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The Effect of Public Transportation Accessibility on Food Insecurity

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I examine whether access to public transportation reduces the probability of food insecurity for households. The data set combines information from the Current Population Survey Food Security Supplement and the National Transit Database from 2006 to 2009. I address a potential endogeneity problem using the changes in federal governmental transportation funding as instruments. I find evidence of a negative causal effect of public transportation accessibility on food insecurity. An extra bus-equivalent vehicle per 10,000 people decreases the probability of food insecurity of households by 1.6 percentage points. In particular, the impact of public transit is more prominent among poor households and poor African-American households.
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INTRODUCTION

In February 1994, the US Department of Agriculture (USDA), in conjunction with the Census Bureau, created measures of food security at the household level to gauge food accessibility. Food insecurity is important as a direct measure of material hardship, such as food and clothing insufficiency [Mayer and Jencks 1989].[1] Food security status is measured through a survey using a nationally representative sample of households. Heads of these households have responded to 18 questions regarding their year-long ability to obtain food. Households are defined as food insecure if they are unable to acquire adequate food at times during the year due to the lack of money or other resources.[2] Households' food insecurity rate decreased to a minimum of 10.1 percent in 1999, implying that 10.5 million households suffered from food insecurity, and then it went up to a maximum of 14.7 percent (17.4 million households) in 2009. The rate was 14.9 percent in 2011 (USDA, Economic Research Service (ERS) 2012). In response to a large increase in food-insecure households and evidence of its negative health consequences,[3] economists have become interested in analyzing the determinants of food insecurity [Gundersen et al. 2011a].

A number of studies have investigated the impact on food insecurity of such factors as welfare benefits [Gundersen and Oliveira 2001; Borjas 2004; Wilde and Nord 2005; Gundersen and Kreider 2008; Mykerezi and Mills 2010; Gundersen et al. 2011b; 2012], homelessness [Gundersen et al. 2003], and household-income levels [Ribar and Hamrick 2003; Leete and Bania 2010]. Beaulieu [2007] noted that, in addition to socioeconomic factors, access to food also depends on local conditions such as public transportation, proximity to retail grocery stores, as well as the price of food. The availability of local public transportation is expected to influence access to food stores. As described in Blanchard and Lyson [2006; 2002], households without cars, by necessity, must use public transportation if grocery stores are not located within walking distance. If public transportation is not available or readily accessible, then households without cars may go grocery shopping less frequently and just use close convenience stores to buy snack food; people in those households are more likely to report being food insecure, since they cannot access balanced meals [Cafiero 2013]. Limited access to public transportation may lead to another unfavorable consequence; households without cars necessarily spend more time and money to travel to grocery stores. Higher costs may cut the size of meals, increasing food insecurity.

A lack of public transportation matters, particularly to the poor, since they are less likely to own cars. Those who can afford to procure and maintain an automobile will have a greater chance of not running short on money for food. Further, even if some poor people have food stamp vouchers or money for food, they may not be able to spend the vouchers or money unless grocery stores are located in an area accessible without vehicles. US Department of Transportation (USDT) stated that in 2001, the proportion of households without vehicles was around 10 times higher for households with incomes less than $25,000 (20.3 percent) compared with those with incomes equal to or greater than $25,000 (2.3 percent). Berube et al. [2006] also discussed that households without access to automobiles are "disproportionately poor and minority."[4] The authors addressed that disparity in car ownership is considerably noticeable depending on income level as well as race. In particular, even among the poor, African-Americans are less likely than whites to own automobiles.

In a similar vein, it is shown that the food insecurity rate is more prevalent among the poor, compared with non-poor households. In 2010, the rate among low-income households, defined as households with income below 185 percent of the federal poverty level, was about 33 percent, more than two times the national level. Those poor households accounted for roughly 60 percent of US food insecure households. There is also a white-black difference in food insecurity rates; the rate is higher for those who are black (25.1 percent) *vs* those who are white (10.8 percent).

In short, vehicle ownership is strongly associated with income level of a household, and, in turn, income level determines food hardships of a household. Poor households tend to have lower car ownership and higher food insecurity rates compared with non-poor households. Furthermore, the propensity for not owning an automobile as well as of being food insecure is more prominent for the black poor than the white poor. In this paper, I document the role of public transportation accessibility on food insecurity for households. I also examine whether the effect of access to public transit differs by income level and race.

This study presents the first empirical analysis of the impact of public transportation on food insecurity. I use the number of vehicles operated in urbanized areas (UA) from the National Transit Database (NTD) and household food insecurity data from the Current Population Survey Food Security Supplement (CPS-FSS) from 2006 to 2009. The data on public transportation at the UA level are linked to the data on food insecurity for households living in a Metropolitan Statistical Area (MSA). I define the matched area between a UA and an MSA as a local area.

It is, however, hard to identify the effect of public transportation at the local area level on food insecurity because of potential endogeneity. Unobservable public welfare interests of a local government could be correlated with both public transportation accessibility and food insecurity. For example, if a local government is interested in the welfare of the residents, then it may invest more in public transportation system. Similarly, local poverty rates may impact food insecurity through lack of income and lack of car ownership. Local poverty may also be correlated with public transportation accessibility and failure to control for it may result in biased estimates. Without a control for the variation in welfare interests across local governments, the estimated effect of transit vehicles on food insecurity will be biased. I address this empirical difficulty using the Urbanized Area Formula (UAF) Grants,[5] which are federal transit funds at the UA level, as instruments for public transportation. As I discuss below, the decision on the amount of the UAF funds from the *federal* government does not depend on a *local* area's welfare interests. Thus, the federal transit subsidies are expected to have an influence on the number of public transit vehicles but should have no direct impact on a household's food insecurity.

There are two types of grants associated with public transportation: (1) formula grants and (2) discretionary grants. The UAF grants, one of the formula grants, can be justified as viable instruments because the amount of funds is decided solely by the federal government.[6] The federal government calculates the amount of the UAF funds based on several factors such as population, population density, and transit mileage released by the NTD 2 years ago.[7,8] One may doubt the validity of the instrument arguing the possibility that more transit vehicles lead to a higher allocation of federal grants. According to the formula above, the amount of the UAF grants is determined based on the past demographic and transit data of a local area. Thus, there may not exist the problem of reverse causality even with the contemporary grants.

I find that accessibility of public transportation, measured by the number of bus-equivalent vehicles operated in a UA, has a significantly negative effect on food insecurity of a household. One additional bus-equivalent vehicle per 10,000 people decreases the probability of food insecurity of households by 1.6 percentage points. The estimated results indicate that the effect of public transportation on food insecurity is statistically significant for poor households, those earning less than 185 percent of the federal poverty line, and all households. In particular, the relationship is more conspicuous among low-income households, compared with all households. These findings imply that the overall effect on food insecurity from public transportation in the sample of all households stems from the high impact present in the sample of poor households. Furthermore, I find a strong effect of transportation accessibility among the poor African-American households, not among the poor white households. Results are robust to using different measures of public transportation accessibility as well as various measures of food insecurity. Overall, this paper suggests that public transit vehicles may be an important determinant of food insecurity of households, particularly for the poor Black households.

The rest of this paper is organized as follows. In the next section, I provide a literature review. The subsequent section presents an empirical specification, and the latter section describes data construction. The estimated results are in the penultimate section. The final section concludes the paper.

LITERATURE REVIEW

Of previous literature studying the role of public transportation, a study by Glaeser et al. [2008] is the most relevant to this paper. Using decennial Census-tract level data (1980, 1990, and 2000), they examined whether access to public transportation causes the poor to have a higher propensity to reside in central cities. Unlike this paper, where I use food insecurity at the household level as a dependent variable, they used measures of poverty such as poverty rates and household median income at the tract level.[9] Glaeser and his colleagues measured access to public transportation with proximity to a rail transit from a census tract, while I use the number of bus equivalent vehicles actually operated in a local area. The authors considered endogeneity of transit access because public transportation may be built or expanded to support the poor. In order to account for such possible empirical issues, they limited the sample to 16 cities and peripheral districts of New York City where no public transportation systems were added for the convenience of the poor. They concluded that a higher density of poor populations in central cities is attributable to proximity to public transportation.

Contrary to a few economic studies on public transportation, there has been a large literature examining the factors that determine food insecurity. The majority of studies that analyzed the determinants of the increase in food insecurity since the recession in 2001 have focused on the impact of food assistance programs. Some studies have found that food welfare programs decrease the probability of being food insecure, [Borjas 2004; Mykerezi and Mills 2010; Gundersen et al. 2012], while others found no causal effect of the Food Stamp Program (FSP, renamed Supplemental Nutrition Assistance Program or SNAP as of October 2008)[10] [Gundersen and Oliveira 2001] or even a positive association of food stamp participation on food insecurity [Wilde and Nord 2005]. The debate over the impact of food assistance programs on food insecurity has arisen due to various empirical problems. The choice of receiving welfare benefits may be correlated with unobserved factors [Gundersen and Oliveira 2001; Borjas 2004; Wilde and Nord 2005; Mykerezi and Mills 2010; Gundersen et al. 2012].[11] The possibility of misreporting food insecurity status and food assistance participation could also be an obstacle for identification of the effect of FSP on food insecurity [Gundersen and Kreider 2008; Gundersen et al. 2012].

Some studies have focused on food insecurity status of minority households such as homeless female-headed households, American Indians, or immigrants, since those households' food insecurity rate tends to be higher. Gundersen et al. [2003] analyzed the relationship between homelessness and food insecurity for female-headed families in Worcester, Massachusetts, from August 1992 to July 1995. To account for selection, they compiled information of homeless female-headed households and female-headed low-income households residing in houses. They found evidence that families with higher risk of homelessness are more likely to have higher levels of food insecurity. Food insecurity for American Indians was discussed by Gundersen [2008]. The article described that food insecurity levels are higher for American Indians than for non-American Indians, holding everything else constant. Using three different measures of food insecurity,[12] the author suggested that the significance of level differences between American Indians and non-American Indians differs depending on measures of food insecurity. Borjas [2004] took notice of a steep reduction in food insecurity rate among immigrants, compared with natives between 1994 and 1998, although the policy change of Personal Responsibility and Work Opportunity Reconciliation (PRWOR) Act of 1996 has imposed more restriction on the eligibility of immigrants to receive food assistance. With the data of CPS-FSS, Borjas [2004] used the variation across states in the aids to immigrants along with the national experiment of the policy change of the PRWOR and found that a reduction in public assistance leads to an increase in the probability of having food insecurity of households.

EMPIRICAL STRATEGY

Empirical specification

Consider a linear probability model of equation (1) below.

$$FI_{imt} = \alpha + \beta PT_{mt} + \mathbf{Y}'_{mt}\gamma + \mathbf{X}'_{imt}\Omega + Z'_{st}\Psi + \mu_s + \lambda_t + \varepsilon_{imt} \tag{1}$$

where i indicates a household, m is a local area, s stands for a state, and t is an interview year.

The outcome variable, *FI*, is represented by the binary indicator of food insecurity status of each household; the creation of *FI* is explained in the data section. *PT* stands for public transportation accessibility, measured by the number of bus-equivalent vehicles such as subways, light rails, etc. per 10,000 people in a local area in year t: I discuss this variable in more detail below. **Y** represents a vector of annual unemployment rate and population in a local area. The local unemployment rate is used as a proxy for local labor market conditions. **X** is a vector of family characteristics: information of whether a household received food stamp benefits, poverty status, household structure, the number of employed individuals, the elderly, and children in a household, family income, and home ownership. As discussed in previous studies, the FSP is designed to help low-income households obtain food. Therefore, food insecurity may be affected by food stamp receipts at the household level. To control for the possible effect of the program, food stamp participation at the household level is included in this specification.[13] **X** also contains attributes of the household head: education level, race, Hispanic ethnicity, gender, marital status, and age dummies. As proxies for the extent to which state governments are interested in public welfare, I also use a state-level government's generosity measure (public welfare expenditures) and an indicator of poverty by state (food stamp participation rate or takeup rate), and they are denoted by **Z**. The former one is calculated by taking logarithm of public welfare expenditures in $1,000 in each state. The latter is measured by dividing the number of people participating in the FSP by the FSP-eligible people in a state.[14]

The specification contains state dummies[15] and year dummies as fixed effects, μ_s and λ_t, respectively, to control for heterogeneity across states and time. Instead of local fixed effects, I use state fixed effects because local areas within the same state tend to have similar aspects such as quality of roads, weather, etc. which are omitted. To adjust for possible correlation of errors between the households within the same state, standard errors are clustered at the state level.[16] ε represents an idiosyncratic error term.

Endogeneity concerns

The link between public transportation accessibility and food insecurity may be difficult to identify because of unobserved factors such as public welfare interests of a local government. Public welfare interests may be different between a local and a state government. Even after controlling for the state government's generosity, local public transportation accessibility may be driven by a local government's interests in the well-being of the poor. Even if one controls for local political inclination (e.g. by including a mayor's party affiliation in a regression),[17] there can still be unobservables at the local level that are correlated with public transportation accessibility and food insecurity. In other words, unobserved factors may not be fully captured by local political tendencies, and so a potential endogeneity issue still exists.

To overcome this problem, I instrument for the number of bus-equivalent vehicles with public transit funds received from the federal government using the UAF Grants. This UAF Program (Section 5307, 49 U.S.C. Chapter 53) provides financial assistance annually to urbanized areas in forms of transportation capital and operating assistance.[18] Unlike discretionary grants for which urbanized areas request necessary amounts evaluated and granted by the federal government, the decision process for the UAF funding involves only the federal government. In particular, the federal government assigns the amount based on population and population density for the areas between 50,000 and 200,000 residents. For areas with a population of 200,000 or more, the formula is based on "a combination of bus revenue vehicle miles, bus passenger miles, fixed guideway revenue vehicle miles, and fixed guideway route miles" in addition to population and population density. These six factors are an exhaustive list of the criteria that are used to compute the amount of UAF grants.

One requirement for the validity of instruments is their independence from the outcome variable. UAF grants cannot be valid as instrumental variables if any criterion for UAF allocations is also related to the variation in food insecurity. I provide a detailed discussion below on whether and how each of these criteria might be related to food insecurity.

First, in order to control for a potential relationship between population and food insecurity, I consider a measure of population at the local area in all my analyses. Second, population density can be used as an additional control variable because an area with a higher population density may be home to a greater number of people facing food insecurity. Unfortunately, data on population density is not published every year. Alternatively, I address this problem by including yearly and local area fixed effects in additional regressions[19] and find that the effect of public transportation on food insecurity is robust. Finally, it is difficult to believe that public transit services, which are measured as bus revenue vehicle miles, bus passenger miles, fixed guideway revenue vehicle miles, and fixed guideway route miles, are purposely scheduled to decrease food insecurity.

However, more frequent services may be arranged in the areas with more expected passengers including the poor, and those areas likely have higher food insecurity rate. In order to address this possible problem, I include the unemployment rate at the local area level in the regressions of food insecurity to control for local variation in economic conditions, which is a reasonable proxy for poverty status, in addition to time fixed-effects as well as state characteristics.

The possibility of reverse causality from the number of transit vehicles operated to higher allocation of the federal funds is also arguably possible. However, the amount of the UAF funds is computed based on demographic and transit mileage data released by NTD 2 years ago. For example, in order to determine the UAF grants for the fiscal year 2009, the federal government examines those factors from 2007. Hence, reverse causality may not be problematic between the current number of public vehicles and the current UAF grants. Instead of using the current grants, however, I use the past grants as instruments because it takes years for the grants to be actually spent for vehicle-related activities.[20]

The UAF grants from the federal government must be spent within 4 years including the appropriation year. For example, the UAF grants for the 2012 fiscal year have been debated by Congress since October 1, 2011; then the amount was finalized into law after President Obama signed on July 6, 2012; on July 18, 2012, the Federal Transit Administration (FTA) of the US Department of Transportation officially published the dollar amount of FY 2012 funds. Then, grantees, or the transit agencies in an urbanized area, started to commence their projects. For instance, if a grantee places an order for a bus, it may take 2 years for the bus to be delivered.[21] In short, a local area should use up the FY 2012 UAF grants through the FY 2015, but will not be able to spend the grants of the FY 2012 during the 2012 fiscal year or the appropriation year. Hence, I include the past UAF federal grants as instruments, not the grants in the appropriation year. Since there is no information on how the formula amount is actually allocated across 4 fiscal years, the instruments for the number of bus-equivalent vehicles in the current year are the last 3 years' UAF grants whose usage started 1, 2, and 3 years ago. For instance, the UAF grants of the FY 2006, 2007, and 2008 are used as instruments for the number of bus-equivalent vehicles operated in the FY 2009.

One could also be concerned about the variation in the instruments, whether the amount of UAF grants varies enough to capture the change in the number of transit vehicles between UAs and across time. As I explain above, since the population size, for example, is considered for the computation of the apportioned amount, the FTA has calculated *dollar unit value*, the amount of dollars legally assigned to one person. The *dollar unit value* of each factor such as population, population density, etc. varies among areas with different population size and across years. For example, the *dollar unit value* to one person in urbanized areas over 1,000,000 people was calculated as \$3.259 in the fiscal year 2008, but \$1.398 in 2009 [USDT 2008; 2009].[22] For urbanized areas with fewer than 1,000,000 people, it was \$2.986 in 2008 and \$1.282 in 2009.

In summary, to account for a potential endogeneity problem, I use the federal government subsidies, more precisely UAF grants in the past, as instruments for the number of bus-equivalent vehicles. The change in the UAF grants for public transportation is related to the number of vehicles, but it is not expected to affect food insecurity directly.

DATA

Food insecurity

Since 1995, the CPS-FSS has collected information related to food-related needs from a nationally representative sample of about 50,000 households once a year. Households are interviewed for 2 years in a row and then dropped from the sample. More specifically, in any given year, half of the sample consists of households who were surveyed in the previous year and the remaining half consists of newcomers. Interviews are conducted in-person or by telephone with a "knowledgeable household member" in each household. Therefore, food insecurity status is recorded at the household level.

Following Gundersen [2008], I employ cross-sectional analysis by constructing the data set where each household appears only once. Since each household was surveyed for 2 consecutive years, I select households interviewed the second time from 2006 through 2008 and all households interviewed in 2009. I accept Gundersen's approach rather than a panel approach because there is little variation across 2 successive years in the number of family members, income level, and education level for each household head.[23]

The measure of food insecurity is based on 18 questions about food hardships in the past 12 months if the household has children, or 10 questions for households without children: the full set of 18 questions is available in Appendix A. These questions determine "if the household cut the size of meals, skipped meals or was hungry, but didn't eat because it couldn't afford enough food." The CPS-FSS states that one single question may not measure food insecurity status properly, but the combination of 18 or 10 questions should be considered to provide "more reliable measure of food insecurity." To classify 18 or 10 questions into food insecurity categories, the USDA has implemented the Rasch scaling method,[24] which assigns a value to each affirmative response to 18 or 10 food insecurity questions and determines thresholds to define food security, low food security, or very low food security conditions.[25] More specifically, households, regardless of having children, are classified to be food secure if they report at most two positive responses to food insecurity conditions.[26] Households with children are low food secure if they report at least three, but fewer than eight food insecurity conditions, while households without children are low food secure if they report 3–5 food insecurity conditions. Households with children who report eight or more food insecurity conditions are classified as having very low food security, whereas households without children are reported very low food security with at least six food insecurity conditions. Following most of the previous literature [e.g., Borjas 2004], food insecurity is defined to be 1 if a household is low food secure or very low food secure, or 0 if food secure.

Figures 1(a) and 1(b) display the distributions of a set of cumulative responses to food insecurity questions for households. Figure 1(a) is for households with children, and the

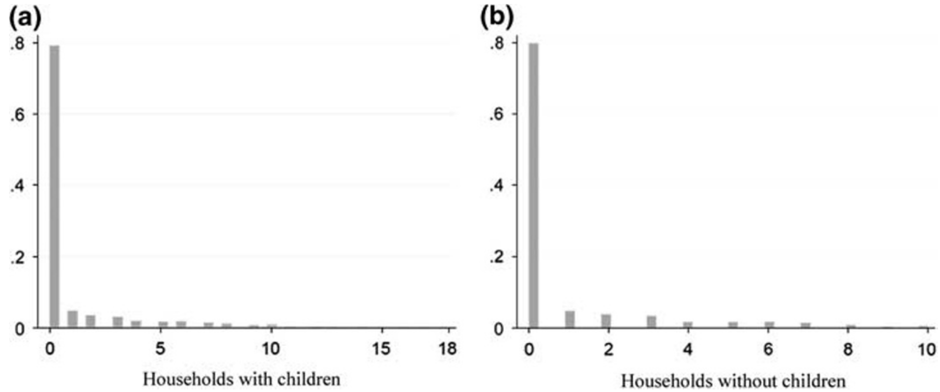

Figure 1. Food insecurity responses for households: (a) Households with children; (b) Households without children.
Note: X-axis refers to the number of affirmative responses to food insecurity questions and y-axis is percent of households.

possible number of affirmative responses varies from 0 to 18. Figure 1(b) is for households without children with a range of index from a minimum of 0 to a maximum of 10. These two figures show almost the same pattern: the percent of households accounting for the number of affirmative answers is comparable in both figures. The majority of the two groups answered zeros: the proportion of food-secure households with children is about 80 percent (Figure 1(a)), and it is the same for households without children (Figure 1(b)). Both groups answered a one survey question affirmatively at a rate of about 5 percent. About 0.7 percent of households with children responded affirmatively to more than 10 food insecurity questions (Figure 1(a)).

Following Rasch scale scores, two affirmative responses are applied as a threshold to identify food insecurity status. As robustness checks, I also use alternative cutoffs such as three, four, five, and six.[27] For example, a household with or without children is classified as food insecure if that household reports at least four food insecure conditions. However, the dichotomous measure does not fully reflect the different degrees of severity in food security/insecurity condition. A zero response implies a fully food secure condition, while 18 indicates the most severe condition of food insecurity. Three affirmative responses indicate far less severe condition of food insecurity than 18 affirmative answers, but both are deemed food insecure when two positive responses are used as a cutoff of being food secure. Therefore, to account for an actual, distinct severity level of food insecurity, I also apply categorical measures of food insecurity.[28] The range of this measure for households with children is 0 to 18 and it is 0 to 10 for households without children.

Food insecurity condition of a household depends on its income level, which is highly associated with car ownership. I expect the effects of public transportation on food insecurity to be different between poor households and non-poor households because of a number of reasons, the primary one being that lack of public transportation should be more of a constraint for poor households as they are less likely to own a car; I provide this discussion in the results section. In this paper, I conduct my analyses by households' poverty level.

Table 1 lists summary statistics of the variables at the household level for the three samples from 2006 to 2009: the first one is for all households; the second one is for poor households, defined as households with income less than 185 percent of federal poverty level; the third one is for non-poor households, defined as households earning

Table 1 Summary statistics for household characteristics, CPS-FSS sample from 2006 to 2009

Variable	*Definition*	*All households*		*Poor*[a] *households*		*Non-poor*[b] *households*	
		Mean	*SD*	*Mean*	*SD*	*Mean*	*SD*
Food insecurity	=1 if a household was food insecure, 0 otherwise	0.13	0.34	0.30	0.46	0.06	0.23
Household variables							
Poor	=1 if household income was below 185% of federal poverty level	0.31	0.46				
FSP beneficiary	=1 if household received food stamp program (FSP) benefits, 0 otherwise	0.07	0.26	0.22	0.41	0.01	0.08
No. of employed individuals	Total number of employed individuals in family	1.26	0.92	0.90	0.93	1.42	0.87
No. of elders	Total number of elders in family	0.27	0.57	0.33	0.59	0.25	0.56
No. of children	Total number of children in family	0.67	1.07	0.92	1.30	0.55	0.92
Single female-headed HH	=1 if household was single female-headed family, 0 otherwise	0.05	0.21	0.10	0.30	0.02	0.15
Low income	=1 if annual family income was less than $35,000, 0 otherwise	0.34	0.47	0.88	0.32	0.10	0.30
Middle income	=1 if annual family income was between $35,000 and $75,000, 0 otherwise	0.32	0.47	0.11	0.32	0.42	0.49
High income	=1 if annual family income was greater than or equal to $75,000, 0 otherwise	0.33	0.47	0.00	0.03	0.49	0.50
Home ownership	=1 if household owned a house, 0 otherwise	0.63	0.48	0.39	0.49	0.74	0.44
Household head variables							
Less than high school	=1 if a household head had less than high-school degree, 0 otherwise	0.11	0.32	0.27	0.44	0.04	0.20
High school	=1 if a household head had high-school degree, 0 otherwise	0.23	0.42	0.32	0.47	0.19	0.39
Less than college	=1 if a household head had less than college degree, 0 otherwise	0.27	0.45	0.27	0.44	0.28	0.45
College	=1 if a household head had at least college degree, 0 otherwise	0.38	0.49	0.14	0.35	0.49	0.50
White	=1 if a household head is white, 0 otherwise	0.78	0.41	0.70	0.46	0.82	0.39
Black	=1 if a household head is black, 0 otherwise	0.14	0.35	0.22	0.41	0.10	0.31
Other race	=1 if a household head is other race, such as Asian, other than white or black, 0 otherwise	0.08	0.27	0.08	0.27	0.08	0.27
Hispanic	=1 if a household head is Hispanic, 0 otherwise	0.17	0.37	0.30	0.46	0.11	0.31
Female	=1 if a household head is female, 0 otherwise	0.49	0.50	0.57	0.50	0.45	0.50
Married	=1if a household head was married, 0 otherwise	0.51	0.50	0.37	0.48	0.58	0.49
30-year younger	=1 if a household head was younger than 30 years old, 0 otherwise	0.14	0.35	0.20	0.40	0.12	0.32
30–39-year-old	=1 if a household head was between 30 and 40 years old, 0 otherwise	0.20	0.40	0.20	0.40	0.20	0.40
40–49-year-old	=1 if a household head was between 40 and 50 years old, 0 otherwise	0.22	0.41	0.18	0.39	0.24	0.43
50–59-year-old	=1 if a household head was between 50 and 60 years old, 0 otherwise	0.19	0.39	0.15	0.35	0.21	0.41
60-year-old and older	=1 if a household head was older than or equal to 60 years old, 0 otherwise	0.25	0.43	0.28	0.45	0.23	0.42
N		28,304		8,418		19,886	

[a]The sample of poor households is the subsample for households with income less than 185 percent of federal poverty level.
[b]Non-poor households are classified as households earnings equal to or greater than 185 percent of the federal poverty line.
Note: I calculate mean and standard deviation using CPS-FSS sampling weights.

more than or equal to 185 percent of the federal poverty line. Similar to the national poverty ratio,[29] poor households in this paper account for 31 percent of the entire sample. In the sample of poor households, 30 percent of households were food insecure, which is, not surprisingly, more than two times higher than the proportion of food insecure households (13 percent) in the entire sample. Only 6 percent of non-poor households were reported being food insecure.

There exist differences between poor and non-poor households. Some variables such as the proportion of food stamp beneficiaries,[30,31] and the number of elders and children in a family have higher mean values for the poor households' sample than for the non-poor households' sample. In contrast, some family and household head characteristics such as the number of employed individuals in a household and college education level of household head have higher mean values in the sample of non-poor households than the poor households. The CPS reports a household's income as a range, not a continuous variable. I classify households into three categories. Households with income less than $35,000 are categorized as low income, less than $75,000 as middle income, and equal to or greater than $75,000 as high income group. These three groups of households, respectively, account for 34, 32, and 33 percent of the entire households. As expected, the majority of the poor households consist of low-income households (88 percent), while middle- and high-income groups account for about 90 percent of non-poor households.[32]

I also construct two subsamples regarding race in low-income households: poor African-American and poor white households.[33] The number of observations of blacks and whites among the poor is 1,852 and 5,958, respectively.[34] The black-white difference in food insecurity rates among poor households is over 10 percentage points (39 percent for blacks and 28 percent for whites).

Transportation data

Annual transit data from 2006 to 2009 are obtained from the NTD.[35] Similar to Taylor et al. [2009], I analyze the public transit system at the urbanized area (UA) level. Transit agencies, which are transit providers that receive UAF Grants from the FTA, are required to compile and submit data to the NTD. The NTD provides the count of vehicles (cars)[36] that are available to the general public and actually operated on a peak day,[37] which is annually reported by transportation mode (such as a bus for carrying transit passengers). I focus on bus, vanpool,[38] subway (heavy rail), light rail, and trolleybus among 15 modes of transportation, since the others are not suitable for food acquisition.[39] For example, it is hard to imagine people who use ferryboats or commuter rails for their daily grocery shopping. Buses and vanpools account for about 90 percent of the number of public transit vehicles operated.

The number of public vehicles operated in a UA is standardized in terms of bus units and used as a proxy for accessibility of public transportation. A capacity of a vehicle varies by each mode of transportation. For example, a bus is not comparable to a subway car/vehicle. According to the 2010 Conditions and Performance Report, a bus, a subway car, and a light rail car has on average 39, 53, and 63 seats, respectively [USDT 2010].[40] Although the majority of passengers tend to stand in a vehicle rather than sit due to the limited seats, a large number of available seats lead to a broader capacity. In other words, more seats are associated with more space to stand for passengers. Therefore, I employ a different capacity measure using "the number of seats on an average vehicle for each mode," by standardizing other vehicles' seats divided by the number of seats of a bus. For example, 20 vehicles of a light rail are equivalent to about 32 buses.

There are multiple transit agencies within a UA, and an agency services a single or multiple transportation modes. Thus, I measure the number of public transit vehicles based on the total number of vehicles across agencies within a UA. For instance, consider a UA that had two transit agencies A and B. If the maximum numbers of vehicles for a bus and a light rail are 100 and 20 and are operated by agency A and agency B, respectively, then in a certain year the number of bus-equivalent vehicles of the UA is 132 after adjusting for the different capacity of a vehicle between a bus and a light rail.

I also consider alternative measures for public transportation accessibility: annual vehicle revenue miles and annual vehicle revenue hours. As discussed in Taylor et al. [2009], those two variables are usually used as measures of transit service supply. Annual vehicle revenue miles (hours) are the total miles (hours) "that vehicles are scheduled to or actually travel while in revenue service and that include the layover/recovery time[41] but exclude deadhead, operator training, and vehicle maintenance testing, as well as school bus and charter services." Similar to the number of bus-equivalent vehicles, I use the vehicle revenue miles (hours) per 10,000 people in a local area to account for different population size.

The amount of the UAF grants is obtained from each fiscal year Statistical Summary provided by the FTA. I collected this information from 2003 because the assigned urbanized areas' names in 2002 were not consistent with the names since 2003. Therefore, data of the UAF federal grants are obtained from 2003 to 2008. Note that 1-year, 2-year, and 3-year-lagged funds are implemented as instruments. The FTA has provided the UAF grants by a UA with two population ranges: over 1,000,000 people and between 200,000 and 1,000,000 people. On the other hand, the amount of grants in areas with more than 50,000 but less than 200,000 people is available by state, not by a UA. Therefore, my local area sample does not contain those areas where the population is less than 200,000, and one of them is Laredo, Texas which has higher food insecurity rate in this sample.

How to match MSAs and UAs

As described above, the CPS-FSS contains food insecurity status of households with their home locations at the metropolitan statistical area (*MSA*) level, while the number of public transit vehicles is available at the urbanized area (*UA*) level. Therefore, I need to match those two different geographic levels. The 2000 Census classifies an MSA and a UA using the population of areas. An MSA is defined as an area which has "at least one urbanized area of 50,000 or more inhabitants," while a UA consists of "core census block groups or blocks that have a population density of at least 1,000 people per square mile." Therefore, I compare the population of counties that commonly belong to an MSA and a UA.

I use the following three-step process for matching. As a first step, I match the names of MSAs and UAs: both MSAs and UAs have "area names" which consist of principle cities and state names according to the Census Bureau. An MSA consists of one or more whole counties, whereas a UA may consist of portions of counties. Therefore, in the second step, I calculate the population in 2000 in overlapped areas between MSAs and UAs.[42] Third, I calculate the population share of areas that simultaneously belong to an MSA and a UA, or the population ratio between the common area and the united areas of an MSA and a UA. Then, I only keep areas if the population share of overlapped areas to the united areas of an MSA and a UA is greater than or equal to 80 percent. This implies that the population density of an MSA is high in a UA where public transportation system is concentrated. Furthermore, the NTD indicates that in some cases transportation system also covers the

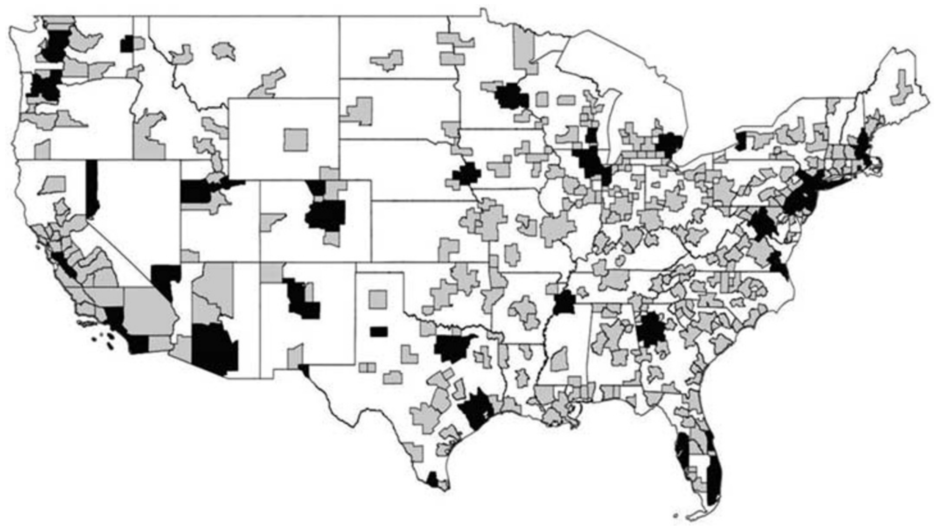

Figure 2. Coverage of the created data set.
Source: 40 Metropolitan Statistical Areas (Black) and 369 MSAs (Gray) in 2003, created by the author based on the Cartographic Boundary Files, Census Bureau.

adjacent area of a UA so that it serves a larger population than is implied by the reported residents of a UA.[43]

Below are the summarized steps to match an MSA and a UA.

Step 1		Step2		Step 3
Name match between an MSA and a UA based on principle cities and state names.	→	Calculate population of the overlapped areas=POP (MSA∩UA)	→	Keep the areas satisfying $((POP(MSA \cap UA))/(POP(MSA \cup UA)))\times 100 \geqslant 80\%$

After the matching process above, 45 matched local areas remain, but 40 areas among them are used in the analyses because the population of five areas[44] is between 50,000 and 200,000 and for those areas instrument variables are not available: see Table A1 for the list of 40 matched local areas. More explanation on how to match an MSA and a UA is provided, together with examples, in Appendix B. I call those matched local areas in my sample *local areas*.

Figure 2 shows the geographic coverage of the data set: gray areas represent the 369 MSAs of the US in 2003, while black areas indicate the 40 matched MSAs. Total population of 40 MSAs accounts for almost the half of the population of 369 MSAs in 2000. Northeast, Midwest, South, and West Census regions contain 4, 7, 14, and 15 local areas, respectively: the proportion of households in each region to total observation in my sample is about 20, 17, 30, and 33 percent, respectively. Furthermore, from 2006 to 2009, the food insecurity rate between the overall US population and the 40 matched areas was virtually identical as 13 percent.

Figures 3(a) to 3(d) display the relationship between the food insecurity rate and the number of bus-equivalent vehicles in 40 local areas of final data set from 2006 to 2009. The horizontal axis represents the number of bus-equivalent vehicles per 10,000 population in each local area, and the vertical axis measures the proportion of households that are food insecure. These four figures consistently show that there may exist a negative relationship between the rate of food insecurity and the number of public vehicles in local areas.

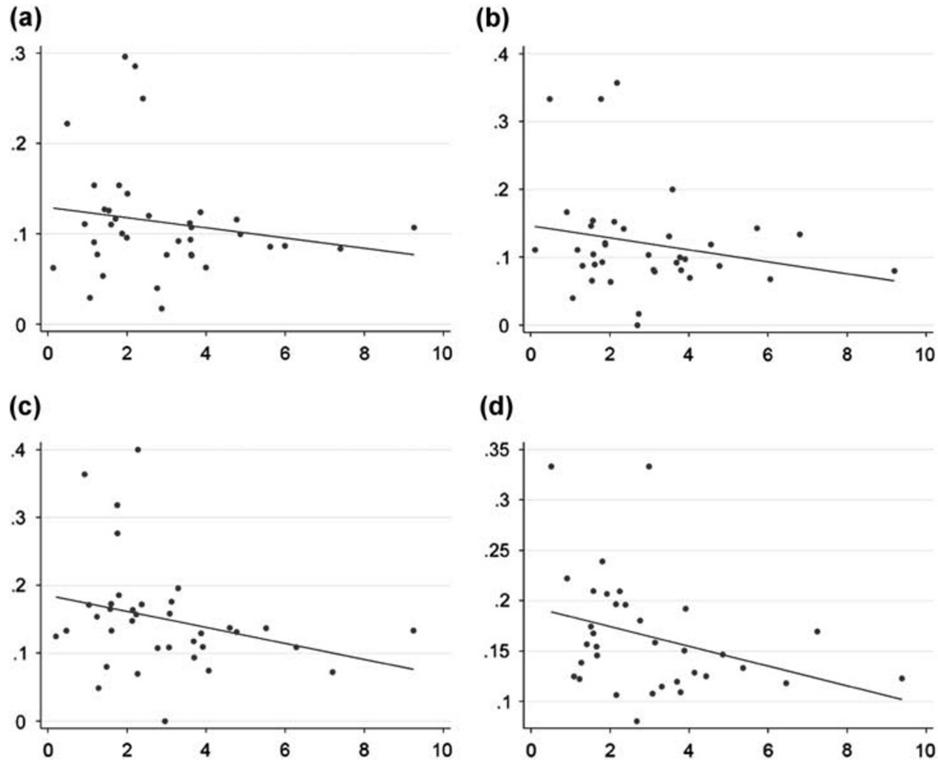

Figure 3. Food insecurity rate *vs* no. of bus-equivalent vehicles in 40 local areas: (a) year 2006; (b) year 2007; (c) year 2008; (d) year 2009.
Notes: X-axis is the number of bus-equivalent vehicles per 10,000 people. Y-axis refers to food insecurity rate.

Other control variables

I obtain the annual unemployment rate and population at the MSA level, respectively, from the Bureau of Labor Statistics and from the Census Bureau from 2006 to 2009. Two annual welfare variables are at the state level from 2006 to 2009. Public welfare expenditures are obtained from the Census Bureau and consist of cash assistance payments such as Temporary Assistance for Needy Families; vendor payments such as medical care; and other public welfare such as support of private welfare agencies. The food stamp participation rate is from USDA Food and Nutrition Service. Summary statistics for above three measures of public transportation accessibility at the UA level as well as other local and state variables are presented in Table 2.

RESULTS

Main results

Using the CPS-FSS sample from 2006 to 2009, I estimate a linear probability model where the dependent variable is dichotomous. Estimates are based on cross-sectional data using equation (1). I use various measures of food insecurity for households with children as a dependent variable: (1) a binary indicator created using a different affirmative response as a cutoff, and (2) a categorical measure of food insecurity between 0 and 18. I also

Table 2 Summary statistics for local and state variables from 2006 to 2009

Variable	*Definition*	*Mean*	*SD*
Local variables			
No. of bus-equi. vehicles per 10,000 pop.[a]	Total number of bus-equivalent vehicles, such as bus, vanpool, subway, light rail, and trolleybus, operated per 10,000 people in a local area	2.92	1.89
Vehicle revenue hours per 10,000 pop.[a]	Total vehicle revenue hours (1,000) per 10,000 people in a local area: total hours "that vehicles are scheduled to or actually travel while in revenue service and that include the layover/recovery time but exclude deadhead, operator training, and vehicle maintenance testing, as well as school bus and charter services."	9.69	5.43
Vehicle revenue miles per 10,000 pop.[a]	Total vehicle revenue miles (1,000) per 10,000 people in a local area: total miles "that vehicles are scheduled to or actually travel while in revenue service and that include the layover/recovery time but exclude deadhead, operator training, and vehicle maintenance testing, as well as school bus and charter services."	141.9	80.11
Unemployment rate	The unemployment rate in a local area	6.12	2.55
Population	Log of population in a local area	14.45	1.10
1-year lag of the federal transit funding	One-year lagged UAF funds ($1,000) from the federal government per 10,000 population	192.2	125.9
2-year lag of the federal transit funding	Two-year lagged UAF funds ($1,000) from the federal government per 10,000 population	172.9	119.0
3-year lag of the federal transit funding	Three-year lagged UAF funds ($1,000) from the federal government per 10,000 population	165.0	96.5
N		144	
State variables			
Welfare expenditures	Log of public welfare expenditures (1,000$) in a state	15.81	0.93
Food stamp participation rate	Food stamp participation rate (takeup rate) in a state	70.59	11.62
N		108	

[a]Since yearly population at the UA level is not available, I use yearly population at the MSA level as a denominator. The standardization using UA population in 2000 does not make a significant difference.
Notes: Local (state) variables are calculated at the local area (state) level, and CPS-FSS sampling weights are not applied for mean and standard deviation.

estimate regressions with food insecurity measures for households without children but do not report the results here because estimates are not significantly different from those for households with children.

Table 3 provides the point estimates of my key parameter, public transportation accessibility measured by the number of bus-equivalent vehicles. I report results of the IV regression (odd-numbered columns) as well as those from OLS (even-numbered columns) for three samples — all households, poor households, and non-poor households; note that poor households are defined as households with an income-to-poverty ratio less than 185 percent. A failure to take into account the potential endogeneity of public transit accessibility will result in biased estimates. Therefore, I use 1-year, 2-year, and 3-year lagged UAF federal grants as instruments. The first-stage coefficients of the instruments are presented at the bottom of Table 3 with F-statistics. For example, the F-statistic of 22.23 in Column (1) suggests that the instruments are strong, and the estimates indicate that there are strongly significant positive effects of transit subsidies on the number of bus-equivalent vehicles. I also test exogeneity of instrument variables, which is not

Table 3 The impact of public transportation accessibility on food insecurity.
Independent variable: the number of bus-equivalent vehicles per 10,000 people.

	All households		*Poor households*		*Non-poor households*	
	IV	*OLS*	*IV*	*OLS*	*IV*	*OLS*
	(1)	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*
By using a different cutoff						
Food insecurity=1, otherwise 0						
1. Using cutoff=2	−0.0160***	−0.0001	−0.0181**	−0.0115*	−0.0157	0.0041
	(0.0052)	(0.0023)	(0.0075)	(0.0058)	(0.0099)	(0.0029)
2. Using cutoff=3	−0.0171***	−0.0001	−0.0241**	−0.0078	−0.0140*	0.0022
	(0.0050)	(0.0025)	(0.0096)	(0.0050)	(0.0083)	(0.0026)
3. Using cutoff=4	−0.0084*	0.0008	−0.0052	−0.0016	−0.0108	0.0012
	(0.0043)	(0.0026)	(0.0076)	(0.0059)	(0.0066)	(0.0021)
4. Using cutoff=5	−0.0105***	0.0006	−0.0151***	−0.0038	−0.0079*	0.0022
	(0.0033)	(0.0015)	(0.0053)	(0.0034)	(0.0047)	(0.0017)
5. Using cutoff=6	−0.0108***	−0.0024**	−0.0201***	−0.0098***	−0.0056	0.0006
	(0.0029)	(0.0010)	(0.0072)	(0.0033)	(0.0041)	(0.0012)
By a categorical measure						
6. Food insecurity=0 to 18	−0.1205***	−0.0208	−0.1599**	−0.1098**	−0.1076*	0.0120
	(0.0333)	(0.0139)	(0.0668)	(0.0401)	(0.0614)	(0.0161)
Dependent variable mean	0.9163		2.0933		0.3791	
Instruments						
1-year lag of grants	0.0025***		0.0027***		0.0024***	
	(0.0005)		(0.0006)		(0.0005)	
2-year lag of grants	0.0016***		0.0020***		0.0015***	
	(0.0003)		(0.0003)		(0.0002)	
3-year lag of grants	0.0026*		0.0028*		0.0024*	
	(0.0013)		(0.0014)		(0.0013)	
F-statistics	22.23		27.20		19.77	
N	28,304	28,304	8,418	8,418	19,886	19,886

Notes: A cutoff is the assigned number of affirmative responses to 18 food insecurity questions. A dichotomous indicator of food insecurity equals one if a household gives to the questionnaire more affirmative responses than the cutoff. Robust standard errors are clustered at the state level in parentheses. *signifies statistical significance at the 10 percent level; **at 5 percent level, and ***at the 1 percent level or less. The CPS-FSS sampling weights are used in each regression. All regressions contain other local, state, household, and household head variables (see Tables 1 and 2) in addition to year and state fixed effects.

reported in this paper. I do not reject the null hypothesis that all instruments are valid and the regression specification is correct.

Following Rasch scale score, a base food insecurity measure is created based on two affirmative responses as the cutoff of being food secure (Panel 1), as explained earlier. As a robustness check, I also employ a different cutoff from three to six affirmative responses (Panels 2 through 5). Each panel reports coefficients from two estimations (an IV and an OLS) for each sample. For example, Panel 1 shows the base estimates for all households reported in first two columns. There is one F-statistic associated with each IV regression because the first stage, which is at the UA level, does not change even if I use a different measure of food insecurity. I present all the coefficient estimates for the controls except for year and state dummies in Table A2. These coefficients do not substantively change across measures of food insecurity or regression specifications.

Column (1) presents the second-stage results in the sample of all households after accounting for endogeneity and suggests that an additional bus-equivalent vehicle is statistically negatively associated with food insecurity regardless of food insecurity measures. In the specification using a binary indicator of food insecurity, the point estimate shows between 0.8 and 1.7 percentage points reduction in the probability of being food insecure with an extra bus-equivalent vehicle per 10,000 people. When poor households are only considered, the negative causal effect is maintained (Column (3)) except for the case with the food insecurity measure from four affirmative responses and the marginal effect becomes less than twice larger (between 1.5 and 2.4 percentage points). Since the non-poor have more access to automobiles compared with the poor, as shown in Berube et al. [2006], it is expected that the non-poor are less likely to be dependent on public transit. In fact, there is little evidence of a significant effect of public transportation on food insecurity among the non-poor (Column (5)). Public transportation marginally matters to non-poor households when three and five affirmative answers are employed as cutoffs. Therefore, the role of public transportation is more critical to the poor than the non-poor. These findings from three samples imply that the overall significant effect of transportation accessibility in the complete sample comes from the effect among the poor.

Point estimates are economically significant. Column (1) of Table 3 reports a −0.016 coefficient with the base food insecurity measure. In my sample, the average number of bus-equivalent vehicles per 10,000 people is roughly 3, assuming an urbanized area has 200,000 residents and 60 bus-equivalent vehicles. Since, on average, 13 percent of households are food insecure in the sample, the local area of the example has approximately 10,039 food insecure households or 26,000 food insecure people.[45] About 1,236 households (or 3,200 people) would become food secure as the number of bus-equivalent vehicles increases from 60 to 61 in the area. In this example, it would cost approximately \$530,000 to purchase and \$375,000 to operate one extra bus per year.[46] Equivalently, if this local area spends roughly \$332,000 to purchase and \$234,000 to operate a bus, the food insecurity rate would decrease by 1 percentage point.

A binary food insecurity measure does not fully address a difference in the degrees of severity in the food security/insecurity condition. More specifically, the more questions were answered affirmatively, the more food insecure households were. Therefore, I employ 2SLS and OLS using the number of affirmative responses to CPS food insecurity questions as a categorical measure and Panel 6 of Table 3 presents the estimated results. Note that the food insecurity measure for households with children ranges from 0 to 18. Consistent to the previous estimates based on a binary indicator, I find evidence of a negative effect of public transportation on the extent of food insecurity among all and low-income households but not among non-low-income households. With addressing the endogeneity issue, the estimate implies that an additional bus-equivalent vehicle would lead to 12 percent (mean = 0.92) decrease in the number of affirmative responses to food insecurity questions of households. Similar to Panels 1 through 5, the coefficient for the poor households' sample is larger than that for the entire sample, 1.3 times larger for the categorical 0-18-scale measure. I do not report here, but I also run regressions with a log-transformed measure of food insecurity.[47] The results consistently support the role of the access to public transportation on food insecurity.

Using the same sample used for the IV estimations, I also report OLS estimates in the even-numbered columns of Table 3. Without addressing an endogeneity issue, the impact of public transportation accessibility on food insecurity is mostly not significantly different from zero. When comparing results between OLS and 2SLS, a failure to control for endogeneity would result in an insignificant effect of transit accessibility on food insecurity. The OLS analysis of the poor sample shows the negative relationship, but the effect is significant for Panels 1, 5, and 6 (Column (4)).

The discrepancy in coefficients between the OLS and the 2SLS estimates may arise from the focus on subpopulation groups in this paper. Specifically, my sample focuses on urban areas with at least 200,000 people since the information for the number of public transportation and UAF grants is not available for rural areas. Also, the significant effects of public transportation accessibility on food insecurity in the 2SLS scheme may represent only the group of households without cars. In other words, my estimates may be driven by households with no cars who reside in urban areas with populations more than 200,000. Therefore, one needs to be careful in extrapolating these results to rural communities with populations less than 200,000.

Imbens and Angrist [1994] and Moffitt [2005] emphasized that the external validity of instruments does not hold if IV does not vary for the entire population. I provide, therefore, estimates for the subsamples of the poor and of the African-American poor who are less likely to own cars and to whom the availability of public transportation as well as food insecurity matter the most. Below, I discuss the possibly different role of public transportation on food insecurity by race among the poor.

Comparison by race among poor households

I find that access to public transportation is important in reducing the probability of facing food insecurity for the poor rather than for the non-poor. In this section, I test whether the role of public transportation differs depending on race among poor households.

Table 4 The impact of public transportation accessibility on food insecurity by race among poor households. Independent variable: The number of bus-equivalent vehicles per 10,000 people.

	Poor black households		*Poor white households*	
	IV *(1)*	*OLS* *(2)*	*IV* *(3)*	*OLS* *(4)*
By using a different cutoff				
Food insecurity=1, otherwise 0				
1. Using cutoff=2	−0.0369[a]	0.0076	−0.0090	−0.0149*
	(0.0292)	(0.0113)	(0.0096)	(0.0078)
2. Using cutoff=3	−0.0711**	−0.0114	−0.0086	−0.0058
	(0.0359)	(0.0142)	(0.0094)	(0.0042)
3. Using cutoff=4	−0.0424[a]	0.0009	0.0087	−0.0007
	(0.0333)	(0.0153)	(0.0086)	(0.0060)
4. Using cutoff=5	−0.0658*	0.0012	0.0024	−0.0038
	(0.0365)	(0.0132)	(0.0050)	(0.0031)
5. Using cutoff=6	−0.0606**	−0.0207**	−0.0065	−0.0072*
	(0.0306)	(0.0092)	(0.0053)	(0.0040)
By a categorical measure				
6. Food insecurity=0 to 18	−0.4268*	−0.0564	−0.0536	−0.1197***
	(0.2521)	(0.1085)	(0.0674)	(0.0399)
Dependent variable mean	2.723		1.939	
Instruments				
1-year lag of grants	0.0029***		0.0027***	
	(0.0007)		(0.0006)	
2-year lag of grants	0.0018**		0.0021***	
	(0.0008)		(0.0003)	
3-year lag of grants	0.0043**		0.0025*	
	(0.0018)		(0.0013)	
F-statistics	6.33		33.37	
N	1,852	1,852	6,566	6,566

[a]indicates significance at 20 percent.
Note: See notes to Table 3.

Table 4 estimates the relationship between public transportation and food insecurity for two subsamples. The results reveal that regardless of food insecurity measures, an extra bus-equivalent vehicle is significantly associated with a lower propensity of being food insecure for poor black households but not for poor white households. In the sample of poor black households, the estimate is −0.0711 (Panel 2), three times higher in magnitude than that in the counterpart of poor households (Table 3).[48] It implies that the significant role of public transit among the poor is driven by the high estimate for the African-American poor.

This finding may raise two questions. The first question is why transit accessibility is a determinant of food insecurity only for the black poor, not for the white poor. The simple answer would be the disparity in car ownership between African-Americans and whites among the poor; that is, poor blacks are less likely than poor whites to have access to cars. Berube et al. [2006] documented that even among the poor, the car ownership rate for whites is higher than that for blacks. If this is the case, access to public transportation would affect food insecurity status differently for the black poor than the white poor. Then, what causes such a racial difference in car ownership even among the poor? Previous researchers described that in addition to household incomes, several factors may contribute to the racial disparity in car ownership. Those factors are discriminations in car prices [Ayres and Siegelman 1995],[49] in interest rates on car loans [Charles et al. 2008],[50] and in car insurance prices [Harrington and Niehaus 1998].[51]

Table 5 The impact of public transportation accessibility on food insecurity.
Independent variable: Vehicle revenue hours (1,000) per 10,000 people.

	All households		*Poor households*		*Non-poor households*	
	IV *(1)*	*OLS* *(2)*	*IV* *(3)*	*OLS* *(4)*	*IV* *(5)*	*OLS* *(6)*
By using a different cutoff						
Food insecurity=1, otherwise 0						
1. Using cutoff=2	−0.0043***	−0.0012	−0.0047**	−0.0115*	−0.0043*	−0.0000
	(0.0012)	(0.0009)	(0.0022)	(0.0058)	(0.0026)	(0.0013)
2. Using cutoff=3	−0.0046***	−0.0009	−0.0063**	−0.0078	−0.0038*	−0.0002
	(0.0012)	(0.0007)	(0.0027)	(0.0050)	(0.0022)	(0.0011)
3. Using cutoff=4	−0.0022**	−0.0005	−0.0014	−0.0016	−0.0029*	−0.0004
	(0.0011)	(0.0008)	(0.0020)	(0.0059)	(0.0017)	(0.0008)
4. Using cutoff=5	−0.0028***	−0.0005	−0.0039***	−0.0038	−0.0021*	0.0001
	(0.0008)	(0.0005)	(0.0015)	(0.0034)	(0.0012)	(0.0006)
5. Using cutoff=6	−0.0029***	−0.0024**	−0.0052**	−0.0098***	−0.0015	−0.0002
	(0.0007)	(0.0010)	(0.0021)	(0.0033)	(0.0011)	(0.0005)
By a categorical measure						
6. Food insecurity=0 to 18	−0.0324***	−0.0123***	−0.0416**	−0.1098**	−0.0293*	−0.0020
	(0.0082)	(0.0043)	(0.0190)	(0.0401)	(0.0160)	(0.0068)
Dependent variable mean	0.9163		2.0933		0.3791	
Instruments						
1-year lag of grants	0.0094***		0.0105***		0.0087***	
	(0.0018)		(0.0019)		(0.0016)	
2-year lag of grants	0.0060***		0.0073***		0.0053***	
	(0.0010)		(0.0012)		(0.0009)	
3-year lag of grants	0.0097**		0.0106**		0.0088**	
	(0.0038)		(0.0041)		(0.0035)	
F-statistics	22.26		25.89		21.85	
N	28,304	28,304	8,418	8,418	19,886	19,886

Note: See notes to Table 3.

Blacks tend to pay higher prices for cars as well as insurance than whites. Therefore, different prices between the two groups can explain the predominately low propensity of owning a car among blacks than whites. Furthermore, initial wealth differences could also account for the black-white gap in car ownership [Gautier and Zenou 2010].[52]

The second concern could be the identification of public transportation. My sample does not contain information regarding whether a household owns an automobile. Hence, it might be argued that the estimate of access to public transportation could be biased because the information of family's car ownership is not controlled for. However, my key variable, access to public transit, is measured at the urbanized area level and the regressions control for a host of household level variables that are correlated with car ownership.

Robustness checks

Alternative measure of public transportation: Vehicle revenue hours and miles

As robustness checks, I use different public transportation measures as a key independent variable: vehicle revenue hours and miles. Tables 5 and 6 show the analyses for three samples classified by income-to-poverty ratio. Each panel and column of Tables 5 and 6 is

Table 6 The impact of public transportation accessibility on food insecurity.
Independent variable: Vehicle revenue miles (1,000) per 10,000 people.

	All households		*Poor households*		*Non-poor households*	
	IV	*OLS*	*IV*	*OLS*	*IV*	*OLS*
	(1)	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*
By using a different cutoff						
Food insecurity=1, otherwise 0						
1. Using cutoff=2	−0.0003***	−0.0000	−0.0003**	−0.0002*	−0.0003	0.0000
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0002)	(0.0001)
2. Using cutoff=3	−0.0003***	−0.0000	−0.0004**	−0.0001	−0.0003*	0.0000
	(0.0001)	(0.0001)	(0.0002)	(0.0001)	(0.0002)	(0.0001)
3. Using cutoff=4	−0.0002**	0.0000	−0.0001	−0.0000	−0.0002	−0.0000
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
4. Using cutoff=5	−0.0002***	−0.0000	−0.0003***	−0.0001	−0.0001*	0.0000
	(0.0001)	(0.0000)	(0.0001)	(0.0001)	(0.0001)	(0.0000)
5. Using cutoff=6	−0.0002***	−0.0001**	−0.0004***	−0.0002**	−0.0001	−0.0000
	(0.0006)	(0.0000)	(0.0001)	(0.0001)	(0.0001)	(0.0000)
By a categorical measure						
6. Food insecurity=0 to 18	−0.0022***	−0.0006*	−0.0030**	−0.0020**	−0.0019*	0.0000
	(0.0006)	(0.0003)	(0.0013)	(0.0009)	(0.0011)	(0.0004)
Dependent variable mean	0.9163		2.0933		0.3791	
Instruments						
1-year lag of grants	0.1317***		0.1446***		0.1227***	
	(0.0262)		(0.0286)		(0.0244)	
2-year lag of grants	0.0919***		0.1107***		0.0828***	
	(0.0140)		(0.0178)		(0.0127)	
3-year lag of grants	0.1230*		0.1327*		0.1123*	
	(0.0656)		(0.0695)		(0.0622)	
F-statistics	24.00		26.88		22.42	
N	28,304	28,304	8,418	8,418	19,886	19,886

Note: See notes to Table 3.

a counterpart of Table 3. Those estimates under alternative measures mostly support the negative impact of public transportation among poor and all households rather than among non-poor households. After controlling for endogeneity, the coefficients of the vehicle revenue hours (miles) in Columns (1) and (3) of Table 5 (Table 6) are statistically significant, meaning that as public transit vehicles travel more in terms of hours (miles), the propensity for being food insecure decreases among complete and particularly low-income households. As in Table 3, the results in Tables 5 and 6 provide some evidence that more accessibility of public transportation is associated with the lower probability of food insecurity in the sample of the non-poor. However, the role of public transit is more crucial to the poor than to the non-poor in terms of significance and the magnitude of estimates. The estimates of the rest controls are fairly similar across different measures of public transportation (See Table A2).

I also apply these alternative measures of access to public transportation to the samples of the black poor and the white poor. The analyses are also available in Tables 7 and 8 where the significance of coefficients is comparable with that in Table 4 of this paper. Estimates from two tables confirm that public transportation accessibility reduces the risk of exposure to food insecurity for poor African-Americans but not for poor whites.

Table 7 The impact of public transportation accessibility on food insecurity by race among poor households. Independent variable: Vehicle revenue hours (1,000) per 10,000 people.

	Poor black households		*Poor white households*	
	IV *(1)*	*OLS* *(2)*	*IV* *(3)*	*OLS* *(4)*
By using a different cutoff				
Food insecurity=1, otherwise 0				
1. Using cutoff=2	–0.0112[a]	0.0013	–0.0023	–0.0044
	(0.0085)	(0.0034)	(0.0027)	(0.0027)
2. Using cutoff=3	–0.0216**	–0.0045	–0.0023	–0.0020
	(0.0107)	(0.0044)	(0.0026)	(0.0017)
3. Using cutoff=4	–0.0129[a]	–0.0016	0.0022	–0.0000
	(0.0098)	(0.0049)	(0.0022)	(0.0019)
4. Using cutoff=5	–0.0198*	–0.0013	0.0006	–0.0012
	(0.0108)	(0.0041)	(0.0013)	(0.0009)
5. Using cutoff=6	–0.0183**	–0.0080**	–0.0017	–0.0021*
	(0.0093)	(0.0033)	(0.0014)	(0.0012)
By a categorical measure				
6. Food insecurity=0 to 18	–0.1300*	–0.0282	–0.0137	–0.0339**
	(0.0747)	(0.0336)	(0.0185)	(0.0142)
Instruments				
1-year lag of grants	0.0102***		0.0106***	
	(0.0026)		(0.0020)	
2-year lag of grants	0.0059**		0.0077***	
	(0.0024)		(0.0011)	
3-year lag of grants	0.0136**		0.0098**	
	(0.0055)		(0.0039)	
F-statistics	6.74		33.00	
N	1,852	1,852	6,566	6,566

[a]indicates significance at 20 percent.
Note: See notes to Table 3.

Table 8 The impact of public transportation accessibility on food insecurity by race among poor households. Independent variable: Vehicle revenue miles (1,000) per 10,000 people.

	Poor black households		*Poor white households*	
	IV	*OLS*	*IV*	*OLS*
	(1)	*(2)*	*(3)*	*(4)*
By using a different cutoff				
Food insecurity=1, otherwise 0				
1. Using cutoff=2	−0.0008[a]	0.0001	−0.0002	−0.0003
	(0.0006)	(0.0002)	(0.0002)	(0.0002)
2. Using cutoff=3	−0.0014*	−0.0002	−0.0001	−0.0001
	(0.0007)	(0.0003)	(0.0002)	(0.0001)
3. Using cutoff=4	−0.0009[a]	0.0000	0.0002	0.0000
	(0.0007)	(0.0003)	(0.0002)	(0.0001)
4. Using cutoff=5	−0.0013*	−0.0000	0.0001	−0.0000
	(0.0008)	(0.0002)	(0.0001)	(0.0001)
5. Using cutoff=6	−0.0012*	−0.0005**	−0.0001	−0.0001*
	(0.0006)	(0.0002)	(0.0001)	(0.0001)
By a categorical measure				
6. Food insecurity=0 to 18	−0.0088*	−0.0014	−0.0009	−0.0020**
	(0.0052)	(0.0021)	(0.0013)	(0.0008)
Instruments				
1-year lag of grants	0.1508***		0.1440***	
	(0.0449)		(0.0277)	
2-year lag of grants	0.0955**		0.1146***	
	(0.0392)		(0.0151)	
3-year lag of grants	0.2011*		0.1180*	
	(0.0982)		(0.0646)	
F-statistics	5.00		42.54	
N	1,852	1,852	6,566	6,566

[a]indicates significance at 20 percent.
Note: See notes to Table 3.

CONCLUSION

This study is the first analysis of whether public transportation accessibility at the local area level is an important determinant of food insecurity. I use a household-level food insecurity measure from the CPS-FSS and the information on public transportation accessibility from the NTD during the period from 2006 to 2009. The results indicate that policy makers can consider an increase in public transit vehicles to reduce food insecurity, especially for the poor.

Using federal governmental funding in the form of the UAF grants as instruments for public transportation accessibility, I find evidence that public transportation lowers food insecurity of households. The significant effect is found for all and low-income households but not for non-low-income households. More specifically, in all households, an additional bus-equivalent vehicle per 10,000 people is associated with a decrease in food insecurity of households by 1.6 percentage points. The marginal effect for the poor is roughly twice larger. These findings imply that the overall effect on food insecurity from public transportation in the sample of all households stems from the high impact estimated in poor households. Moreover, I find strong evidence that having access to public transportation would decrease the risk of exposure to food insecurity particularly for poor African-American households but not for poor white households. This result is consistent with the fact that relative to whites, blacks are less likely to own an automobile. As robustness checks, I use various food insecurity measures such as applying different cutoffs and a categorical measure between 0 and 18 instead of a binary indicator of food insecurity status. The relationship between food insecurity and public transportation is also examined with alternative measures of public transportation such as vehicle revenue hours and miles. Those estimates under alternative measures all support the negative causal effect. Overall, these results highlight the important role of public transportation availability in reducing food insecurity.

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APPENDIX A

Below are 18 questions related to food insecurity from the Food Security Supplements of the CPS.

1. "We worried whether our food would run out before we got money to buy more." Was that often, sometimes, or never true for you in the last 12 months?
2. "The food that we bought just didn't last and we didn't have money to get more." Was that often, sometimes, or never true for you in the last 12 months?
3. "We couldn't afford to eat balanced meals." Was that often, sometimes, or never true for you in the last 12 months?
4. In the last 12 months, did you or other adults in the household ever cut the size of your meals or skip meals because there wasn't enough money for food? (Yes/No)
5. (If yes to question 4) How often did this happen — almost every month, some months but not every month, or in only 1 or 2 months?
6. In the last 12 months, did you ever eat less than you felt you should because there wasn't enough money for food? (Yes/No)
7. In the last 12 months, were you ever hungry, but didn't eat, because there wasn't enough money for food? (Yes/No)
8. In the last 12 months, did you lose weight because there wasn't enough money for food? (Yes/No)
9. In the last 12 months did you or other adults in your household ever not eat for a whole day because there wasn't enough money for food? (Yes/No)
10. (If yes to question 9) How often did this happen — almost every month, some months but not every month, or in only 1 or 2 months?

(Questions 11–18 were asked only if the household included children age 0–17)

11. "We relied on only a few kinds of low-cost food to feed our children because we were running out of money to buy food." Was that often, sometimes, or never true for you in the last 12 months?
12. "We couldn't feed our children a balanced meal, because we couldn't afford that." Was that often, sometimes, or never true for you in the last 12 months?

13. "The children were not eating enough because we just couldn't afford enough food." Was that often, sometimes, or never true for you in the last 12 months?
14. In the last 12 months, did you ever cut the size of any of the children's meals because there wasn't enough money for food? (Yes/No)
15. In the last 12 months, were the children ever hungry but you just couldn't afford more food? (Yes/No)
16. In the last 12 months, did any of the children ever skip a meal because there wasn't enough money for food? (Yes/No)
17. (If yes to question 16) How often did this happen — almost every month, some months but not every month, or in only 1 or 2 months?
18. In the last 12 months did any of the children ever not eat for a whole day because there wasn't enough money for food? (Yes/No)

Source: USDA, ERS (2012)

Table A1 A list of 40 Metropolitan Statistical Areas in my sample matched to urbanized areas

Metropolitan Statistical Area	*Region*	*Metropolitan Statistical Area*	*Region*
Albuquerque, NM	West	Milwaukee-Waukesha-West Allis, WI	Midwest
Atlanta-Sandy Springs-Marietta, GA	South	Minneapolis-St. Paul-Bloomington, MN-WI	Midwest
Boston-Cambridge-Quincy, MA-NH	Northeast	New York-Northern New Jersey-Long Island, NY-NJ-PA	Northeast
Bradenton-Sarasota-Venice, FL	South	Omaha-Council Bluffs, NE-IA	Midwest
Buffalo-Niagara Falls, NY	Northeast	Palm Bay-Melbourne-Titusville, FL	South
Chicago-Naperville-Joliet, IL-IN-WI	Midwest	Philadelphia-Camden-Wilmington, PA-NJ-DE-MD	Northeast
Colorado Springs, CO	West	Phoenix-Mesa-Scottsdale, AZ	West
Dallas-Fort Worth-Arlington, TX	South	Port St. Lucie, FL	South
Denver-Aurora-Broomfield, CO	West	Portland-Vancouver-Beaverton, OR-WA	West
Detroit-Warren-Livonia, MI	Midwest	Reno-Sparks, NV	West
El Paso, TX	South	Rockford, IL	Midwest
Flint, MI	Midwest	Salt Lake City, UT	West
Fort Collins-Loveland, CO	West	San Diego-Carlsbad-San Marcos, CA	West
Houston-Sugar Land-Baytown, TX	South	San Jose-Sunnyvale-Santa Clara, CA	West
Las Vegas-Paradise, NV	West	Seattle-Tacoma-Bellevue, WA	West
Los Angeles-Long Beach-Santa Ana, CA	West	Spokane, WA	West
Lubbock, TX	South	Tampa-St. Petersburg-Clearwater, FL	South
McAllen-Edinburg-Mission, TX	South	Tucson, AZ	West
Memphis, TN-MS-AR	South	Virginia Beach-Norfolk-Newport News, VA	South
Miami-Fort Lauderdale-Pompano Beach, FL	South	Washington-Arlington-Alexandria, DC-VA-MD-WV	South

Table A2 The impact of public transportation accessibility on food insecurity.
Independent variable: the number of bus-equivalent vehicles per 10,000 people. By using cutoff=2: Food insecurity=1, otherwise 0.

	All households		*Poor households*		*Non-poor households*	
	IV (1)	*OLS* (2)	*IV* (3)	*OLS* (4)	*IV* (5)	*OLS* (6)
Local variable						
Unemployment rate	0.004	0.005	0.010	0.010	−0.001	0.000
	(0.005)	(0.005)	(0.011)	(0.011)	(0.004)	(0.003)
Population	0.017**	−0.002	0.015	0.008	0.018	−0.006
	(0.008)	(0.005)	(0.013)	(0.008)	(0.012)	(0.006)
State variables						
Welfare expenditures	0.034	0.044	0.077	0.080	−0.016	−0.001
	(0.052)	(0.052)	(0.119)	(0.125)	(0.041)	(0.041)
Food stamp participation rate	−0.001	−0.000	−0.001	−0.001	−0.000	0.000
	(0.001)	(0.001)	(0.003)	(0.003)	(0.001)	(0.001)
Household variables						
Poor	0.074***	0.074***				
	(0.009)	(0.009)				
FSP beneficiary	0.252***	0.252***	0.217***	0.217***	0.488***	0.489***
	(0.014)	(0.015)	(0.016)	(0.017)	(0.030)	(0.031)
No. of employed individuals	−0.011***	−0.010***	−0.031***	−0.030***	−0.000	−0.000
	(0.003)	(0.003)	(0.007)	(0.008)	(0.003)	(0.003)
No. of elderly	−0.033***	−0.033***	−0.071***	−0.071***	−0.013***	−0.013***
	(0.005)	(0.006)	(0.013)	(0.014)	(0.004)	(0.004)
No. of children	0.014***	0.014***	0.017***	0.017***	0.012***	0.012***
	(0.003)	(0.003)	(0.006)	(0.006)	(0.004)	(0.004)
Single Female-headed HH	0.044***	0.045***	0.013	0.013	0.072***	0.073***
	(0.012)	(0.012)	(0.026)	(0.026)	(0.022)	(0.022)
Middle income	−0.045***	−0.045***	−0.065***	−0.065***	−0.037***	−0.037***
	(0.008)	(0.008)	(0.016)	(0.017)	(0.010)	(0.010)
High income	−0.087***	−0.088***	−0.168	−0.169	−0.075***	−0.077***
	(0.009)	(0.010)	(0.120)	(0.121)	(0.010)	(0.011)
Home ownership	−0.055***	−0.055***	−0.067***	−0.067***	−0.043***	−0.042***
	(0.008)	(0.008)	(0.013)	(0.014)	(0.008)	(0.009)
Household head variables						
High school	−0.035***	−0.035***	−0.041***	−0.041***	−0.034***	−0.034**
	(0.011)	(0.011)	(0.015)	(0.015)	(0.013)	(0.013)
Less than college	−0.034***	−0.034***	−0.026	−0.026	−0.041***	−0.041***
	(0.011)	(0.011)	(0.020)	(0.020)	(0.015)	(0.015)
College	−0.069***	−0.070***	−0.071***	−0.072***	−0.072***	−0.073***
	(0.012)	(0.012)	(0.021)	(0.022)	(0.015)	(0.015)
Black	0.045***	0.045***	0.052***	0.052***	0.042***	0.042***
	(0.006)	(0.006)	(0.013)	(0.013)	(0.006)	(0.006)
Other race	−0.003	−0.004	−0.013	−0.014	0.003	0.001
	(0.008)	(0.008)	(0.025)	(0.026)	(0.006)	(0.006)
Hispanic	0.032***	0.030***	0.035***	0.034***	0.024***	0.021***
	(0.007)	(0.007)	(0.011)	(0.012)	(0.007)	(0.007)
Female	0.008**	0.008**	0.015	0.015	0.007**	0.007**
	(0.003)	(0.003)	(0.009)	(0.010)	(0.003)	(0.003)
Married	−0.003	−0.003	0.010	0.010	−0.014**	−0.014**
	(0.004)	(0.004)	(0.012)	(0.013)	(0.006)	(0.006)
30–39-year old	0.019**	0.018**	0.049***	0.049***	0.002	0.001
	(0.008)	(0.008)	(0.014)	(0.014)	(0.008)	(0.008)
40–49-year old	0.028***	0.027***	0.071***	0.071***	0.007	0.007
	(0.007)	(0.007)	(0.018)	(0.018)	(0.007)	(0.007)
50–59-year old	0.025***	0.024***	0.062***	0.062***	0.004	0.004
	(0.006)	(0.006)	(0.019)	(0.020)	(0.006)	(0.006)
60-year-old and older	−0.019*	−0.019*	−0.028	−0.029	−0.016**	−0.016**
	(0.010)	(0.010)	(0.033)	(0.033)	(0.007)	(0.008)
N	28,304	28,304	8,418	8,418	19,886	19,886

Note: See notes to Table 3.

APPENDIX B

How to match MSA-level to UA-level data?

Households' home locations are available at the MSA level, whereas public transportation data are available at the UA level. Therefore, it is necessary to match those two of different geographic levels. The Census 2000 classifies an MSA and a UA using the *population* of areas. An MSA is defined as an area which has "at least one urbanized area of 50,000 or more inhabitants," whereas a UA consists of "core census block groups or blocks that have a population density of at least 1,000 people per square mile." Therefore, I compare the population of counties that commonly belong to an MSA and a UA.

Both MSA and UA have an "area name" which consists of principle cities and a state name according to the Census Bureau. There are three cases for which an MSA and a UA are treated to be equivalent.[53] First, although state name is the same in both regional areas, sometimes the remaining part of the name (area name) could be different between an MSA and a UA. In this case, if an MSA and a UA share the same name for one or more principle cities, I treat them to be equal.

For example, let's consider an MSA named "Atlanta-Sandy Springs-Marietta, GA" and a UA named "Atlanta, GA." "Sandy Springs" and "Marietta" are the cities that belong respectively to Fulton and Cobb counties, and both of them commonly belong to the MSA and the UA. Hence, these MSA and UA are treated to be equivalent, although the names are not perfectly the same. Second, an MSA and a UA may have exactly the same "area name," but they may have slightly different state name. An example is "El Paso, TX" for an MSA and "El Paso, TX-NM" for a UA. Third, an MSA and a UA have a similar area name and similar state name: "New York-Northern New Jersey-Long Island, NY-NJ-PA," for an MSA and "New York-Newark, NY-NJ-CT" for a UA. In the second and third cases, I also treat two corresponding MSA and UA to be equivalent.

An MSA consists of one or more whole counties, whereas a UA may consist of portions of counties. Therefore, in the second step, I calculate the population in 2000 in overlapped areas between an MSA and a UA. The population of county portions in a UA is obtained from the US Environmental Protection Agency "which calculates population for each portion of either an incorporated place or a county within a UA based on the population values provided by the 2000 US Census Tiger data." Consider an MSA, "Reno-Sparks, NV" and a UA, "Reno, NV." The MSA consists of two counties, Washoe and Storey, whose populations are 339,486 and 3,399, respectively. On the other hand, the UA consists of a portion of Washoe county with 303,689 residents in 2000. Since Washoe county commonly belongs to the MSA and the UA, the population over the overlapped area is 303,689.

Third, I calculate the population share of areas that simultaneously belong to an MSA and a UA, or the population ratio between the common area and the united areas of an MSA and a UA. Then, I only keep areas if the population share of overlapped areas to the united areas of an MSA and a UA is greater than or equal to 80 percent. Hence, in the final sample, when an individual is randomly selected in a certain MSA or a UA, the probability for the person to live in the common area of an MSA and a UA is at least 80 percent. In the above example, "Reno-Sparks, NV," the MSA and "Reno, NV" the UA are selected as a matched area in the final sample since their population ratio is about 89 percent. Through this procedure, 45 matched areas are selected, but 40 out of 45 remain in the final data set due to the availability of transportation data.

Figures B1(a) to B1(d) present four matched area examples out of the final 40 local areas, and belong to South, Midwest, South, and Northeast, respectively. Gray areas indicate an MSA area, while black regions are a UA. In Figure B1(a), whole areas of the

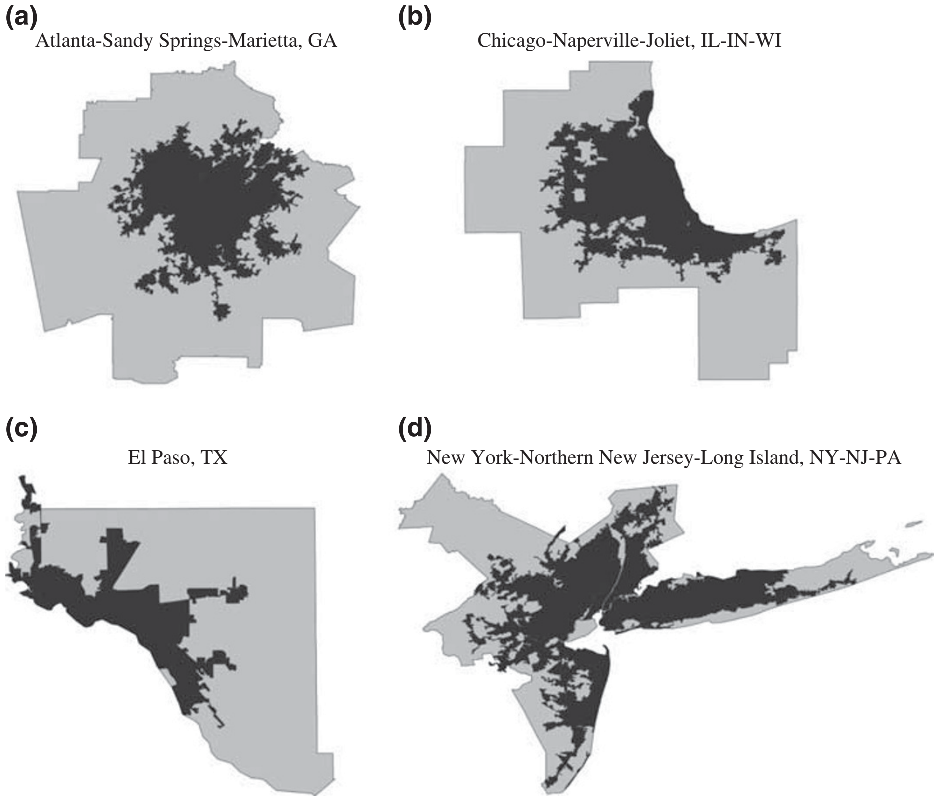

Figure B1. Example of comparison of an MSA (Gray) and a UA (Black): (a) Atlanta-Sandy Springs-Marietta, GA; (b) Chicago-Naperville-Joliet, IL-IN-WI; (c) El Paso, TX; (d) New York-Northern New Jersey-Long Island, NY-NJ-PA.

UA named "Atlanta, GA" is contained in the MSA named "Atlanta-Sandy Springs-Marietta, GA." In Figure B1(b), the UA, "El Paso, TX-NM," belongs to Texas and New Mexico at the same time, while the MSA "El Paso, TX" is contained only in Texas. As observed, there is little area outside of the MSA "El Paso, TX," "Dona Ana" county which belongs to state New Mexico and the population is 26,336. The population of county portion "Dona Ana" within the UA is 3.7 percent to the population of the united areas of an MSA and a UA, meaning that the population in this area is negligible.[54] Similarly, there are portions of counties (Fairfield in Connecticut, Mercer and Warren in New Jersey, Dutchess and Orange in New York) belonging to a UA, but not to an MSA "New York-Northern New Jersey-Long Island, NY-NJ-PA." The population of those areas is about 60,000 and occupies less than 0.5 percent of the united areas of the UA and the MSA of "New York-Northern New Jersey-Long Island, NY-NJ-PA."

As shown in exemplary maps, the whole area of a UA sometimes is not completely contained in an MSA. However, I compare the population of common counties in an MSA and a UA, and pick up the matched areas whose common areas between an MSA and a UA have at least 80 percent of the combined population. It implies that the population density of an MSA is high in a UA where public transportation system is concentrated. Although an MSA and a UA seem geographically different, in my final data set the majority of people, at least 80 percent, reside in the matched areas of an MSA and a UA where public transportation is highly concentrated.

Notes

1. Mayer and Jencks [1989] documented that food insecurity is a better measure for material hardship than income level or official poverty rate. Nutritional outcomes may be used as an alternative to food insecurity; however, I focus on the latter because of data availability. Specifically, I explain below, to match my interesting variable, public transportation data, to the outcome variable, residence information is necessary, but it is not available in nutrition data source such as the National Health and Nutrition Examination Survey.
2. Note that food insecurity is not a measure of an amount of calories for surviving but a measure of subjective satisfaction. See Cafiero [2013] for more explanations about food insecurity.
3. Bhattacharya et al. [2004] found a significantly negative impact of food insecurity on nutritional outcomes among adults and the elderly. Cook et al. [2004] suggested that food insecurity of households is associated with poor health outcomes of children.
4. Using the 2000 five percent Public Use Microdata Sample of the US Census of Population and Housing, the authors showed that around 12 percent of the white poor, defined as people in households with income less than 100 percent of the federal poverty level, had no automobiles, while 33 percent of the black poor did not own automobiles. Among near poor individuals, those in households with income-to-poverty ratios between 100 and 200 percent of the federal poverty line, the black-white gap in car ownership was 12 percentage points (21 percent of blacks, compared with 9 percent of whites).
5. The federal government has subsidized the UAF grants to urbanized areas since the fiscal year 1984, after the establishment of the Surface Transportation Act of 1982.
6. I do not use the other formula grants because they are designed for special purposes such as aids for job access, elderly persons, rural transit assistance, etc.
7. See FTA Apportionments, Allocations, and Program Information of each fiscal year for more information.
8. In contrast, local governments participate in the decision on the amount of discretionary grants. Therefore, those discretionary funds might be endogenous because local areas take into account their own transportation systems in their decision making.
9. As pointed earlier, Mayer and Jencks [1989] argued that poverty rates do not measure material deprivation reasonably well. However, food insecurity is a type of direct measure of material hardship for food.
10. This paper uses the FSP rather than SNAP for the program name because the former has been used for the majority of my sample period.
11. Gundersen and Oliveira [2001] and Mykerezi and Mills [2010] used a simultaneous equation model with a measure of food insufficiency from the Survey of Income and Program Participants (SIPP) and a food insecurity measure from the Panel Survey of Income Dynamics, respectively. Gundersen et al. [2012] employed non-parametric method using data from the National Health and Nutrition Examination Survey.
12. Three measures are the food insecurity rate, the food insecurity gap, and the square of food insecurity gap. The food insecurity gap is the difference between a Rasch scaling score and the assigned cutoff. I explain the Rasch scaling score and the cutoff in a data section.
13. As discussed in many studies [Gundersen and Oliveira 2001; Borjas 2004; Wilde and Nord 2005; Gundersen and Kreider 2008; Mykerezi and Mills 2010; Gundersen et al. 2011a, b; 2012], a food stamp variable is likely to be endogenous. Thus, the coefficient of food stamp participation in this paper does not provide a meaningful interpretation, but it is a control variable.
14. If a state is more interested in providing welfare aid, it is likely to have less strict program rules and have broad outreach to inform potentially eligible persons of such welfare programs. Then, the food stamp participation rate in the state will be higher [Bitler et al. 2003].
15. State dummies are created based on the location of each household.
16. I also employ clustering at the local area level. Following Wooldridge [2010], moreover, I calculate robust (heteroskedasticity-corrected) standard errors since the number of clusters at the state or local area level may be not sufficient enough. The conclusion reported below is not substantially different from results with the standard errors computed differently.
17. Using "percent of votes cast for Democrat in 2000," Taylor et al. [2009] demonstrated that a local area with more voters favorable to Democratic likely has higher levels of public transit supply.
18. The capital funding is spent on vehicle-related activities such as new vehicles, replacement of vehicles and maintenance equipment, while the operating budget is expenditures on training, planning and salaries of staff, etc.
19. I do not report the estimates here.
20. The reverse causality issue may still be a concern if the variation in the local public transportation usage shows persistent dynamics over time. To test the existence of reverse causality, I use future years' federal

grants as instruments instead as opposed to previous years and find that future grants, unlike previous years, are weak instruments with F-values of 7.7.

21. I really appreciate the detailed explanations from John Giorgis in the FTA.
22. Information of data unit value is available in Table 5 of FTA Apportionments, Allocations, and Program in each fiscal year.
23. Given that only half of the households in the sample are replaced every year, the households are allowed to appear either once or twice depending on the construction of the data set. The results are not substantially different between them.
24. Assessment variables such as abilities are available from survey responses, but it is hard for those variables to be recoded into a binary measure. The Rasch model is designed to provide a criterion to create a dichotomous measure. See Andrich [1988] for more information on the Rasch scale model.
25. A one-to-one match between Rasch scale scores and the number of affirmative responses to food questions was presented in Table 10 of Gundersen [2008]. The labels "low food security" and "very low food security" started to be used since 2005, which correspond to "food insecurity without hunger" and "food insecurity with hunger," respectively, before 2005.
26. Positive responses to food insecurity conditions are "often", "sometimes", "almost every month," "some months but not every month" or "yes."
27. Using eight as a cutoff leaves less variation, and so I do not use eight.
28. Bickel et al. [2000] also pointed out that categorical 0-18 and 0-10-scale measures would be more appropriate. For example, a study by Howard [2011] employed a food insecurity scale measure between 0 and 18 for his analysis.
29. US Census Bureau presented that roughly 30 percent of households have their incomes less than 185 percent of the federal poverty threshold for the period 2006–2009. Poverty ratios employed by specified ratios of poverty thresholds are available in the US Census Bureau, Current Population Survey, Annual Social and Economic Supplement by each year.
30. The USDA screens out respondents based on the question whether a household received FSP benefits. Specifically, if income level of a household was not below 185 percent poverty level and simultaneously "the household never ran short of money and tried to make food or food money go further in the past 12 month," then the question related to FSP was not asked. Therefore, I assign those households who were screened out to no-beneficiaries of FSP.
31. About 7 percent of households in the entire sample were food stamp beneficiaries. This food stamp program (FSP) prevalence rate is lower than national level rate that was on average about 10 percent during the same period. This is presumably because the food insecurity rate and FSP prevalence rate are systemically associated and my sample does not contain some urbanized areas with higher food insecurity rate due to transportation data availability, which is discussed in next section below.
32. In the sample of poor households, there are 11 households belonging to high income category. It is assured because the total number of family members in those households is large between 8 and 12. Of 1,095 non-poor but food insecure households, 190 households were in the high-income group. There could be two explanations for that. Higher number of family members in the household could be one reason. The second could be that all of those households resided in large metropolitan areas such as Atlanta, New York, Seattle, San Diego, Los Angeles, Washington D.C, etc. Owing to higher living costs, they might respond being food insecure. Note that responses to food insecurity questions are subjective, not objective, and involve satisfaction for food.
33. I do not report summary statistics for poor African-Americans and for poor whites, but they are available on request. Owing to the small number of observations (608), I do not include poor non-black minority households as a third subsample.
34. In this sample, the number of the white poor is three times larger than that of the black poor, which is similar to the entire US population.
35. The NTD reports annual data over a 12-month fiscal year. Data are available at the Annual Databases: http://www.ntdprogram.gov/ntdprogram/data.htm.
36. For example, a survey (a long train) consists of, on an average, six to eight cars, whereas a light rail (a short train) constitutes one to four cars.
37. According to the NTD, vehicles operated in abnormal days or one-time special events are excluded.
38. Vanpool (also known as "Demand response") is defined as "a transit mode comprised of vans or small buses operating as a ride sharing arrangement, providing transportation to a group of individuals traveling directly between their homes and a regular destination within the same geographical area."
39. I exclude automated guide way, commuter rail, ferryboat, inclined plane, monorail, and publico, but inclusion of those types of public transportation is not sensitive to estimates. According to the NTD, a cable car has been only operated in San Francisco which is not in my sample, and jitney (a type of bus) is not also considered in the data set because the only one transit agency in California provided the service

until 2005. Similarly, Alaska railroad is excluded from transportation modes because Alaska is not in my sample.

40. See the link for the average number of seats by each transit mode: http://www.fhwa.dot.gov/policy/2010cpr/execsum.htm#c4t.
41. Layover/recovery time is "a planned time allowance between the arrival time of a just completed trip and the departure time of the next trip in order to allow the route to return to schedule if traffic, loading, or other conditions have made the trip arrive late."
42. Population of overlapped areas between MSAs and UAs are only available in 2000.
43. In my sample, there are 31 such areas reporting "a measure of access to transit service in terms of population" that is larger than the UA.
44. Five matched areas are "Decatur, IL," "Fargo, ND-MN," "Laredo, TX," "Panama City-Lynn Haven- Panama City Beach, FL," and "Pueblo, CO." Honolulu in Hawaii is also one of matched areas satisfying matching process. However, it is not included in final data set because it is a non-continental area of the US.
45. According to the Census Bureau, there were 2.59 persons per household from 2006 to 2010.
46. The cost to purchase a vehicle accounts for the majority of capital expenditures and the vehicle price ($531,605) of a diesel bus, which is "the most common type of bus in the US" (see Figure 1 in USDT, FTA, 2007). I use $375,187 as the total operation cost for a diesel bus (Figure 2). These estimated prices are 2006 values and in 2007 dollars.
47. The food insecurity is defined to be zero if the household is fully food secure. For log transformation, I added one to each value of categorical 0-18 scale in order to retain the fully food secure households in the sample. For example, if the food insecurity is zero, it is scaled up to one, which is log-transformed.
48. In the sample of poor black households, the F-value of the first stage is less than ten, which is presumably because the number of observations is small.
49. However, there is disagreement about the existence of racial discrimination in a car price. Ayres and Siegelman [1995] found evidence that the black pay more for car purchase than the white using information of new car dealership in Chicago, while Goldberg [1996] found no evidence with a national sample. To my knowledge, none of papers has yet studied the racial discrimination in the price of a used car which is more affordable for low-income households.
50. Using the Survey of Consumer Finances data set, Charles et al. [2008] documented that the auto loan interests are higher for blacks, which is more conspicuous for financing arms of vehicle manufacturers such as General Motors Acceptance Corporation than for traditional banks.
51. Harrington and Niehaus [1998] studied the insurance data from Missouri.
52. Theoretically, they show that initial wealth difference leads to racial disparity in car ownership, resulting in differences in labor market outcomes such as employment status and wages.
53. Based on name comparison, there is one more case in which two UAs occupy an MSA: an example is an MSA "Beaumont-Port Arthur, TX," and two UAs, "Beaumont, TX" and "Port Arthur, TX." However, these nine MSAs are eventually not in my final sample.
54. Population of the portion of a county "Dona Ana" occupies 3.9 percent of the population of the UA "El Paso, TX-NM."

References

Andrich, David. 1988. *Rasch Models for Measurement*. Newbury Park, CA: Sage.

Ayres, Ian, and Peter Siegelman. 1995. Race and Gender Discrimination in Bargaining for a New Car. *American Economic Review*, 85(3): 304–321.

Beaulieu, Lionel J. 2007. Strengthening Our Nation's Food Assistance Programs. In collaboration with the RIDGE Program, Southern Rural Development Center.

Berube, Alan, Elizabeth Deakin, and Steven Raphael. 2006. Socioeconomic Differences in Household Automobile Ownership Rates: Implications for Evacuation Policy. Program on housing and urban policy conference paper series, University of California, Berkeley, Working Paper.

Bhattacharya, Jayanta, Janet Currie, and Steven Haider. 2004. Poverty, Food Insecurity, and Nutritional Outcomes in Children and Adults. *Journal of Health Economics*, 23(4): 839–862.

Bickel, Gary, Mark Nord, Cristoper Price, William Hamilton, and John Cook. 2000. Guide to Measuring Household Food Security: Revised 2000. US Department of Agriculture, Food and Consumer Service, Office of Analysis and Evaluation.

Bitler, Marianne P., Janet Currie, and John Karl Scholz. 2003. WIC Eligibility and Participation. *Journal of Human Resources*, 38(s): 1139–1179.

Blanchard, Troy, and Thomas Lyson. 2002. Access to Low Cost Groceries in Nonmetropolitan Counties: Large Retailers and the Creation of Food Deserts. Paper presented at the Measuring Rural Diversity Conference, Washington DC.

————. 2006. Food Availability and Food Deserts in the Nonmetropolitan South. Food Assistance Needs of the South's Vulnerable Population, Number 12.

Borjas, George J. 2004. Food Insecurity and Public Assistance. *Journal of Public Economics*, 88(7–8): 1421–1443.

Cafiero, Carlo. 2013. What do we Really Know about Food Security? NBER working paper No. 18861.

Charles, Kerwin Kofi, Erik Hurst, and Melvin Stephens. 2008. Rates for Vehicle Loans: Race and Loan Source. *American Economic Review*, 98(2): 315–20.

Cook, John T., Deborah A. Frank, Carol Berkowitz, Maureen M. Black, Patrick H. Casey, Diana B. Cutts, Alan F. Meyers, Nieves Zaldivar, Anne Skalicky, Suzette Levenson, Tim Heeren, and Mark Nord. 2004. Food Insecurity is Associated with Adverse Health Outcomes among Human Infants and Toddlers. *Journal of Nutrition*, 134(6): 1432–1438.

Gautier, Pieter A., and Yves Zenou. 2010. Car Ownership and the Labor Market of Ethnic Minorities. *Journal of Urban Economics*, 67(3): 392–403.

Glaeser, Edward L., Matthew E. Kahn, and Jordan Rappaport. 2008. Why Do the Poor Live in Cities? The Role of Public Transportation. *Journal of Urban Economics*, 63(1): 1–24.

Goldberg, Pinelopi Koujianou. 1996. Dealer Price Discrimination in New Car Purchases: Evidence from the Consumer Expenditure Survey. *Journal of Political Economy*, 104(3): 622–654.

Gundersen, Craig. 2008. Measuring the Extent, Depth, and Severity of Food Insecurity: An Application to American Indians in the USA. *Journal of Population Economics*, 21(1): 191–215.

Gundersen, Craig, and Brent Kreider. 2008. Food Stamps and Food Insecurity: What Can Be Learned in the Presence of Nonclassical Measurement Error? *Journal of Human Resources*, 43(2): 352–382.

Gundersen, Craig, Brent Kreider, and John Pepper. 2011a. The Economics of Food Insecurity in the United States. *Applied Economic Perspectives and Policy*, 33(3): 281–303.

————. 2011b. Partially Identifying the Impact of the Supplemental Nutrition Assistance Program on Food Insecurity among Children: Addressing Endogeneity and Misreporting Using the SIPP. National Poverty Center Working Paper Series.

————. 2012. The Impact of the National School Lunch Program on Child Health: A Nonparametric Bounds Analysis. *Journal of Econometrics*, 166(1): 79–91.

Gundersen, Craig, and Victor Oliveira. 2001. The Food Stamp Program and Food Insufficiency. *American Journal of Agricultural Economics*, 84(3): 875–887.

Gundersen, Craig, Linda Weinreb, Cheryl Wehler, and David Hosmer. 2003. Homelessness and Food Insecurity. *Journal of Household Economics*, 12(3): 250–272.

Harrington, Scott E., and Greg Niehaus. 1998. Race, Redlining, and Automobile Insurance Prices. *Journal of Business*, 71(3): 439–469.

Howard, Larry L. 2011. Does Food Insecurity at Home Affect Non-Cognitive Performance at School? A Longitudinal Analysis of Elementary Student Classroom Behavior. *Economics of Education Review*, 30(1): 157–176.

Imbens, Guido W., and Joshua D. Angrist. 1994. Identification and Estimation of Local Average Treatment Effects. *Econometrica*, 62(2): 467–475.

Leete, Laura, and Neil Bania. 2010. The Effect of Income Shocks on Food Insufficiency. *Review of Economics of the Household*, 8(4): 505–526.

Mayer, Susan E., and Christopher Jencks. 1989. Poverty and the Distribution of Material Hardship. *Journal of Human Resources*, 24(1): 88–114.

Moffitt, Robert. 2005. Remarks on the Analysis of Causal Relationships in Population Research. *Demography*, 42(1): 91–108.

Mykerezi, Elton, and Bradford F. Mills. 2010. The Impact of Food Stamp Program Participation on Household Food Insecurity. *American Journal of Agricultural Economics*, 92(5): 1379–1391.

Ribar, David C., and Karen S. Hamrick. 2003. Dynamics of Poverty and Food Sufficiency. U.S. Department of Agriculture, Food Assistance and Nutrition Research, Report No. 36, Washington DC.

Taylor, Brian D., Douglas Miller, Hiroyuki Iseki, and Camille Fink. 2009. Nature and/or Nurture? Analyzing the Determinants of Transit Ridership across US Urbanized Areas. *Transportation Research Part A: Policy and Practice*, 43(1): 60–77.

U.S. Department of Agriculture. 2012. Household Food Security in the United States. Economic Research Report No. 125. Economic Research Service.

U.S. Department of Transportation. 2010. Status of the Nation's Highways, Bridges, and Transit: Conditions & Performance. Report to Congress, Federal Highway Administration, Federal Transit Administration, http://www.fhwa.dot.gov/policy/2010cpr/pdfs/cp2010.pdf (accessed April 4, 2012).

U.S. Department of Transportation, Federal Transit Administration. 2007. Transit Bus Life Cycle Cost and Year 2007 Emissions Estimation.

————. 2008. Fiscal Year Apportionments, Allocations, and Program Information. Federal Transit Administration.

————. 2009. Fiscal Year Apportionments, Allocations, and Program Information. Federal Transit Administration.

Wilde, Parke, and Mark Nord. 2005. The Effect of Food Stamps on Food Security: A Panel Data Approach. *Review of Agricultural Economics*, 27(3): 425–432.

Wooldridge, Jeffrey M. 2010. *Econometric Analysis of Cross Section and Panel Data*. Cambridge, MA, London, England: The MIT Press.