. Data that further divides food trade flows at the county level into more specific categories, such as fresh fruits and vegetables, meat, eggs, dairy, etc. would be helpful to determine which food trade matters the most to food insecurity, and may improve explained differences in food insecurity among county types. In addition, food trade flows from more recent years should also be examined in order to determine whether the results we present are consistent across time.

2.8 Appendix A

Table 2.6: Metropolitan County Regression Results (RUCC 1 – 3)

	RUCC 1		RUCC 2		RUCC 3	
Observations	403		324		343	
Variables	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.
GDP per Capita	0.007	(0.006)	0.023**	(0.010)	-0.014***	(0.005)
Net SCTG 1	-1.828	(3.052)	0.602	(0.744)	1.628	(2.351)
Net SCTG 2	0.212	(0.242)	-0.005	(0.329)	-0.023	(0.534)
Net SCTG 3	-0.503	(0.638)	0.497	(0.362)	0.319	(0.496)
Net SCTG 4	-2.445*	(1.404)	1.295	(1.044)	-1.225	(1.068)
Net SCTG 5	0.661	(2.140)	2.759**	(1.225)	2.993	(1.878)
Net SCTG 6	0.666	(1.112)	0.027	(0.988)	1.775	(2.015)
Net SCTG 7	-0.306	(0.311)	0.182	(0.249)	0.335	(0.566)
Establishments	0.002***	(0.001)	0.003***	(0.001)	0.001	(0.002)
Mideast	0.089	(0.776)	0.047	(0.572)	0.666	(1.036)
Great Lakes	1.273*	(0.705)	1.097*	(0.615)	1.287	(1.004)
Plains	1.268	(0.887)	0.450	(0.683)	-0.973	(1.021)
Southeast	2.251***	(0.707)	3.879***	(0.587)	3.182***	(1.001)
Southwest	4.087***	(0.680)	5.215***	(0.685)	4.585***	(1.031)
Rocky Mountains	1.191	(0.930)	2.468***	(0.613)	1.235	(1.016)
Far West	2.311***	(0.705)	2.404***	(0.700)	3.031***	(1.076)
Constant	11.193***	(0.666)	11.029***	(0.719)	13.148***	(0.969)

Note: Cluster robust standard errors are presented. Errors are clustered at the county level.
Note: *** p>0.01, ** p>0.05, * p>0.1

Table 2.7: Non-rural County Regression Results (RUCC 4 – 7)

	RUCC 4		RUCC 5		RUCC 6		RUCC 7	
Observations	215		104		602		447	
Variables	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.
GDP per Capita	-0.063***	(0.018)	-0.082***	(0.021)	-0.014***	(0.003)	-0.005	(0.004)
Net SCTG 1	-1.380	(1.794)	-1.615	(2.915)	-1.116	(2.022)	-3.272*	(1.808)
Net SCTG 2	0.437	(0.357)	-0.647	(1.111)	-0.130	(0.292)	0.640**	(0.312)
Net SCTG 3	0.107	(0.624)	-0.728	(0.898)	-0.099	(0.640)	-0.580	(1.367)
Net SCTG 4	0.590	(1.392)	1.133	(2.153)	-0.363	(0.845)	-0.073	(0.826)
Net SCTG 5	0.955	(2.749)	4.081	(6.383)	-2.865	(2.065)	-6.064*	(3.398)
Net SCTG 6	-6.276**	(2.896)	-0.340	(2.227)	-3.525	(2.152)	8.121*	(4.775)
Net SCTG 7	0.137	(0.646)	-3.038*	(1.697)	-0.623	(0.592)	-1.182*	(0.654)
Establishments	0.017	(0.014)	0.032	(0.042)	0.004	(0.006)	0.005*	(0.003)
Mideast	0.828	(0.607)	0.434	(0.430)	-2.831***	(0.634)	-0.247	(1.048)
Great Lakes	1.847***	(0.605)	2.372***	(0.770)	-1.176**	(0.574)	0.732	(0.911)
Plains	0.843	(0.784)	1.892**	(0.764)	-1.897***	(0.608)	-0.858	(0.899)
Southeast	5.483***	(0.725)	8.913***	(1.330)	3.271***	(0.604)	6.414***	(0.958)
Southwest	6.021***	(0.720)	5.006***	(0.633)	2.293***	(0.596)	2.853***	(0.922)
Rocky Mountains	4.618***	(0.769)	2.463***	(0.715)	0.852	(0.706)	1.034	(0.903)
Far West	4.218***	(0.730)	2.079***	(0.799)	0.791	(0.662)	3.433***	(1.074)
Constant	14.145***	(0.952)	15.435***	(1.140)	15.111***	(0.549)	13.160***	(0.889)

Note: Cluster robust standard errors are presented. Errors are clustered at the county level.
Note: *** p>0.01, ** p>0.05, * p>0.1

Table 2.8: Rural Counties Regression Results (RUCC 8 – 9)

	RUCC 8		RUCC 9	
Observations	235		431	
Variables	Coef.	S.E.	Coef.	S.E.
GDP per Capita	-0.002***	(0.001)	-0.000	(0.000)
Net SCTG 1	2.070	(3.390)	-3.179	(2.360)
Net SCTG 2	-0.508	(0.600)	-0.307	(0.241)
Net SCTG 3	-0.549	(0.644)	-1.614*	(0.851)
Net SCTG 4	-1.262	(1.428)	-0.384	(0.929)
Net SCTG 5	4.796	(4.129)	0.243	(3.846)
Net SCTG 6	1.815	(5.786)	-0.759	(3.376)
Net SCTG 7	-0.991	(1.447)	1.390	(1.891)
Establishments	-0.084**	(0.036)	-0.084***	(0.024)
Mideast	-1.827	(1.564)	0.756	(0.569)
Great Lakes	0.104	(1.314)	1.209*	(0.723)
Plains	-1.342	(1.296)	-1.075	(0.664)
Southeast	4.021***	(1.311)	5.277***	(0.698)
Southwest	3.058**	(1.317)	2.349***	(0.686)
Rocky Mountains	0.803	(1.319)	0.397	(0.655)
Far West	2.689**	(1.355)	2.422***	(0.770)
Constant	13.336***	(1.253)	12.830***	(0.582)

Note: Cluster robust standard errors are presented.

Errors are clustered at the county level.

Note: *** p>0.01, ** p>0.05, * p>0.1

2.9 Appendix B

Table 2.9: Oaxaca Decomposition - Metropolitan vs. Non-metropolitan, non-rural Counties

	Explained		Unexplained	
Observations	2,438		2,438	
	Coef.	Std. Err.	Coef.	Std. Err.
Total	-0.183**	(0.087)	1.398***	(0.133)
GDP per Capita	-0.007	(0.015)	-0.297	(0.256)
Net SCTG 1	-0.002	(0.003)	-0.000	(0.003)
Net SCTG 2	0.012	(0.010)	0.006	(0.004)
Net SCTG 3	-0.004	(0.013)	0.001	(0.003)
Net SCTG 4	-0.005	(0.006)	-0.001	(0.003)
Net SCTG 5	0.013	(0.009)	-0.008	(0.007)
Net SCTG 6	0.014	(0.012)	-0.003	(0.006)
Net SCTG 7	0.000	(0.001)	0.000	(0.003)
Establishments	-0.042**	(0.017)	0.005	(0.036)
New England	0.021**	(0.010)	0.004	(0.011)
Mideast	0.094***	(0.021)	-0.040*	(0.022)
Great Lakes	0.003	(0.012)	-0.067*	(0.040)
Plains	-0.165***	(0.031)	-0.053	(0.042)
Southeast	-0.196***	(0.053)	0.856***	(0.101)
Southwest	0.102***	(0.030)	-0.076**	(0.036)
Rocky Mountains	-0.003	(0.005)	-0.009	(0.016)
Far West	-0.018	(0.013)	-0.001	(0.022)
Constant			1.081***	(0.285)

Note: Cluster robust standard errors are presented. Errors are clustered at the county level.
Note: *** p>0.01, ** p>0.05, * p>0.1

Table 2.10: Oaxaca Decomposition - Non-metropolitan, Non-rural vs. Rural Counties

	Explained		Unexplained	
Observations	2,034		2,034	
	Coef.	Std. Err.	Coef.	Std. Err.
Total	0.527***	(0.127)	0.829***	(0.155)
GDP per Capita	0.021	(0.024)	-0.361*	(0.207)
Net SCTG 1	-0.002	(0.004)	-0.001	(0.003)
Net SCTG 2	-0.001	(0.004)	0.010	(0.008)
Net SCTG 3	0.008	(0.008)	0.015	(0.016)
Net SCTG 4	-0.000	(0.002)	0.002	(0.004)
Net SCTG 5	-0.007	(0.009)	0.001	(0.005)
Net SCTG 6	0.002	(0.003)	-0.013	(0.024)
Net SCTG 7	0.000	(0.003)	0.001	(0.002)
Establishments	0.011	(0.021)	0.208***	(0.052)
New England	-0.010	(0.007)	-0.003	(0.006)
Mideast	-0.090***	(0.017)	-0.006	(0.007)
Great Lakes	-0.070***	(0.016)	-0.057*	(0.031)
Plains	0.411***	(0.054)	0.081	(0.100)
Southeast	0.163**	(0.083)	0.067	(0.105)
Southwest	0.069**	(0.029)	0.079*	(0.046)
Rocky Mountains	0.007	(0.007)	0.054	(0.034)
Far West	0.013	(0.012)	-0.011	(0.021)
Constant			0.763***	(0.285)

Note: Cluster robust standard errors are presented. Errors are clustered at the county level.
Note: *** p>0.01, ** p>0.05, * p>0.1

Table 2.11: Oaxaca Decomposition - Metropolitan vs. Rural Counties

	Explained		Unexplained	
Observations	1,736		1,736	
	Coef.	Std. Err.	Coef.	Std. Err.
Total	-0.764***	(0.118)	0.623***	(0.174)
GDP per Capita	-0.019	(0.020)	0.054	(0.158)
Net SCTG 1	0.001	(0.002)	-0.000	(0.002)
Net SCTG 2	-0.001	(0.007)	0.009	(0.009)
Net SCTG 3	-0.009	(0.019)	-0.016	(0.014)
Net SCTG 4	-0.010	(0.008)	0.002	(0.002)
Net SCTG 5	0.010	(0.009)	0.001	(0.005)
Net SCTG 6	0.027*	(0.015)	-0.005	(0.022)
Net SCTG 7	0.000	(0.001)	0.000	(0.001)
Establishments	-0.049**	(0.019)	-0.209***	(0.051)
New England	0.030***	(0.011)	0.009	(0.008)
Mideast	0.132***	(0.028)	0.018*	(0.010)
Great Lakes	0.036**	(0.016)	0.027	(0.034)
Plains	-0.626***	(0.069)	-0.085	(0.093)
Southeast	-0.250***	(0.053)	0.680***	(0.113)
Southwest	0.019	(0.035)	-0.141***	(0.042)
Rocky Mountains	-0.022	(0.014)	-0.051*	(0.028)
Far West	-0.034**	(0.016)	0.014	(0.022)
Constant			0.318	(0.252)

Note: Cluster robust standard errors are presented. Errors are clustered at the county level.
Note: *** p>0.01, ** p>0.05, * p>0.1

Table 2.12: Oaxaca Decomposition - Metropolitan vs. Non-metropolitan Counties

	Explained		Unexplained	
Observations	3,104		3,104	
	Coef.	Std. Err.	Coef.	Std. Err.
Total	-0.440***	(0.086)	1.210***	(0.126)
GDP per Capita	-0.011	(0.010)	0.027	(0.159)
Net SCTG 1	-0.001	(0.002)	0.001	(0.003)
Net SCTG 2	0.004	(0.008)	0.007	(0.005)
Net SCTG 3	-0.010	(0.013)	0.001	(0.005)
Net SCTG 4	-0.006	(0.005)	-0.000	(0.003)
Net SCTG 5	0.013	(0.008)	0.000	(0.004)
Net SCTG 6	0.015	(0.012)	-0.006	(0.006)
Net SCTG 7	0.000	(0.001)	0.000	(0.002)
Establishments	-0.041**	(0.017)	-0.002	(0.029)
New England	0.023***	(0.009)	0.007	(0.010)
Mideast	0.109***	(0.020)	-0.016	(0.020)
Great Lakes	0.020**	(0.009)	-0.023	(0.036)
Plains	-0.336***	(0.036)	-0.081*	(0.042)
Southeast	-0.254***	(0.054)	0.865***	(0.092)
Southwest	0.070***	(0.025)	-0.092***	(0.030)
Rocky Mountains	-0.013*	(0.007)	-0.020	(0.015)
Far West	-0.023*	(0.012)	0.000	(0.020)
Constant			0.540***	(0.199)

Note: Cluster robust standard errors are presented. Errors are clustered at the county level.
Note: *** p>0.01, ** p>0.05, * p>0.1

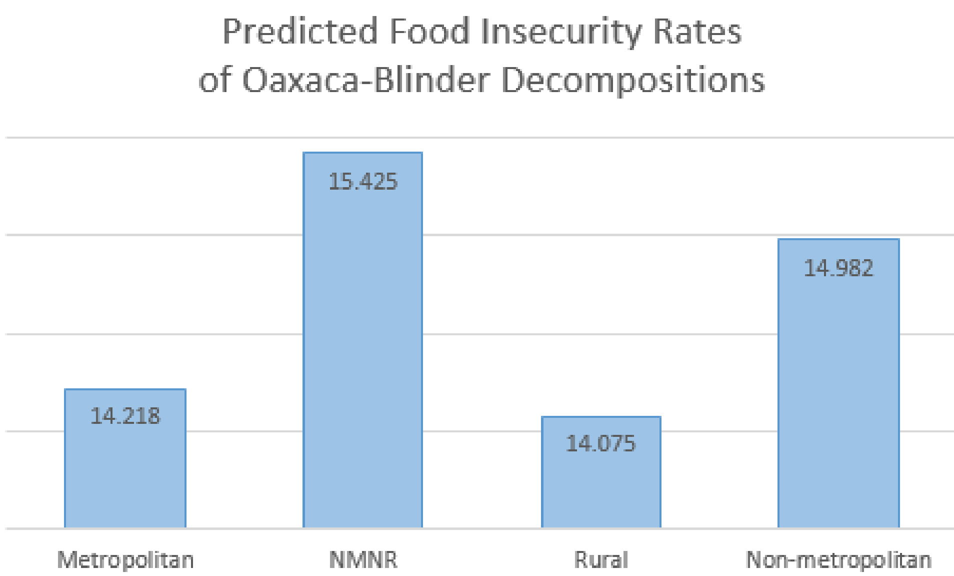
2.10 Appendix C

As shown in Table 2.13, the results discussed above change when introducing demographic variables used to construct the food insecurity estimates, such as poverty rate, median income, etc. For example, the only net trade categories that are significant are agricultural products (SCTG 3) and milled grain products (SCTG 6). Agricultural products reduce food insecurity by 0.277% for NMNR counties only, while milled grain products increase food insecurity rates by over 5% in rural areas and 0.468% in the pooled model. While our main results in Table 2.5 are not causal, we caution the validity of the results in Table 2.13. As expected, the variables used in the creation of the food insecurity estimates (median income, unemployment rate, poverty rate, percent black, percent Hispanic, and home ownership rate) are all strongly significant for each county group, as well as the pooled sample.

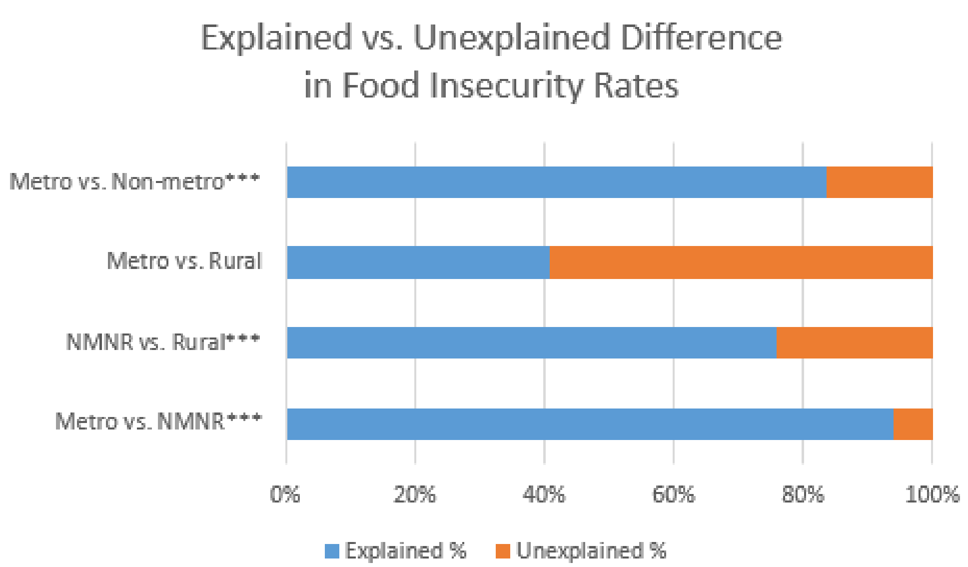
Table 2.13: Pooled and County Group Regression Results Using Highly Collinear Variables

	Pooled		Rural		NMNR		Metro	
Observations	3,104		666		1,368		1,070	
Variables	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.
GDP per capita	-0.000**	(0.000)	-0.000	(0.000)	-0.000	(0.000)	-0.004**	(0.002)
Rural	-0.429***	(0.077)						
NMNR	-0.103*	(0.055)						
Net SCTG 1	-0.007	(0.208)	0.285	(0.928)	0.224	(0.470)	-0.200	(0.202)
Net SCTG 2	-0.080	(0.057)	0.035	(0.117)	-0.145	(0.111)	-0.036	(0.086)
Net SCTG 3	-0.063	(0.081)	-0.202	(0.259)	-0.277*	(0.149)	0.040	(0.100)
Net SCTG 4	0.049	(0.168)	0.041	(0.404)	-0.163	(0.239)	0.172	(0.236)
Net SCTG 5	0.100	(0.322)	-0.120	(1.744)	-0.457	(0.661)	0.214	(0.384)
Net SCTG 6	0.468*	(0.250)	5.345***	(1.519)	0.451	(0.558)	0.223	(0.273)
Net SCTG 7	0.022	(0.061)	-0.241	(0.598)	-0.094	(0.149)	0.065	(0.067)
Establishments	-0.000	(0.000)	-0.012	(0.007)	-0.002**	(0.001)	-0.000	(0.000)
Median Income	-0.053***	(0.005)	-0.106***	(0.013)	-0.057***	(0.012)	-0.040***	(0.006)
Unemployment Rate	0.499***	(0.013)	0.530***	(0.028)	0.459***	(0.019)	0.501***	(0.021)
Poverty Rate	0.152***	(0.009)	0.087***	(0.017)	0.151***	(0.015)	0.170***	(0.018)
Percent Black	0.083***	(0.002)	0.088***	(0.005)	0.088***	(0.003)	0.071***	(0.004)
Percent Hispanic	-0.054***	(0.002)	-0.045***	(0.006)	-0.051***	(0.003)	-0.060***	(0.004)
Home Ownership Rate	-0.113***	(0.005)	-0.114***	(0.008)	-0.124***	(0.007)	-0.124***	(0.010)
Mideast	-1.614***	(0.191)	-2.623***	(0.739)	-2.099***	(0.283)	-1.019***	(0.264)
Great Lakes	-0.342*	(0.181)	-1.643***	(0.420)	-0.768***	(0.263)	0.366	(0.262)
Plains	0.221	(0.184)	-0.827**	(0.394)	-0.207	(0.264)	0.968***	(0.285)
Southeast	-0.290	(0.185)	-1.003**	(0.407)	-0.672**	(0.273)	0.118	(0.268)
Southwest	3.330***	(0.197)	2.545***	(0.427)	2.415***	(0.286)	4.345***	(0.302)
Rocky Mountains	1.214***	(0.196)	-0.084	(0.414)	0.707**	(0.280)	2.282***	(0.305)
Far West	-0.049	(0.193)	-0.786	(0.479)	-0.512*	(0.284)	0.375	(0.273)
Constant	18.441***	(0.545)	22.017***	(1.245)	20.094***	(1.047)	18.040***	(1.026)

Note: Cluster robust standard errors are presented. Errors are clustered at the county level.
Note: *** p>0.01, ** p>0.05, * p>0.1



(a) Predicted Food Insecurity Rates
of Oaxaca-Blinder Decompositions



(b) Explained vs. Unexplained Differences
of Oaxaca Blinder Decompositions

Note: Cluster robust standard errors are presented. Errors are clustered at the county level.
Note: *** p>0.01, ** p>0.05, * p>0.1

Figure 2.4: Oaxaca-Blinder Decomposition Results with Highly Collinear Variables

Chapter 3

Manuscript 2: The Role of Infrastructure on Food Flows in the United States

3.1 Abstract

The determinants of trade flows have been extensively studied at the international level. One such important driver of trade includes infrastructure connecting one trading partner to another. However, little analysis of the impact of infrastructure on food trade across smaller spatial scales, such as the county level, has been conducted. We use food flow data for two separate categories of trade to determine what aspects of county infrastructure impact county food flows. Results show that ports, roadways, and food processing and manufacturing plants all impact food flows in both food categories we analyze in our study. With these insights, we suggest law makers pursue policy that will promote flexibility in the food supply chain and invest in quality infrastructure to promote county food flows.

3.2 Introduction

When discussing the economy of any political body, whether it is as small as a city, or as large as an entire nation, the topic of trade is a key component. Trade has been referred to as an "engine of growth," given that the outcomes often associated with it are the creation of jobs, reduction of poverty, and increased economic opportunity (World Bank, 2021). The United States is a key player in many aspects of trade, such as being a major world producer of commodities like cotton, soybeans, and corn, while at the same time leading world imports of items like coffee, alcoholic beverages, and avocados. However, one oft overlooked fact is that the United States exports only 8.5% of its agricultural production, and local production satisfies 91.2% of its national intermediate and final demands (Timmer et al., 2015; Dall'Erba, Chen, and Nava, 2021). While U.S. food trade has been well studied at the international level, little analysis has been given to intra-national food trade.

An important unanswered question in food trade literature is whether food trade is similar or different across spatial scales (Konar et al., 2018). For example, at the largest scale, countries trade based on their comparative advantage or national trade policies, while at the smallest scale, households can share goods with others who have experienced negative effects from events like a death in the family, outbreak of pests, or a drought (Jackson, Rodriguez-Barraquer, and Tan, 2012; Baggio et al., 2016). In between these two extremes on the spatial scale, Dall'Erba, Chen, and Nava (2021) show that droughts negatively impact state exports, while at the same time significantly increasing that state's demand for imports. Most analyses studying food trade at subnational levels focus on network analysis. For example, Konar et al. (2018) examine the network properties of food flows at three spatial levels. Venkatramanan et al. (2017) examine food flows within Nepal and address factors that impact food flow networks, such as production locations, population distribution, cultural factors, storage and transport infrastructure, and economic activity. Lin, Dang, and Konar (2014) and Lin et al. (2019) examine food flow networks within the United States at the regional and county level, respectively. These analyses underpin the importance of understanding global and subnational supply chains, as well as vulnerabilities within food supply chains (Lin et al., 2019). Furthermore, determining drivers of food trade across different spatial scales will help policy makers react quickly and efficiently when intra-national supply chains experience a shock such as a pandemic, natural disaster, drought, or other national emergency.

Infrastructure is an important aspect to consider when examining food trade, no matter the spatial scale. International trade literature suggests infrastructure does impact trade. For example, Nordås and Piermartini (2004) develop indicators for the quality of infrastructure in a country, and find that the quality of infrastructure has a large and significant impact on trade flows. In addition, the authors conclude that port efficiency has the largest impact on trade. Portugal-Perez and Wilson (2012) determine that physical infrastructure is increasingly important the richer a country becomes. Ismail and Mahyideen (2015) find that improvements in transport infrastructure such as road density network, air transport, railways, ports, and logistics results in increased trade flows. Improving infrastructure endowments and quality results in decreased trade costs and increased international trade flows (Donaubauer et al., 2018). Landlocked countries have 50% higher transport costs and 60% lower trade volumes than coastal countries, but overcome a substantial portion of this disadvantage by improving infrastructure (Limão and Venables, 2001). Additionally, Limão and Venables (2001) determine that poor infrastructure accounts for 40% of predicted transport costs for coastal countries and as much as 60% for landlocked countries. Trade is dependent on exporter and importer access to well developed transport infrastructure, and low infrastructure quality limits market access for products (Francois and Manchin, 2013). Xu and Yang (2021) find that improvement in domestic transportation infrastructure reduces trade costs between inner regions as well as international markets, which improves inner regions' global market access and amplifies their welfare gains from trade cost reductions.

Clearly, literature supports the fact that trade infrastructure has important implications for welfare gains, reducing trade costs, and promoting trade. However, literature also shows that food trade flows and its relationship with infrastructure has important policy implications for food access. For example, identifying the most important roadway infrastructure components to food access will support policies that will aid public access to food during disruptive events (Novak, Sullivan, and Niles, 2021a). Food distribution channels provide access to fresh, whole foods, and transfer fruits and vegetables from farms to retailers (Rosenbaum et al., 2017; Bublitz et al., 2019). Yet, some impoverished communities lack access to supermarkets, and important distribution channel that offers healthy food choices at lower prices (Bublitz et al., 2019). Studying the link between food trade and infrastructure will help strengthen policy recommendations to improve food access.

Given the importance of studying food trade across spatial scales, its relationship with infrastructure, and the important policy implications surrounding food access and infrastructure, we are motivated to determine the connection between county food trade and county infrastructure in the United States. County trade in the United States has been little studied, mostly due to lack of data. State level trade has been shown to mitigate effects of shocks like drought when exporting states increase their profit by importing to states experiencing a drought, in addition to increasing crop grower's profits (Dall'Erba, Chen, and Nava, 2021). Other studies in the past have examined intranational trade across state borders or Canadian provinces (for example, John McCallum (1995); Wolf (2000); Hillberry and Hummels (2003); Millimet and Osang (2007); McAusland and Millimet (2013); Agnosteva, Anderson, and Yotov (2019)). However, we are able to use food flow estimates created by Lin et al. (2019) to offer several expansions to existing literature on intranational food trade. First, we analyze food trade at a county level to determine the role of infrastructure on food flows at the county level. Secondly, our analysis offers policy makers better understanding of food flows at the sub-national level and gives insight on the role of county infrastructure in facilitating trade. In this way, policy makers are better equipped to meet policy goals surrounding food access and food trade, especially for those in impoverished communities and for all communities in times the food supply chain may experience shocks like pandemics, natural disasters, or other national emergencies.

3.3 Data

In assembling our data, we consider factors that literature has shown to impact trade, such as GDP and farm income, distance, as well as infrastructure data relating to food/agriculture and transportation, discussed in detail below. Beverly and Neill (2022) discuss in detail the description of the seven food trade categories given in the food flow data, whereas in this analysis we only utilize two of the seven available food trade categories. In addition, it is important to note that in order to remain consistent with food trade and food flow literature, we use the term 'food trade' to refer to international food trade, and 'food flow' to refer to the movement of food within a country. Descriptions of variables we use in our analysis are given in Table 3.1, while summary statistics for descriptive variables are given in Table 3.2.

Table 3.1: Description of Variables

Variable	Description
Distance	Great circle distance between counties (in 1000s miles)
Farm Income (Origin County)	Farm income per county
GDP (Destination County)	Gross domestic product in 2012 chained dollars
Employment	Number of people in a county employed in food processing and manufacturing
Establishments	Number of food processing and manufacturing establishments in a county
Agland Acres	The number of agland acres in a county
Interstate Dummy	Indicator variable for whether a county has an interstate
Principal Arterial Dummy	Indicator variable for whether a county has a freeway or expressway
Principal Arterial - Other Dummy	Indicator variable for whether a county has another type of principal arterial
Port	Indicator variable for whether the county has a port
Grocery Stores per 1000 People	The number of grocery stores per 1000 population
Supercenters per 1000 People	The number of supercenters in a county per 1000 population
Fast Food Restaurants per 1000 People	The number of fast food restaurants in a county per 1000 people
Full Service Restaurants per 1000 People	The number of full service restaurants in a county per 1000 people
Cereal Grains	Flow of cereal grains from origin to destination county
Agricultural Products	Flow of agricultural products from origin to destination county

Table 3.2: Summary Statistics of Descriptive Variables

Variable	**Mean**	**Std. dev.**	**Min**	**Max**
Distance (in 000s of miles)	0.550	0.557	0.001	5.144
Farm Income (Origin County) (in billions)	0.009	0.012	0.000	0.109
GDP (Destination County) (in 100s of millions)	19.237	55.917	0.011	594.533
Origin Employment	0.088	0.200	0.000	2.680
Origin Establishments	0.029	0.164	0.000	3.606
Destination Employment	0.089	0.232	0.000	2.680
Destination Establishments	0.035	0.187	0.000	3.606
Origin Agland Acres (in millions)	0.080	0.182	0.000	1.780
Origin Interstate	0.643	0.479	0.000	1.000
Origin Principal Arterial	0.453	0.498	0.000	1.000
Origin Other Principal Arterial	0.927	0.261	0.000	1.000
Destination Agland Acres (in millions)	0.061	0.154	0.000	1.780
Destination Interstate	0.666	0.472	0.000	1.000
Destination Principal Arterial	0.479	0.500	0.000	1.000
Destination Principal Arterial - Other	0.926	0.261	0.000	1.000
Origin Port	0.350	0.477	0.000	1.000
Destination Port	0.378	0.485	0.000	1.000
Grocery Stores per 1000 People	0.204	0.126	0.000	2.994
Super Centers per 1000 People	0.019	0.018	0.000	0.246
Fast Food Restaurants per 1000 People	0.640	0.227	0.000	5.797
Full Service Restaurants per 1000 People	0.734	0.386	0.000	13.043

3.3.1 Food Flow Data

This study uses a novel data set constructed by Lin et al. (2019), which uses a combination of machine learning, network properties, production and consumption statistics, mass balance constraints, and linear programming to downscale Freight Analysis Framework (FAF) data to the county and county-equivalent level in the United States. It is noted that this data set allows for intermediate and final consumption of goods. In other words, commodity transformation like food processing and other intermediate steps in the supply chain is included. In addition, we exclude "self-loops," or food flows where the origin and destination county are the same, from the analysis. Finally, the full data set we use in this analysis has almost 120,000 food flows where a county had flows in at least one SCTG category. We do not consider observations between counties that did not have any food flows for any SCTG category, as we assume flows between these counties are infeasible.

The data from Lin et al. (2019) examines trade flows from the first seven Standard Classification of Transported Goods codes, which pertain to food. We examine two trade categories from this data set: agricultural products and other prepared foodstuffs, fats, and oils (hereafter referred to as other foodstuffs). Agricultural products are labeled under SCTG category 3, and represent a wide array of items, such as vegetables (fresh, chilled, or dried), fruits and nuts (edible, fresh, chilled, or dried), oil seeds, bulbs, live plants, cut flowers, unmanufactured tobacco, sugar beet, sugar cane, and raw cotton. Other foodstuffs are labeled as SCTG category 7, and also represents a variety of foods, including dairy products like milk, cheese, butter, yogurt, etc., processed or prepared vegetables, fruit, or nuts (i.e. frozen vegetables, canned/pickled vegetables, potato chips, jams, frozen fruit/vegetable juices, etc.), processed coffee, processed tea, spices, animal or vegetable fats/oils, sugar, sugar syrups, cocoa, other edible preparations not elsewhere classified (like soups, broths, tofu, sauces and sauce mixes, etc.), and non-alcoholic beverages[1].

Traditional Gravity Model Data

County gross domestic product (GDP) is collected from the Bureau of Economic Analysis (Bureau of Economic Analysis, 2020)[2]. Information on farm income by county as well as agland acres per county is gathered from the National Agricultural Statistics Service (NASS). We follow Koo, Karemera, and Taylor (1994) in replacing an exporting entity's GDP with its farm income, representing

[1]For a more descriptive list of items in SCTG categories, see https://www2.census.gov/programs-surveys/cfs/technical-documentation/code-list/2012-manual.pdf

[2]Some Virginia GDP measures consist of one or two independent cities. Those with populations less than 100,000 are combined with an adjacent county. Separate estimates for the jurisdictions making up the combination area are not available. Because of this, some Virginia counties cannot be included in the analysis

a metric for production capacity for agricultural commodities. In addition, we control for the amount of agland acres in origin and destination counties, as this is another measure of production volume that may not be accurately captured in the farm income metric. Distance information for each county is gathered from the National Bureau of Economic Research (National Bureau of Economic Research, 2010). These distances are great-circle distances. Great-circle distances are the most commonly used distances in international trade (Disdier and Head, 2008). For this analysis, distance is rescaled to represent thousands of miles.

Food and Agriculture Infrastructure Data

Data regarding food processing and manufacturing is gathered from the U.S. Cluster Mapping Project (U.S. Cluster Mapping Project, Institute for Strategy and Competitiveness, Harvard Business School, 2012). This data set includes information on the number of people employed in food processing and manufacturing, as well as the number of food processing and manufacturing establishments in each county. Variables from the Food Environment Atlas maintained by the Economic Research Service are also utilized. Specifically, we use variables on the number of grocery stores per, the number of supercenters, the number of fast food restaurants , and the number of full-service restaurants - all scaled by per thousand people in a county (U.S. Department of Agriculture (USDA), Economic Research Service (ERS), 2015). Grocery stores in this data set include supermarkets and smaller grocery stores that primarily sell canned and frozen foods; fresh fruits and vegetables; and fresh and prepared meats, fish, and poultry. Large merchandise stores that also sell food like supercenters are not included in this grocery store category. Supercenters include warehouse club stores that sell groceries as well as apparel, furniture, or appliances, which is why we also control for supercenters since they also contribute to food demand for a county. Fast food restaurants are defined as establishments that primarily engage in providing food services (excluding snack bars and nonalcoholic beverage bars) where customers order food and pay before eating. Full-service restaurants are defined as establishments where customers order food, are served while seated, and pay after eating. We include these measures to capture demand of food flows from manufacturers, consumers, and retailers that could potentially drive food flows between two county trading partners.

Transportation Infrastructure Data

As discussed previously, international trade literature shows infrastructure is an important determining factor for trade flows and trade costs. As such, we include measures for both the presence of certain road networks, as well as ports in origin and destination counties.

Information on the presence of highways and roads in a county are constructed from the Highway Performance Monitoring System (HPMS) data maintained by the Federal Highway Administration (Federal Highway Administration, 2020). Dummy variables for whether a county has an interstate, other freeway and expressway, or other principal arterial road are utilized. The U.S. Department of Transportation defines interstates, other freeway and expressways, and other principal arterials as follows:[3] Interstates are designated as such by the Secretary of Transportation, and "are designed and constructed with mobility and long-distance travel in mind;" other freeways and expressways are similar to interstates, typically have directional travel lanes separated by a physical barrier, and have access limited to on- and off-ramps; finally, other principal arterials also provide high degree of mobility as major centers of metropolitan areas and through rural areas alike.

In addition to information on the Federal Highway System, we also control for the port access of each county. Dummy variables for whether a county has a port is collected from Koordinates US Bureau of Transportation Statistics (BTS) (2016). This data set is sourced from the U.S. Bureau of Transportation Statistics and contains information on commercial facilities at the principal U.S. Coasts, Great Lakes, and Inland Ports.

[3] For more information about the classification of the Federal Highway System, see U.S. Department of Transportation, Federal Highway Administration (2013)

3.4 Methods

In our analysis, we employ two different gravity models: the traditional gravity model, and the Poisson pseudo-maximum likelihood (PPML) model. It is generally accepted that the PPML model is superior to the traditional gravity model, for reasons outlined below. As such, we only discuss the results of the PPML regressions in our results.

3.4.1 Traditional Gravity Model

Gravity models have been used in economics since Tinbergen (1962) to model the gravitational force between two objects. Traditionally, the gravity model has assumed that the force between the objects is directly proportional to the mass of the objects and inversely proportional to the distance between the two objects. In its most basic form, the gravity equation of trade takes the following form:

$$X_{ij} = \beta_0 Y_i^{\beta_1} Y_j^{\beta_2} D_{ij}^{\beta_3} \varepsilon_{ij} \tag{3.1}$$

where X_{ij} is trade flow between two entities i and j, Y is the gross domestic product (GDP), D is the distance between the two entities, and ε is the error term. It is traditional to econometrically model the above by log-linearizing the equation to yield:

$$\ln X_{ij} = \ln \beta_0 + \beta_1 \ln Y_i + \beta_2 \ln Y_j + \beta_3 \ln D_{ij} + \ln \varepsilon_{ij} \tag{3.2}$$

For our specification on food flow between counties, the analysis follows a traditional gravity model structure:

$$X_{ij} = \beta_0 + \beta_1 DIST_{ij} + \beta_2 FARM_i + \beta_3 GDP_j + \beta_4 AG_i + \beta_5 AG_j + \boldsymbol{\gamma}\mathbf{F} + \boldsymbol{\delta}\mathbf{T} + \varepsilon_{ij} \tag{3.3}$$

where X is the logged trade flow of SCTG category between exporting counties i and importing counties j (in billions of kilograms); $DIST$ is the distance between the origin and destination county; $FARM$ is the logged farm income; GDP is the logged gross domestic product; AG is the logged agland acres in each county; $\mathbf{F}$ is a vector of farm and agricultural infrastructure variables with parameter estimates $\boldsymbol{\gamma}$ for origin and destination counties such as the logged employment of food processing and manufacturing workers and the logged number of food processing and manufacturing establishments in a county, as well as the logged number of grocery stores, supercenters, fast food restaurants, and full service restaurants in the destination county; $\mathbf{T}$ is a vector of transportation infrastructure variables with parameter estimates $\boldsymbol{\delta}$ such as a dummy variable indicating if the county has an interstate, a dummy variable indicating if the county has a principal arterial highway, a dummy variable indicating whether or not the county has a principal arterial (other) highway, a dummy variable for whether a county contains a port; and ε is the normally distributed error term. We use the above equation to analyze two regressions - one for agricultural products and one for other foodstuffs.

The log-linearized gravity model cannot consider the case where X_{ij} for a given pair of entities is observed to be zero, since the logarithm of zero is undefined. Some investigators skirt around this problem by dropping zero observations or substituting zero observations with $X_{ij}+1$. This generally leads to inconsistent estimators of parameters (Santos-Silva and Tenreyro, 2006). Secondly, the traditional gravity model assumes that all error terms have the same variance for all pairs of i and j. Santos-Silva and Tenreyro (2006) find evidence that the error terms in a typical log-linear specification of the gravity model are heteroskedastic, which would lead to inconsistent estimates of the traditional gravity equation. Thirdly, omitting zero trade flows as the traditional gravity model does can lead to biased estimates primarily due to sample selection issues (Santos Silva and

Tenreyro, 2011; Helpman, Melitz, and Rubinstein, 2008; Martin and Pham, 2020). Hence, we adopt the Poisson framework, discussed below.

PPML Model

Due to the likelihood of econometric issues facing the traditional gravity model, we employ the use of the Poisson pseudo-maximum likelihood model proposed by Santos-Silva and Tenreyro (2006). The PPML model for use in analyzing trade is discussed in Santos-Silva and Tenreyro (2006), and summarized here. Assuming y and x are linked by a constant elasticity model of the form $y_i = \exp(x_i\beta)$ we can represent the stochastic model as follows:

$$y_i = \exp(x_i\beta) + \varepsilon_i \tag{3.4}$$

where $y_i \geq 0$ and $E[\varepsilon_i|x_i] = 0$. Equation 3.4 can be rewritten as:

$$y_i = \exp(x_i\beta)\eta_i \tag{3.5}$$

where y is the variable of interest, x contains the explanatory variables, and $\eta_i = 1 + \frac{\varepsilon_i}{\exp(x_i\beta)}$ is the error term, with $E[\eta|x_i] = 1$.

Assuming the variance is proportional to the conditional mean (i.e. $E[y_i|x] = \exp(x_i\beta) \propto V[y_i|x]$) (McCullagh and Nelder, 1989; Santos-Silva and Tenreyro, 2006), the first-order conditions for the PPML model are:

$$\sum_{i=1}^{n}[y_i - \exp(x_i\tilde{\beta})]x_i = 0 \tag{3.6}$$

which is the pseudo-maximum likelihood result noted by Gourieroux, Monfort, and Trognon (1984). In order to take into account the heteroskedasticity in the model, we employ Eicker-White standard errors (Eicker, 1963; White, 1980).

Thus, our analysis uses the following equation to obtain the PPML estimates:

$$X_{ij} = \exp[\beta_0 + \beta_1 DIST_{ij} + \beta_2 FARM_i + \beta_3 GDP_j + \beta_4 AG_i + \beta_5 AG_j + \boldsymbol{\gamma}\mathbf{F} + \boldsymbol{\delta}\mathbf{T}]\eta_{ij} \tag{3.7}$$

where X_{ij} represents the (unlogged) trade flow between two counties, i and j, and η is the Eicker-White estimated error term. The remaining variables are in the same logged format as discussed in Equation 3.3. As with the traditional gravity model above, we estimate two PPML regressions, one for agricultural products and one for other foodstuffs.

3.5 Results

Results for the two traditional gravity model regressions and the two PPML regressions are presented below and in Tables 3.3 and 3.4. We discuss the results for the PPML regressions regarding agricultural products, followed by the results for the regressions regarding other foodstuffs. For logged regressors, the coefficient values presented are elasticities. For regressors not in logged form, we discuss the semi-elasticity in the results below, given by $100 \times \exp((\beta) - 1)\%$.

Table 3.3: Results for Agricultural Products

	Agricultural Products			
	Naïve		PPML	
	Coef.	S.E.	Coef.	S.E.
Distance	-1.915***	(0.030)	-1.639***	(0.055)
Farm Income (Origin County)	0.357***	(0.048)	0.165***	(0.054)
GDP of Destination County	0.287***	(0.051)	0.142***	(0.046)
Origin Employment	-0.046	(0.035)	0.083***	(0.032)
Origin Establishments	0.165***	(0.049)	0.030	(0.055)
Destination Employment	0.014	(0.033)	0.091***	(0.030)
Destination Establishments	0.060	(0.051)	0.053	(0.051)
Origin Agland Acres	0.146***	(0.028)	0.177***	(0.029)
Origin Interstate Dummy	-0.422***	(0.101)	0.041	(0.083)
Origin Principal Arterial Dummy	0.117	(0.103)	-0.123	(0.097)
Origin Principal Arterial - Other Dummy	-0.154	(0.202)	0.114	(0.154)
Destination Agland Acres	-0.010	(0.023)	0.089***	(0.028)
Destination Interstate Dummy	-0.128	(0.112)	0.037	(0.098)
Destination Principal Arterial Dummy	-0.162	(0.109)	-0.020	(0.095)
Destination Principal Arterial - Other Dummy	0.496**	(0.209)	0.296*	(0.155)
Origin Port Dummy	0.255***	(0.095)	0.200**	(0.083)
Destination Port Dummy	0.195**	(0.095)	0.202**	(0.086)
Grocery Stores per Thousand Population	-0.058	(0.071)	-0.010	(0.045)
Super Centers per Thousand Population	-0.074***	(0.023)	-0.055***	(0.019)
Fast Food Restaurants per Thousand Population	0.020	(0.053)	0.008	(0.032)
Full Service Restaurants per Thousand Population	-0.157*	(0.087)	-0.212***	(0.049)
Constant	10.202***	(0.517)	-10.056***	(0.457)
Observations	11,497		119,281	
R-squared	0.215		0.088	

Note: Robust standard errors are presented in parentheses.
Note: *** p>0.01, ** p>0.05, * p>0.1

Table 3.4: Results for Other Foodstuffs

	Other Foodstuffs			
	Naïve		PPML	
	Coef.	S.E.	Coef.	S.E.
Distance	-1.101***	(0.018)	-1.001***	(0.017)
Farm Income (Origin County)	0.073***	(0.023)	0.103***	(0.020)
GDP of Destination County	0.340***	(0.025)	0.349***	(0.022)
Origin Employment	0.180***	(0.017)	0.248***	(0.014)
Origin Establishments	0.216***	(0.023)	0.237***	(0.019)
Destination Employment	0.045***	(0.015)	0.030**	(0.012)
Destination Establishments	-0.022	(0.022)	0.077***	(0.017)
Origin Agland Acres	0.074***	(0.013)	0.063***	(0.013)
Origin Interstate Dummy	0.169***	(0.052)	0.106**	(0.042)
Origin Principal Arterial Dummy	0.320***	(0.050)	0.111***	(0.039)
Origin Principal Arterial - Other Dummy	0.094	(0.105)	0.060	(0.084)
Destination Agland Acres	0.068***	(0.012)	0.057***	(0.011)
Destination Interstate Dummy	0.020	(0.055)	-0.118**	(0.046)
Destination Principal Arterial Dummy	0.025	(0.054)	-0.055	(0.044)
Destination Principal Arterial - Other Dummy	0.111	(0.101)	-0.277***	(0.088)
Origin Port Dummy	-0.022	(0.046)	-0.117***	(0.039)
Destination Port Dummy	-0.103**	(0.047)	-0.152***	(0.037)
Grocery Stores per Thousand Population	0.016	(0.047)	-0.036	(0.034)
Super Centers per Thousand Population	-0.010	(0.012)	-0.007	(0.010)
Fast Food Restaurants per Thousand Population	-0.013	(0.039)	0.050**	(0.021)
Full Service Restaurants per Thousand Population	-0.042	(0.057)	-0.122***	(0.036)
Constant	6.836***	(0.258)	-9.169***	(0.234)
Observations	55,714		119,281	
R-squared	0.070		0.267	

Note: Robust standard errors are presented in parentheses.
Note: *** p>0.01, ** p>0.05, * p>0.1

3.5.1 Agricultural Products

The results for food flows of agricultural products are given in Table 3.3. One notable difference between the two models are the number of observations. The naive model only considers approximately 11,500 observations, whereas the PPML model includes about 120,000 observations.

We find that distance, farm income of origin county, and GDP of destination county are significant and have the expected coefficient signs found in the trade literature. In other words, as distance increases by 1%, food flow volumes decrease by 1.6%; as farm income increases 1%, trade flow volumes increase by 0.17%, and as GDP of the destination county increases 1%, trade flow volumes increase by 0.14%. In addition, we also find that as the amount of agland acres in origin and destination counties increases by 1%, agricultural trade flows increase by 0.18% and 0.09%, respectively. Agland acres is one indication of a county's production capability. Counties may be either producing raw agricultural products themselves for transport to other counties, explaining the positive relationship of agland acres with trade flow in origin counties. Destination counties may be producing agricultural products themselves with the goal of using trade flows to create a value-added product, like canned fruits and vegetables, sauces, etc.

The only food processing and manufacturing variables that we find significant in the PPML model are the origin and destination employment variables. Origin employment increases agricultural product trade volumes by 0.08% and destination employment increases agricultural volumes by 0.09%. A food processing and manufacturing plant demands more labor only if work is available for the newly hired workers; hence, the plants move more agricultural products through their facilities and the counties experience increased trade flows.

The physical infrastructure that we find significant for agricultural products include the presence of other principal arterials in the destination county, and the presence of a port in the origin and destination counties. The presence of a other principal arterial roadways increase trade flows by 34%, while the presence of origin and destination ports both increase trade volumes by 22%. These findings are consistent with Limão and Venables (2001), who found that landlocked countries experience 40% lower trade volumes than coastal countries. We find the same phenomena happening at the county level with agricultural trade flows. In addition, the presence of a port likely makes it easier for transport of agricultural products to ultimately export to another country, or for processing of raw agricultural products into other consumables.

We find that supercenters discourage food flows of agricultural products by 0.06%. We also find that full service restaurants discourage food flows of agricultural products by 0.21%. Agricultural products include a wide array of items, including fresh cut flowers, unprocessed tobacco, live plants, and raw cotton. Since many of these products still need to be processed for human consumption or are otherwise inedible, then as more businesses that do not typically sell these types of products (like supercenters or full service restaurants) increase within a county, then the less flow of items like raw cotton and unprocessed tobacco will be observed between counties.

3.5.2 Other Foodstuffs

The results for the naive and PPML gravity models for Other Foodstuffs are given in Table 3.4. Like the analysis for agricultural products, one notable difference between the two models are the number of observations. The naive model has about 56,000 observations, compared to the full sample of about 120,000 observations employed by the PPML model.

Similar to the findings for agricultural products, we find that distance, farm income of origin county, and GDP of destination county are all strongly significant across the two models. The findings also have the expected sign based on the trade literature. We find that as distance increases between two counties by 1%, food flows of other foodstuffs decrease by 1.% as well. We also find that as farm income of the origin county and GDP of the destination county increase by 1%, the food flows of other foodstuffs increase by 0.103% and 0.35%, respectively. Additionally, we find that agland acres has a positive relationship with Other Foodstuffs in both origin and destination counties. As an origin or destination county increases agland acres by 1%, trade flows of Other Foodstuffs increases by 0.06%. As is the case with agricultural products, agland acres in origin counties may be indicating a county's production capability for such items as milk and raw cane or beet sugar, which is then transported to other counties. Destination counties may use their own production capabilities to transform items like milk and raw sugar into a value-added product.

With regards to food processing and manufacturing facilities, we find that both origin and destination employment as well as origin establishments are strongly significant. As employment increases

1% in the origin and destination counties, trade flows of other foodstuffs increase by 0.25% and 0.03%, respectively. Similar to the agricultural product results, food processing and manufacturing plants only demand more labor when there is work for the new employee, thus more employees result in more work for plant; hence, trade flow volumes increase. We also find that as origin and destination establishments increase, flows of Other Foodstuffs increase 0.24% and 0.08%, respectively. It is likely the food processing and manufacturing facilities between counties are taking items like milk, cheese, or sugar to be processed further into other food items, hence why an additional establishment in either the origin or destination county would increase trade flows of Other Foodstuffs.

The presence of an interstate is significant for both origin and destination counties, while the presence of a principal arterial is significant for the origin county and the presence of other principal arterial roadways is significant for the destination county. The presence of an interstate in an origin county increases trade flows of Other Foodstuffs by 11%, while the presence of an interstate in a destination county decreases trade flows of Other Foodstuffs by 11%. The presence of an interstate in a destination county could decrease trade flows if it is an indication that the destination county has multiple trade partners. Since the origin county may be competing with other trade partners, this would explain how the presence of an interstate in a destination county decreases trade flows of Other Foodstuffs.

While distance considers great circle distances between counties, it does not pick up on the remoteness of a county relative to other trading partners (Wolf, 2000). Other principal arterial roadways in the destination county may represent a more remote county since these roadways are not as connected as major highways and principal arterials, which explains why the presence of other principal arterial roadways in a destination county decreases trade flows of Other Foodstuffs by 24%. Similarly, the presence of ports may also be picking up on a "remoteness" factor, and given the nature of the types of food items in this category (items that require refrigeration or freezing for transport), this would explain why trade flows decrease by 11% and 14% when the origin or destination county contains a port, respectively.

Finally, we find that fast food restaurants and full service restaurants in a destination county are significant for trade flow of Other Foodstuffs. However, they have mixed impacts on trade flows of Other Foodstuffs. A one percent increase in fast food restaurants per thousand population is found to increase food flows of other foodstuffs between counties by 0.05%, while a one percent increase in full service restaurants is found to decrease food flows of other foodstuffs between counties by 0.12%. This may be due to the types of items consumed at each type of restaurant. Individuals who consume fast food have a higher intake of energy, fat, saturated fat, and carbonated soft drinks (i.e. types of food prevalent in the Other Foodstuffs category), and lower intakes of fruits and vegetables than those who do not eat fast food (Paeratakul et al., 2003). Frequent use of full-service restaurants is also associated with a higher intake of vegetables (Larson et al., 2011; Befort et al., 2006). Additionally, Befort et al. (2006) find that for some demographics, increased fruit intake is positively associated with full-service restaurants and not with fast-food restaurants. This explains why the more fast food restaurants per thousand people increases food flows of other foodstuffs while full service restaurants per thousand people decreases food flows of other foodstuffs.

3.6 Policy Implications

Our work offers several policy insights regarding the U.S. food supply chain. Namely, we confirm the importance of infrastructure and its role in county trade in the United States, as well as create supply chains flexible enough to respond to shocks in the food supply chain (Aday and Aday, 2020). Understanding the nuances of our nation's food supply chains can help policy makers react quickly and efficiently in times of pandemics, natural disaster, and other national emergencies.

We find that for both trade flows of agricultural products and Other Foodstuffs, the number of people employed at food processing and manufacturing facilities in origin and destination counties promotes trade flows. Our nation experienced a shock to these metrics first hand during the COVID-19 pandemic, when food processing and manufacturing plants became "COVID-19 hotspots" and resulted in numerous workers forced to quarantine and entire plants to shut down production altogether (Soucheray, 2020). During times when workers or the number of processing plants are restricted, it is important for policy makers to support the movement of workers as well as ensure safety measures to protect workers and prevent plant shut-downs (Aday and Aday, 2020).

It is also imperative policy makers support infrastructure such as roadways to promote trade of Other Foodstuffs. As pointed out by Novak, Sullivan, and Niles (2021b), "identifying the roadway infrastructure components that are most critical to food access is imperative in supporting policy goals centering on" public food access during shocks such as extreme weather events. In addition, ports are important to maintaining welfare benefits (Xu and Yang, 2021) and are key indicators for the promotion of trade in agricultural products. Continued investment in quality infrastructure can also lower transport costs (Donaubauer et al., 2018; Limão and Venables, 2001), which benefit both consumers and producers.

3.7 Conclusions

Food flow network analysis is beginning to be studied more closely across different spatial scales. However, little work has been done to determine the relationship between infrastructure and its impact on county trade flows in the United States. Our study utilizing the PPML gravity model finds that infrastructure plays an important role in promoting food flows of two SCTG categories: agricultural products and Other Foodstuffs.

When considering infrastructure like food processing and manufacturing facilities, roadways, ports, and establishments like grocery stores, supercenters, and restaurants, we find mixed results across the two SCTG categories. For agricultural products, we find that ports are larger drivers of food flows between counties than roadways. For other foodstuffs, the opposite is true: ports do not drive flows, while roadways are important drivers of food flows for this SCTG category. We also find that all food processing and manufacturing variables are statistically significant and positive for other foodstuffs, while only the employment metric drives food flows of agricultural products.

Our findings suggest policy measures that will promote flexible food supply chains, mobility of workers, and continued investment in quality infrastructure such as roadway networks and ports. However, further work is needed to determine whether these results hold across time, as our analysis only employs one year of food flow data. In addition, data that is disaggregated from broad SCTG categories would help understand drivers of specific food commodities. For example, data where fresh fruits and vegetables are separated from data including live plants, cut flowers, and unmanufactured tobacco may yield different results from those presented in this paper due to the nature of these products. Further disaggregated data would be helpful to understanding our food supply chain and its important implications on food security (Ercsey-Ravasz et al., 2012; Konar et al., 2018).

Chapter 4

Manuscript 3: Reactions to Food Safety Recalls Among Food Insecure and Food Secure Households

4.1 Abstract

Food safety recall impacts across populations can vastly differ, and the behavioral reactions to food safety concerns along the spectrum of food insecure persons is understudied. We use a vignette approach to examine reactions of food secure and food insecure individuals to a hypothetical food safety recall, and determine how reactions vary with price, travel time to a grocery store for a refund of a recalled product, and risk of sickness from consuming the recalled product. Our results indicate reactions are heterogenous across demographics of respondents. We recommend government entities and private sectors to use multiple avenues to target these groups and promote information regarding food safety and food safety recalls.

4.2 Introduction

Even though the United States is one of the world's most developed nations, food safety is still a concern for its government and its citizens. The U.S. Food and Drug Administration (FDA) issued over 200 recalls for various food and beverage products in 2021, as well as major recalls for items like powdered infant formula and peanut butter in 2022[1]. While food safety recalls are not uncommon, their impact across populations can vastly differ. For example, those with peanut allergies are unaffected by food safety recalls related to peanut butter. Similarly, food insecure households may experience food recalls differently than food secure households because food insecure persons prioritize food over other health activities (Berkowitz, Seligman, and Choudhry, 2014). Such different behavioral reactions to food safety concerns along the spectrum of food secure persons has been understudied. Most of the previous literature at the intersection of food safety and food security revolves around SNAP participants perceptions about risks (Neill and Holcomb, 2019) and the fact that food safety is a vital part of a healthy society which can increase the welfare of food insecure populations (Kinsey, 2005).

The impacts of food safety recalls on food have been studied across a range of products, but primarily involve studies of meat, poultry, or eggs due to availability of data. In addition, most studies focus on consumer demand in the presence of food safety recalls (Marsh, Schroeder, and Mintert, 2004; Thomsen, Shiptsova, and Hamm, 2006) or the effect on prices (McKenzie and Thomsen, 2001; Lusk and Schroeder, 2002; Neill and Chen, 2022). There are also several studies on the effects of food safety on fresh produce that focus again on price reactions (Adams, 2020) and demand (Arnade, Calvin, and Kuchler, 2008; Richards and Nganje, 2014). Across both food groups, the impact of food recalls and food safety concerns is clearly an increase in prices and a reduction in demand. For example, food safety recall events significantly reduce demand among beef, pork, and poultry products (Marsh, Schroeder, and Mintert, 2004). Moreover, meat recalls have spillover effects such that beef recalls have negative effects on pork and positive affects on poultry demand. Medium-sized beef recalls with severe health consequences even influence live cattle futures prices (Lusk and Schroeder, 2002). Impacts of food safety recalls on retail shell egg prices vary in magnitude and direction, and last longer than one week (Neill and Chen, 2022). Neill and Chen (2022) also found that large recall events impact prices moreso than small recall events. For fresh produce,

[1]https://www.fda.gov/safety/recalls-market-withdrawals-safety-alerts

Adams (2020) determined food safety recalls of romaine lettuce have mixed affects on price returns. Spinach recalls in 2006 caused decreased sales amongst bagged and bulk spinach, as well as bagged and bulk spring mix (Arnade, Calvin, and Kuchler, 2008). While these studies indicate prices and consumer demand are directly impacted by food safety recalls, other analyses determine the welfare effects of food safety recalls are not always straight forward. For example, Richards and Nganje (2014) calculated changes in willingness-to-pay (WTP) for food items facing a food safety recall and found that a recall causes both a shift and rotation in the demand for the food item, but changes in WTP can have opposite signs depending on the type of consumer (i.e. knowledgeable versus occasional consumers).

Given the clear impacts of food safety recalls on price and demand, as well as the mixed impacts of recalls on different types of consumers, it is plausible that the ramifications of food safety recalls differ depending on socioeconomic and demographic factors. For example, some studies have determined that minority populations suffer from greater rates of some foodborne illness than Caucasions (Quinlan, 2013). Another study determined that the association of low socioeconomic status and foodborne illness varied depending on the pathogen, and that socioeconomic status should be considered when targeting consumer level public health interventions for foodborne illness (Newman et al., 2015). Therefore, it is reasonable to assume that food insecure individuals are likely to react to food safety recalls differently than those who are food secure. One reason for this is the fact that food insecurity is more prevalent among households near the poverty line (Coleman-Jensen et al., 2019). In addition, households in the lowest income quintile in the United States spend over a quarter of their income on food, while households in the middle, fourth, and highest income quintiles spend 12%, 10%, and 7% of their income on food, respectively[2]. Given the likelihood of food insecure households being near the poverty line and the share of income food insecure households spend on food as a result, these households may value the consumption of food products differently than food secure households. This is of particular interest because food insecurity is highly stressful (Laraia et al., 2017), and food insecure individuals may prioritize

[2]https://www.ers.usda.gov/data-products/chart-gallery/gallery/chart-detail/?chartId=58372

food over health activities like refilling a prescribed medication, or may skip doses of prescribed medicine due to cost (Berkowitz, Seligman, and Choudhry, 2014). As part of our study, we find that food insecure individuals are less patient and more willing to take risks compared to food secure individuals, as shown in Figure 4.1. This is similar to findings of Neill and Holcomb (2019), which find that SNAP recipients have a lower perceived risk of *E. coli* being present in fresh produce from smaller farms. Given the challenges food insecure people face and differences in risk preference and patience measures, we hypothesize food insecure individuals will react differently to food safety recalls than food secure households.

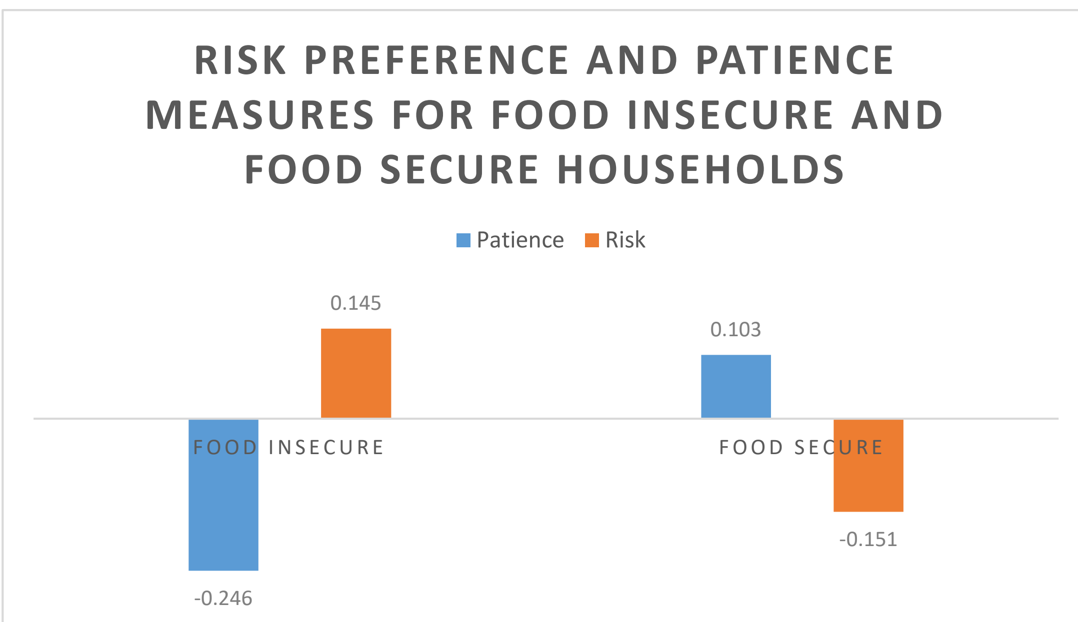


Figure 4.1: Risk and Patience Among Food Secure vs. Food Insecure Households

Our findings suggest that attributes about specific food items, the ability to return the product for a refund, and demographic factors significantly impact a consumer's decision to obtain a refund, throw away, or consume an item facing a food safety recall. We also find that reactions to food safety recalls differ among certain groups of consumers, such as those who are food insecure, receive SNAP benefits, or are nonwhite. As a result, we recommend that both government entities and the private sector utilize multiple avenues to target these groups to promote information regarding food safety and food safety recalls, such as social media and information campaigns.

This work offers an expansion to existing literature in both the food safety and food insecurity realms. First, we use a vignette approach to examine reactions of both food insecure and food secure individuals to a hypothetical food safety recall. Secondly, we determine how decisions to react to a food safety recall vary with factors such as price, travel time to a grocery store for a refund of a recalled product, and risk of sickness from consuming the recalled product. Knowing how different population groups react to food safety recalls can help policy makers as they shape public health interventions for foodborne illness and work to tackle food insecurity.

The remainder of this article is as follows: a discussion of the survey data collected and the vignette approach, the empirical model and results of the study, a discussion of policy implications and solutions, and concluding remarks about our approach and areas for future work.

4.3 Survey Design and Data Collection

We utilize survey methodology to understand consumers' decisions to seek a refund, throw away, or consume eggs and romaine lettuce that are subject to a hypothetical food safety recall. The choice of food items for this study is not arbitrary. We choose to study recall decisions surrounding eggs and romaine due to the differing factors associated with each item. First, eggs must be cooked before consumption, while romaine lettuce is eaten raw. Second, eggs are a considered a cheaper source of protein relative to meat and meat alternatives, while romaine is a common vegetable consumed by many households - albeit not the cheapest nor most expensive. Finally, both food items have been subject to a number of recalls over the past decade. By examining products with different dietary functions, we are able to determine how attributes and demographic factors influence decision making for a food safety recall across food groups. Decisions are analyzed via a multinomial logit regression to determine socioeconomic and demographic factors as well as personality traits such as risk preference and a measure of patience that are determining factors of a respondent's reaction to a food safety recall.

The vignette method is a type of stated preference experiment where respondents are asked to make hypothetical decisions (regarding products, situations, etc.) with differing levels of attributes. Social psychology was the first field to use this methodology (Alexander and Becker, 1978), and has expanded to several fields, including marketing and management (Aguinis H. and Bradley K.J., 2014) as well as economics (Kapteyn, Smith, and van Soest, 2007; Epstein, Mason, and Manca; Ellison and Lusk, 2018). Survey respondents are asked about hypothetical scenarios, and the vignette method has proven to recover the true effects of attributes of interest in real-world scenarios Hainmueller, Hangartner, and Yamamoto (2015).

The vignette in our analysis has three attributes - price, risk of sickness, and travel time to store - each varied at three levels. From the 27 possible vignettes ($3^3 = 27$), we selected a subset of nine vignettes such that each variable was uncorrelated with the others (an orthogonal, fractional factorial design).

We elicit each participants consumption pattern for each of the food items and then randomly assign them to evaluate one of the nine vignettes. Each respondent answered a vignette for both romaine and egg food safety recalls if they consumed each one at least once a month. If they responded by indicating that they never consumed one of the food items, then they were not presented with the vignette for that food item. If they never consumed both food items then they were not included in the experiment.

Examples of the basic vignette for romaine lettuce and eggs are shown below:

Romaine Vignette:

Imagine you just found out about a food safety recall for romaine lettuce you recently purchased due to the risk of *E. coli*. The estimated risk of *E. coli* from the consumption of the lettuce is about [**1 in 3 (33%); 1 in 6 (17%); 1 in 9 (11%)**]. The lettuce cost you [**$2.00; $2.70; $3.30**] per pound. Assuming the grocery store where you can return the lettuce for a refund is a [**20; 30; 40**] minute round trip, what would you do?

Eggs Vignette:

Imagine you just found out about a food safety recall for large, Grade A eggs you recently purchased due to the risk of salmonella. The estimated risk of salmonella from the consumption of the eggs is about [**1 in 100 (1%); 1 in 200 (0.5%); 1 in 300 (0.33%)**]. The eggs cost you [**$1.60; $1.80; $2.00**] per dozen. Assuming the grocery store where you can return the eggs for a refund is a [**20; 30; 40**] minute round trip, what would you do?

We utilized data from Centers for Disease Control and Prevention (2022) in order to create realistic probabilities of sickness from *E. coli* and salmonella. We first gather the total number of cases from the foodborne illness of interest over 2017-2020, regardless of the source of contamination. Then, we gather the total number of illnesses for the foodborne illness of interest with the specific food causing the illness. For example, the risk of illness from romaine facing a food safety recall for *E. coli* is calculated as follows:

$$\text{Risk of illness for romaine} = \frac{\text{\# of } \textit{E. coli} \text{ cases caused by consuming romaine lettuce contaminated by } \textit{E. coli}}{\text{\# of illnesses caused by } \textit{E. coli}}$$

We calculate the risk of illness caused by consuming romaine contaminated by *E. coli* to be $\frac{617}{3{,}588} \approx$ 17% and the risk of illness caused by consuming eggs contaminated by salmonella to be $\frac{103}{13{,}472} \approx$ 0.7%. From these base calculations, we choose the three levels of risk to be 1 in 3; 1 in 6; and 1 in 9 for romaine lettuce and 1 in 100; 1 in 200; and 1 in 300 for shell eggs.

To determine the price level attributes, we gathered price data from the Federal Reserve Bank of Saint Louis and rounded to the nearest 10 cents. For romaine, we used the average price of romaine from February 2020 (the last price point recorded for 2020) and December 2021 (the highest price for romaine lettuce over the past five years) to determine a base price point of $2.70 (U.S. Bureau of Labor Statistics, 2022b). For shell eggs, we used the average price between February 2021 and February 2022 to determine a base price point of $1.80 (U.S. Bureau of Labor Statistics, 2022a). Travel time to a store to obtain a refund of a food item facing a food safety recall is based on research showing the average time individuals in low-income areas spend traveling to a grocery store is 19.5 minutes (Ver Ploeg et al., 2009; Hamrick and Hopkins, 2012).

To determine the food insecurity status of survey respondents, we utilize the 18 survey items from the U.S. Household Food Security Survey Module (Bickel et al., 2000). Households are considered food insecure if they answer affirmatively to three or more questions in the survey. In addition to the vignette and food security portions of the survey, we ask respondents to answer questions regarding their personal risk preference and patience. Risk preference is a predominant factor in decision making, and is critical for economic analysis and policy prescriptions (Charness, Gneezy, and Imas, 2013). In order to measure personal risk preference and patience, we use the survey questions and methods outlined in previous studies by Falk et al. (2016) and Falk et al. (2018). For the personal risk preference measure, each survey respondent was asked about their willingness to take risks, and answered five questions about their preference for a 50/50 chance of receiving differing amounts of money as a sure payment. For the patience measure, each survey respondent was asked about their willingness to give up something beneficial today in order to gain something even more beneficial in the future, and answered five questions about their choice between differing amounts of money today versus in the future.[3]. Finally, we also ask respondents demographic questions about their age, gender, race, education, political affiliation, income, whether children are present in the household, and whether they are recipients of SNAP benefits.

[3]The survey questions for U.S. residents we utilized in the analysis can be downloaded from https://www.briq-institute.org/global-preferences/downloads

We collect a nationally representative sample of consumers in the United States via an online panel. We had 1050 completed surveys, and after removing inconsistent responses based on an inattention question we were left with 860 responses for analysis. Comparing food insecure and food secure individuals, we find several differences in characteristics. Notably, food secure individuals in our study have lower measures of personal risk preference (indicating a person is more risk averse). Additionally, 35% of food insecure individuals are also SNAP recipients, compared to about 7% of food secure individuals. The food insecure group had more nonwhite respondents, less college education, more children in the household, and more respondents who were low income compared to the food secure group. Summary statistics and descriptions of variables used in the analysis are presented in Table 4.1. We present the mean of our explanatory variables across the two groups of interest - food insecure and food secure persons.

Table 4.1: Socio-Demographic Variables and Definitions

Variable	Definition	*Food Insecure* Mean	*Food Secure* Mean
Personal Risk Preference	Measure of personal risk preference	0.145	-0.151
Patience	Measure of patience	-0.246	0.103
Female	1 if female; 0 otherwise	0.643	0.463
SNAP	1 if current SNAP recipient; 0 otherwise	0.353	0.068
Age	Current age	35.042	44.506
Food Budget > $100	1 if weekly food budget > $100; 0 otherwise	0.592	0.672
Nonwhite	1 if respondent identified as nonwhite; 0 otherwise	0.118	0.084
College	1 if obtained a college degree; 0 otherwise	0.462	0.641
Democrat	1 if identifies as a Democrat; 0 otherwise	0.378	0.342
Children in HH	1 if children under 18 are in household; 0 otherwise	0.424	0.172
Low Income	1 if income is less than $40,000; 0 otherwise	0.471	0.190
Medium Income	1 if income is between 40,000−99,999; 0 otherwise	0.332	0.476
High Income	1 if income is $100,000 or more; 0 otherwise	0.197	0.334
Number of observations		238	622

4.4 Methods

Our analysis makes use of a multinomial logit regression to determine how attributes such as price, risk of sickness, and travel time to a store and demographic variables affect a person's decision to obtain a refund, throw away, or consume a food facing a food safety recall. Given the three possible outcomes, the corresponding probability π that a person i chooses a specific outcome j are as follows (Greene, 2012):

$$\pi(Y_i = j) = \frac{\exp(X\beta^j)}{\sum_{j=1}^{3} exp(X\beta^j)} \tag{4.1}$$

where X are explanatory variables and β^j is a set of coefficients that are estimated and correspond to each outcome j. In order to identify our model, we set the base outcome to be the decision to throw away the food item. Therefore, all coefficient estimates are relative to the decision to throw away the recalled food.

Specifically, we model each person's decision to obtain a refund, throw away, or consume a food item that has a food safety recall as follows:

$$\begin{aligned} Choice_i = \beta_{0j} + \beta_{1j}Price_i + \beta_{2j}Store_i + \beta_{3j}Sick_i + \beta_{4j}FI_i \\ + \beta_{5j}RiskPref_i + \beta_{6j}Patience_i + \beta_{7j}FIRisk_i + \beta_{8j}FIPatience_i + \alpha_{\mathbf{j}}\mathbf{Z_i} + \varepsilon_{ij} \end{aligned} \tag{4.2}$$

where $Choice$ is the decision of individual i to obtain a refund, throw away, or consume a food item facing a food safety recall (outcome j). The vignette variables are denoted by $Price$, $Store$, and $Sick$. FI is the food insecure dummy variable, $RiskPref$ is a measure of the respondent's personal risk preference, and $Patience$ is a measure of the respondent's patience. $FIRisk$ and $FIPatience$ are interaction terms between the food insecurity dummy and the respondent's risk preference and patience measures, respectively. The matrix of demographic variables is denoted as $\mathbf{Z}$ which includes the following: $Child$ is a dummy variable indicating the presence of children in the household; $Female$ is an indicator for whether the respondent identified as female; $SNAP$ is an indicator for whether the respondent is a SNAP benefit recipient; Age is the age of the respondent; $Nonwhite$, $College$, Dem, $MInc$, $HInc$ are the indicator variables for whether the respondent identifies as nonwhite, has a college degree, identifies with the Democratic party, has a medium level of income, has a high level of income, respectfully. Finally, ε is the normally distributed error term. We model the choice to obtain a refund, throw away, or consume each food item separately - i.e. eggs impacted by a food safety recall due to risk of salmonella and a second model for romaine lettuce impacted by a food safety recall due to risk of *E. coli*.

Our study design has several assumptions. First, we assume consumers' reactions to food safety recalls are not impacted by attributes outside of our experimental design, such as the timing of the recall relative to the purchase. For example, it is possible that enough time has lapsed between the purchase of a food item and the recall of said food item due to risk of foodborne illness that the consumer has already consumed the food or thrown it away due to spoilage. Our experiment also assumes the respondent is aware of the recall since we explicitly inform them. In reality, it is possible that consumers who have purchased a food item facing a food safety recall have varying amounts of awareness in regards to the recall. Media coverage around the time of the recall event has shown to impact consumers' decisions (Neill and Chen, 2022). Also, we do not have a proper measure of respondents' time use. Respondents who have less leisure time available may react differently to a food safety recall than those who have ample leisure time. Finally, our results may be dependent on the choice of food items in our analysis, and may not be comparable outside of recalls for romaine lettuce or eggs. However, we believe our analysis offers new insight to policy makers and researchers on the reactions to food safety recalls across groups of individuals.

4.5 Results

The survey respondents' decisions are summarized in Figure 4.2. The percentage of respondents who decided to seek a refund are similar for both eggs and romaine lettuce under a food safety recall. Approximately 27.8% of respondents said they would seek a refund for romaine lettuce, while 27.1% would seek a refund for eggs. However, decisions to throw away or consume are different for romaine and eggs that have been recalled due to risk of a foodborne illness. For romaine lettuce, 70.1% of respondents said they would throw away the romaine, while only 2.2% said they would consume. In contrast, 60.6% of those surveyed responded they would throw away eggs impacted by a food safety recall, and 12.3% would consume. The percentage differences in how survey respondents react to a food safety recall is likely due to the fact that eggs can be cooked to reduce the chance of foodborne illness (CDC, 2022), while romaine lettuce is primarily eaten raw.

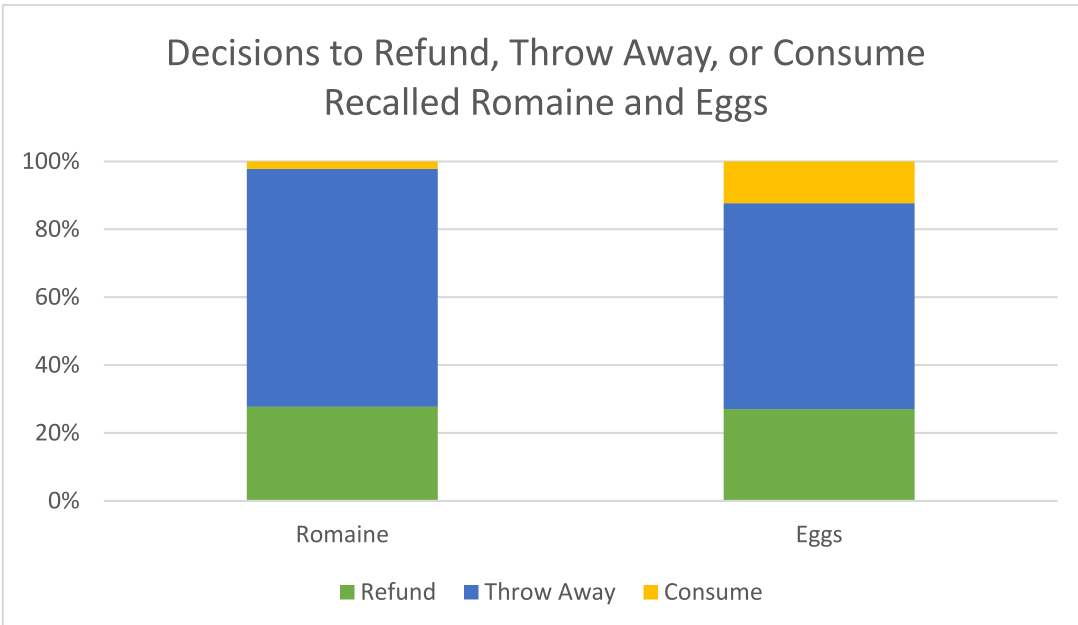


Figure 4.2: Survey Responses to Seek Refunds, Throw Away, or Consume Food Under a Food Safety Recall

The results of the multinomial logistic regressions for both romaine lettuce and shell eggs are given in Table 4.2. All regressions use the decision to throw away affected food items as the base outcome. We find that for the three choice attributes, only price and travel time to store were significant factors in the decision to refund or consume food items facing a food safety recall. Risk of sickness was not a significant factor. We find that price is significant for consumption of eggs despite a recall event compared to throwing the eggs away. For romaine, we find that price is significant for both obtaining a refund and consuming recalled romaine relative to throwing the romaine away. For each dollar increase in price, the log-odds of consuming eggs increases by 1.26, while the log-odds of consuming romaine increases by 0.77. A one dollar increase in price results in an increase in the log-odds of obtaining a refund for romaine by 0.27. Given that one primary reason for reducing food waste is to save money (Quested, Ingle, and Parry, 2013; Graham-Rowe, Jessop, and Sparks, 2014; Neff, Spiker, and Truant, 2015; Thyberg and Tonjes, 2016), it makes sense that consumers are more likely to refund or consume a recalled product over throwing it away as price increases.

Table 4.2: Regression Results from Egg and Romaine Lettuce Vignette

	Eggs		***Romaine***	
	Refund	Consume	Refund	Consume
Variables				
Price	0.549	1.262*	0.273*	0.772*
	(0.517)	(0.745)	(0.161)	(0.433)
Travel Time to Store	-0.047***	0.016	-0.034***	-0.005
	(0.010)	(0.015)	(0.011)	(0.040)
Risk of Sickness	0.168	0.295	-0.006	-0.033
	(0.291)	(0.394)	(0.010)	(0.029)
Children in HH	0.123	0.499	0.364	0.771
	(0.243)	(0.318)	(0.247)	(0.567)
Female	-0.138	-0.137	-0.368*	-0.869
	(0.187)	(0.248)	(0.196)	(0.598)
SNAP Benefit Recipient	0.179	0.343	0.138	1.897**
	(0.273)	(0.349)	(0.285)	(0.756)
Age	0.024***	0.009	0.031***	-0.015
	(0.008)	(0.011)	(0.008)	(0.034)
Nonwhite	0.542**	-1.560**	0.001	-13.049***
	(0.275)	(0.750)	(0.301)	(0.399)
College	-0.151	-0.160	0.096	0.118
	(0.185)	(0.251)	(0.190)	(0.703)
Democrat	0.263	0.127	0.377**	-0.133
	(0.177)	(0.238)	(0.179)	(0.664)
Medium Income	-0.103	0.194	-0.342	0.777
	(0.231)	(0.340)	(0.244)	(0.818)
High Income	-0.267	-0.090	-0.391	1.037
	(0.282)	(0.376)	(0.288)	(0.896)
Food Insecure	0.565**	0.173	0.332	0.738
	(0.226)	(0.303)	(0.242)	(0.802)
Personal Risk	0.033	0.219	-0.006	-0.151
	(0.140)	(0.184)	(0.145)	(0.257)
Patience	0.006	0.257	-0.012	0.455
	(0.124)	(0.179)	(0.127)	(0.498)
Food Insecure × Personal Risk	0.337	0.564*	0.414*	0.064
	(0.232)	(0.299)	(0.243)	(0.566)
Food Insecure × Patience	0.522**	-0.079	0.302	-0.018
	(0.252)	(0.331)	(0.275)	(0.664)
Constant	-1.603	-5.096***	-1.794**	-5.777**
	(1.134)	(1.573)	(0.778)	(2.650)

Note: Robust standard errors are presented in parentheses.
Note: *** p>0.01, ** p>0.05, * p>0.1

Travel time to the store is strongly significant for obtaining a refund for both eggs and romaine lettuce. For eggs, we find that for each minute the travel time to the store increases, the log-odds of obtaining a refund is reduced by approximately 0.05 compared to throwing recalled eggs away. The log-odds of obtaining a refund for recalled romaine lettuce is reduced by 0.03 compared to throwing away lettuce facing a food safety recall for each minute the travel time to the store increases. As travel time to a store for a refund of a food item facing a food safety recall increases, travel costs also increase (such as cost of gas for driving a vehicle, cost of transportation such as a bus ticket, and time lost to do other activities). This increase in costs to the consumer explain why the log-odds of seeking a refund of a food item facing a food safety recall decrease as travel time increases.

For romaine lettuce facing a food safety recall, female consumers are less likely than males to seek a refund relative to throwing away the recalled romaine. This is likely contributable to the fact that women have less leisure time than men, and the overall differences in time use between men and women (Thrane, 2000; Sayer, 2005; Van der Lippe et al., 2011).

Being a SNAP benefit recipient is significant and increases the log-odds of the decision to consume romaine lettuce facing a food safety recall by 1.9 compared to non-recipients, relative to the decision to throw the affected lettuce away. SNAP recipients are the most price-conscious and employ price-saving efforts soon after receiving their benefits (Zaki and Todd, 2021). This fact coupled with the relatively short window of consumption before romaine lettuce spoils likely drives SNAP recipients to consume rather than throw away romaine lettuce that has been recalled due to a food safety risk. In addition, Neill and Holcomb (2019) find that SNAP participants have lower perceived risk of *E. coli* being present in purchased food, which also explains the increased log-odds of SNAP recipients consuming romaine under a food safety recall relative to throwing it away.

Age is a significant factor and increases the log-odds of refunding eggs or romaine facing a food safety recall by 0.025 and 0.031, respectively. Our results are similar to Schafer et al. (1993), who found that age is related to food safety behavior. In addition, consumer expenditures vary by age (Foster, 2015). For example, the share of the food budget spent on food at home increases with age (Foster, 2015). It is likely that as age increases, respondents are more likely to seek a refund relative to throwing away a food item facing a food safety recall due to spending habit differences among different age groups.

We find for nonwhite consumers, the log-odds of seeking a refund increases by 0.54 (compared to white consumers), relative to throwing away eggs facing a food safety recall, while the log-odds ratio of consuming eggs decreases by 1.56 relative to throwing away eggs facing a food safety recall. When considering romaine lettuce impacted by a food safety recall, we find the log-odds of consumption is reduced by 13 compared to throwing away the romaine. Democrats are more likely to seek a refund relative to throwing away romaine lettuce. The log-odds of seeking a refund increase by 0.392 relative to throwing away romaine lettuce impacted by a food safety recall when the consumer identifies with the democratic party. This may be due to the link between personality and political choice (Capara, Barbaranelli, and Zimbardo, 1999; Caprara et al., 2006).

Our results indicate that food insecure persons are more likely than food secure persons to seek a refund of eggs under a food safety recall. The log-odds of seeking a refund for eggs increases by 0.57 relative to throwing away the eggs under the recall. Since food insecurity is stressful to individuals (Laraia et al., 2017), and food insecure persons may focus all their efforts on finding food (Hadley and Crooks, 2012), it is plausible that food insecure individuals are returning eggs facing a food safety recall to buy food not at risk for foodborne illness.

While the measures for personal risk and patience alone are not significant factors for whether a respondent chooses to seek a refund or consume a food item facing a food safety recall relative to throwing the food away, we do find the interaction term between food insecurity and personal risk measures, as well as the interaction term between food insecurity and patience, to be significant in our model. Specifically, we find that a food insecure person's log-odds of consuming eggs facing a food safety recall relative to throwing the eggs away increases the more risk-loving they are. Given the relatively low cost of eggs compared to other protein sources (Farrell, 2013; Conrad et al., 2017), the fact eggs are rich in nutrients such as amino acids, choline, vitamins A, B, D, and iron

(FAO, 1985; Griffin, 2016; USDA Agricultural Research Service, 2019), and the chance of getting sick from eggs is reduced when the eggs are cooked until the white and yolk are firm (CDC, 2022), food insecure persons may be trading the benefits of egg consumption for their household despite the risk of sickness, especially when cooking eggs properly. Additionally, a risk-loving food insecure person has higher log-odds of seeking a refund for recalled romaine lettuce compared to throwing the food away. Since food insecure individuals consume less vegetables (Leung et al., 2014; Kendall, Olson, and Frongillo, 1996), they may be willing to return to the store for a refund for another fresh vegetable they can consume, despite the recall and their higher personal risk preferences.

We find that food insecure individuals with higher patience measures have increased log-odds of returning to the store for a refund of eggs facing a food safety recall relative to throwing them away. More patient, food insecure individuals may be willing to seek a refund compared to throwing away contaminated eggs due to the opportunity to buy uncontaminated eggs or another cheap protein source with the refund given.

Finally, the constant term is the intercept for the base group of respondents who have no children, are white, male, do not hold a college degree, do not receive SNAP benefits, do not identify politically as Democrat, and are low income. The base group has lower log-odds of refunding or consuming an item facing a food safety recall compared to throwing the item away.

4.6 Policy Analysis and Implications

Our results offers several insights to researchers studying food safety recalls and policy makers looking to implement effective strategies surrounding the consumer decision to heed food safety recalls. For researchers, we find several factors that should be considered when studying the reactions of food safety recalls in the future. Since travel time to stores is strongly significant for the decision to obtain a refund, any further studies should include this attribute to accurately model decision-making of consumers facing a food safety recall.

For the government, the goal of a food recall is "to protect the public from products that may cause health problems or possible death" by removing "food products from commerce when there is reason to believe the products may be adulterated or misbranded [4]." By implication, a "successful" reaction of a consumer to a food safety recall would result in consumers who have purchased a potentially harmful food item throwing the item away or returning the item to the store for a refund. Our results indicate that not all consumers would be willing to throw away or obtain a refund for eggs or romaine facing a food safety recall. Specifically, SNAP benefit recipients are found to have higher log-odds of consuming romaine under a food safety recall. As indicated previously, there are several explanations for this phenomenon, including the fact that SNAP benefit recipients view risk differently than consumers not receiving SNAP benefits. Furthermore, we do not find that SNAP recipients are more likely to decide to refund romaine lettuce facing a recall. In order to encourage SNAP recipients specifically to throw away or refund an impacted food item such as romaine lettuce, policy makers can focus on targeting SNAP recipients during a food safety recall. Possible policy interventions to encourage SNAP recipients to react as desired to a food safety recall could be education of those recipients on the risks of consuming a product impacted by a food safety recall. Since there are opportunities for public and private sectors to partner together to successfully co-regulate food safety (Garcia Martinez et al., 2007), government officials and food companies could work together to provide this information to SNAP recipients. Another opportunity would be offering refunds for products that does not require consumers to travel to the store in order to return the item.

Other notable demographic groups in our analysis include nonwhite respondents. Survey takers who identified as nonwhite were more likely to react successfully to a food safety recall for both eggs and romaine lettuce (i.e. they were more likely to seek a refund and less likely to consume an impacted product). Additionally, food insecure persons were more likely to refund eggs under a food safety recall, and no more likely to consume eggs facing a recall compared to throwing away

[4] https://www.fsis.usda.gov/food-safety/safe-food-handling-and-preparation/food-safety-basics/understanding-fsis-food-recalls

the eggs. Policy makers should continue to promote the importance of food safety among these groups such as *Food Safe Families*, a national food safety public education campaign headed by the USDA[5], and continue to promote these materials in multiple languages to keep this information accessible to those consumers identifying as nonwhite. Given the success of social media tools to disseminate public health messages (Mayer and Harrison, 2012), both public and private sectors should work together to circulate relevant information regarding food safety recalls to consumers.

4.7 Conclusions

The nuances of decision making when consumers are faced with a hypothetical food safety recall of romaine lettuce and eggs. Specifically, we aim to determine how decision making is similar or different across food insecure and food secure persons. Using the vignette method and multinomial logit regression, we find the outcome depends on contextual factors such as price and travel time to a store and demographics.

We add to the food insecurity and the food safety literature by determining attributes affecting a decision facing individuals who have purchased items subject to a food safety recall. We show there are some differences in how food insecure persons react to recalls of shell eggs, and we find other demographic groups react differently to food safety recalls. Specifically, we find SNAP benefit recipients have higher log-odds of consuming romaine lettuce facing a food safety recall compared to throwing it away. We also find that nonwhite consumers have higher log-odds of seeking a refund and lower log-odds of consuming eggs affected by a food safety recall relative to throwing the eggs away. Additionally, they have lower log-odds of consuming romaine lettuce under a food safety recall relative to the decision to throw it away. Our findings are relevant to researchers and policy makers, as decisions to react to a food safety recall differ based on demographics and product specific factors.

[5]https://www.usda.gov/topics/health-and-safety

Our findings set the stage for further research surrounding the factors that influence decision-making under a food safety recall. We demonstrate that attributes regarding a food safety recall are important to how consumers react to food safety recalls, and we also determine these decisions can differ based on demographic factors. Future work should focus on other variables not utilized in this analysis, such as timing of the recall event relative to purchase date or the amount of leisure time available to consumers. For example, time use of SNAP benefit recipients is often an ignored component in policy analysis (Davis and You, 2011; You and Davis, 2019). Even though we assume our respondents are aware of a food safety recall, this may not always be the case. Therefore, analysis on awareness of food safety recalls among food insecure and food secure persons is needed, as this could differ between the two groups. Research accounting for these metrics would provide better understanding of the decision making process consumers undergo when faced with a food safety recall, and would better inform policy makers on the best practices to prevent foodborne illness among consumers. In addition, this research highlights the importance of accounting for the link between food safety and food waste in future research. Food waste is a natural part of the food system, predominately due to food safety concerns, like food facing a food safety recall or food that is spoiled and unfit for consumption.

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