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Essays on Poverty and Infant Health

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This dissertation is dedicated to my husband, Hong Lee, and my son, William Youl Lee.

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ABSTRACT

In this dissertation, I offer three independent studies that each contribute to the literature on poverty and infant health. The first essay examines whether access to public transportation reduces food insecurity in the U.S. Potential endogeneity problem is addressed with instruments of federal transportation funding. I provide new evidence of a negative causal effect of public transportation accessibility on food insecurity, which is more prominent among poor African-American households. The second essay examines the relation between savings of poor households and a welfare program called the Supplemental Nutritional Assistance Program (SNAP). Eligibility for SNAP benefits requires households to own limited value of assets. Beginning in 2001, states were given the authority to formulate their own rules regarding how vehicles are counted towards this asset limit in the SNAP. Using the Survey of Income and Program Participation, the results suggest that liberalizing vehicle asset rules increases vehicle assets of households with a high ex ante probability of program participation. Particularly, this increase in car value can be attributed primarily to low educated single parents who already owned a car before the policy change buying more expensive cars. The third essay examines how notifications of governmental authorities mitigate the effect of air pollutants on infant health outcomes in Korea. Using a data set of 1.5 million babies, and air status information from 250 weather stations in Korea between 2003 and 2011, the results indicate that the public warnings against the yellow sand events improve birth outcomes.

CHAPTER 1. INTRODUCTION

This dissertation consists of three essays that each contribute to the literature on poverty and infant health. In the second chapter, I examine whether access to public transportation reduces food insecurity in the U.S. In the third chapter, I analyze how poor households' savings behavior is determined by the Supplemental Nutrition Assistance Program existing literature failed to examine. In the fourth chapter, I investigate the impact of a government's air quality notifications on infant health, using yellow sand storms as a natural experiment.

1.1 The Effect of Public Transportation Accessibility on Food Insecurity

I examine whether access to public transportation reduces the probability of food insecurity for households. The dataset 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.

1.2 The Impact of SNAP Vehicle Asset Limits on Asset Allocation in Low-Income Households

The Supplemental Nutritional Assistance Program is a means-tested income transfer program, and eligibility for program benefits requires that households own less than a threshold value in assets. Beginning in 2001, states were given the authority to formulate their own rules regarding how vehicles are counted towards this asset limit. I use data for single parents with low education from the Survey of Income and Program Participation to examine the effects of state vehicle asset rules on vehicle assets and debts, car ownership, liquid assets holdings, as well as non-housing wealth. I estimate the effects of state vehicle asset rules using a difference-in-differences specification, as well as a household fixed effects specification that tracks households over time. I exploit within-household differences in timing of the state vehicle asset policy changes to identify the effect of state vehicle asset rules on the outcomes of interest. Results show that liberalizing vehicle asset rules increases vehicle assets of households with a high ex ante probability of program participation. After vehicle asset rules are relaxed, households own cars that are worth $2,000 more compared to before the policy change, and they take on more debt in order to finance their vehicles. I find that this increase in car value can be attributed primarily to low educated single parents who already owned a car before the policy change buying more expensive cars. Liberalizing vehicle asset rules has no impact on liquid asset holdings and no impact on non-housing wealth.

1.3 The Impact of Air Quality Notifications on Infant Health: Evidence from Korea

Naturally-occurring yellow sand outbreaks worsen air quality in Korea. To warn Koreans about these dust storms, Korean Meteorological Administration issues public notifications, and advise individuals to take protective action. Using a data set of about 1.5 million Korean babies born between 2003 and 2011, I investigate the impact of these dust warnings on birth outcomes. Identification of the effect of the warnings comes from the exogenous yellow sand outbreaks that are caused by winds that carry dust particles from China and Mongolia to Korea. My results indicate that the public warnings against the yellow sand events improve birth outcomes. Back of the envelope calculations suggest that the present value of the net benefit of each public dust warning is about $4 million.

CHAPTER 2. THE EFFECT OF PUBLIC TRANSPORTATION ACCESSIBILITY ON FOOD INSECURITY *

2.1 Introduction

In February 1994, the U.S. 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).

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* This Chapter is a pre-print of an article forthcoming in the *Eastern Economic Journal*.

[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.

A number of studies have investigated the impact on food insecurity of such factors as welfare benefits (Gundersen et al. 2012; 2011b; Mykerezi and Mills 2010; Gundersen and Kreider 2008; Wilde and Nord 2005; Borjas 2004; Gundersen and Oliveira 2001), homelessness (Gundersen et al. 2003), and household-income levels (Leete and Bania 2010; Ribar and Hamrick 2003). 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. U.S. 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 to non-poor households. In 2010, the rate among low-income households, defined as households with income below 185% 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 U.S. 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) versus 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 to 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

[4] Using the 2000 five percent Public Use Microdata Sample of the U.S. 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).

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,

[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.

population density and transit mileage released by the NTD two 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% of the federal poverty line, and all households. In particular, the relationship is more conspicuous among low-income households, compared to 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.

[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.

The rest of this paper is organized as follows. In section 2.2, I provide a literature review. Section 2.3 presents an empirical specification, and section 2.4 describes data construction. The estimated results are in section 2.5. Section 2.6 concludes the paper.

2.2 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

[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.

programs decrease the probability of being food insecure, (Gundersen et al. 2012; Mykerezi and Mills 2010; Borjas 2004), 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 et al. 2012; Mykerezi and Mills 2010; Wilde and Nord 2005; Borjas 2004; Gundersen and Oliveira 2001).[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 et al. 2012; Gundersen and Kreider 2008).

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

[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.

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 to 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.

2.3 Empirical strategy

2.3.1 Empirical specification

Consider a linear probability model of the equation (2.1) below.

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

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:

[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.

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

[13] As discussed in many studies (Gundersen, Kreider, and Pepper 2012; 2011a; 2011b, Mykerezi and Mills 2010, Gundersen and Kreider 2008, Wilde and Nord 2005, Borjas 2004, Gundersen and Oliveira 2001), 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, Currie and Scholz 2003).

[15] State dummies are created based on the location of each household.

between the households within the same state, standard errors are clustered at the state level.[16] ε represents an idiosyncratic error term.

2.3.2 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 Urbanized Area Formula (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

[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.

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 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 are 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

[19] I do not report the estimates here.

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 two 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 four 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 U.S. 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 two 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

[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.

year. Since there is no information on how the formula amount is actually allocated across four fiscal years, the instruments for the number of bus-equivalent vehicles in the current year are the last three years' UAF grants whose usage started one, two, and three 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.

[22] Information of data unit value is available in Table 5 of FTA Apportionments, Allocations, and Program in each fiscal year.

2.4 Data

2.4.1 Food insecurity

Since 1995, the Current Population Survey Food Security Supplement (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 two 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 dataset where each household appears only once. Since each household was surveyed for two 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 two 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 twelve 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

[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 dataset. The results are not substantially different between them.

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 three to five 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 2.1 displays the distributions of a set of cumulative responses to food insecurity questions for households. Figure 2.1.,A. is for households with children, and the possible number of affirmative responses varies from 0 to 18. Figure 2.1.,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 2.1.,A.), and it is the same for

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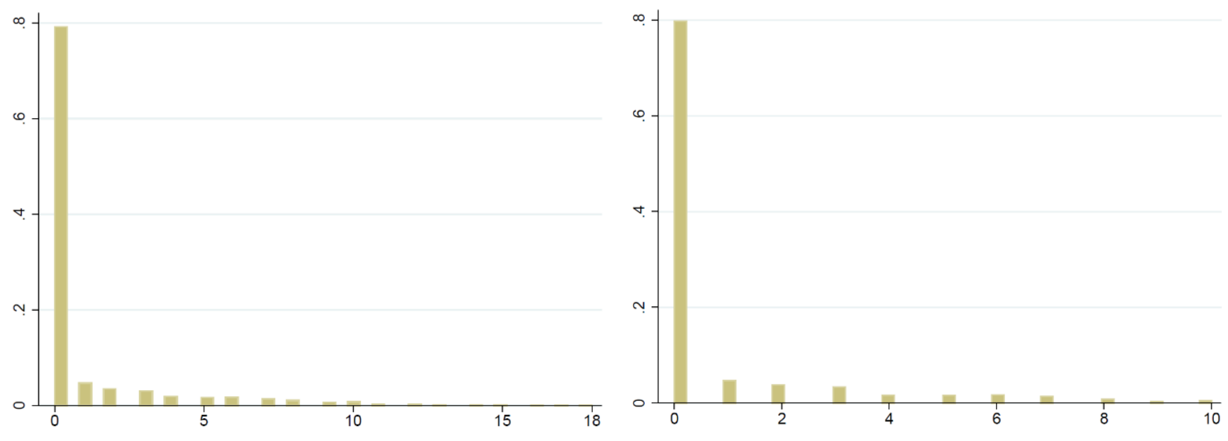
[24] Assessment variables such as abilities are available from survey responses, but it is hard for those variables to be recoded into a binary measure. The Rasch model is designed to provide a criterion to create a dichotomous measure. See Andrich (1988) for more information on the Rasch scale model.

[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."

households without children (Figure 2.1.,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 2.1.A.).



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.

Figure 2.1 Food insecurity responses for households

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

[27] Using eight as a cutoff leaves less variation, and so I do not use eight.

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 2.1 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% of federal poverty level; the third one is for non-poor households, defined as households earning more than or equal to 185% 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.

[28] Bickel et al. (2000) also pointed out that categorical 0 to18 and 0 to10 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] U.S. Census Bureau presented that roughly 30% of households have their incomes less than 185% of the federal poverty threshold for the period of 2006 to 2009. Poverty ratios employed by specified ratios of poverty thresholds are available in the U.S. Census Bureau, Current Population Survey, Annual Social and Economic Supplement by each year.

Table 2.1: Summary statistics for household characteristics, CPS-FSS sample from 2006 to 2009

Variable	Definition	All Households Mean	All Households SD	Poor [a] Households Mean	Poor [a] Households SD	Non-Poor [b] Households Mean	Non-Poor [b] Households 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

Table 2.1 continued

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	

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

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

[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% 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% 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. Due 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. Due to the small number of observations (608), I do not include poor non-black minority households as a third subsample.

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).

2.4.2 Transportation data

Annual transit data from 2006 to 2009 are obtained from the National Transit Database (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 Urbanized Area Formula (UAF) Grants from the Federal Transit Administration, 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.

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[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 U.S. 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 of 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.

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 were 100 and 20 and were operated by agency A and agency B, respectively, then in a certain year the number of bus-equivalent vehicles of the UA would be 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

[40] See the link for the average number of seats by each transit mode: http://www.fhwa.dot.gov/policy/2010cpr/execsum.htm#c4t

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 one-year, two-year, and three 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.

2.4.3 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

[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."

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

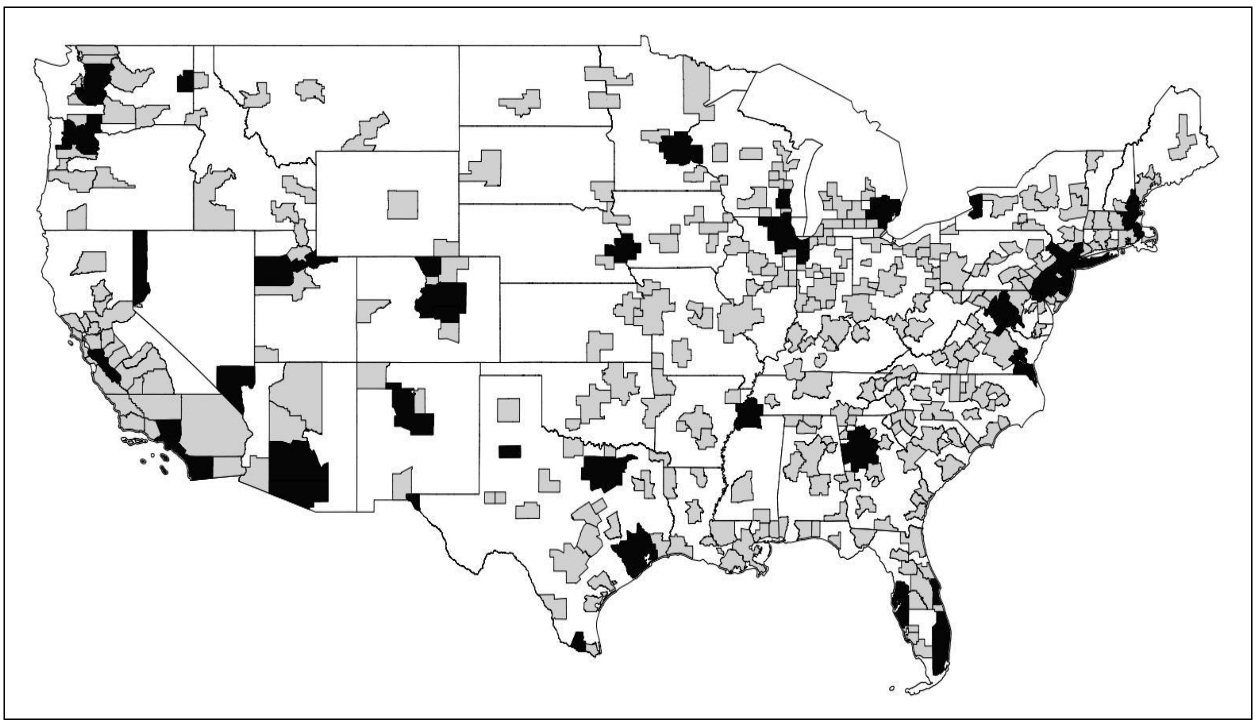
Below are the summarized steps to match an MSA and a UA.

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 $= \mathrm{POP}(\mathrm{MSA} \cap \mathrm{UA})$	→	Keep the areas satisfying $\frac{\mathrm{POP}(\mathrm{MSA} \cap \mathrm{UA})}{\mathrm{POP}(\mathrm{MSA} \cup \mathrm{UA})} \times 100 \geq 80\%$

[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.

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 Appendix Table D.1 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 2.2 shows the geographic coverage of the dataset: gray areas represent the 369 MSAs of the U.S. 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



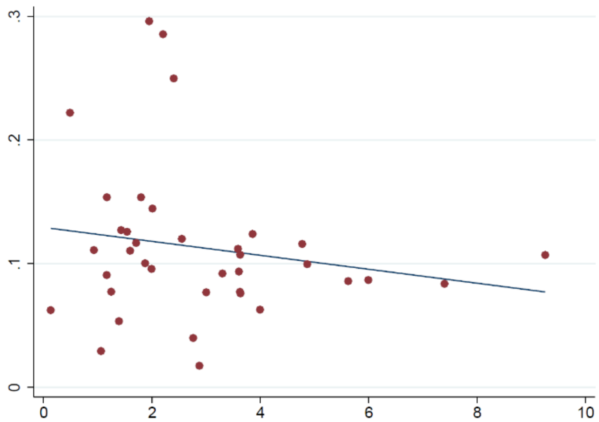
Source: 40 Metropolitan Statistical Areas (Black) and 369 MSAs (Gray) in 2003, created by the author based on the Cartographic Boundary Files, Census Bureau.

Figure 2.2 Coverage of the created dataset

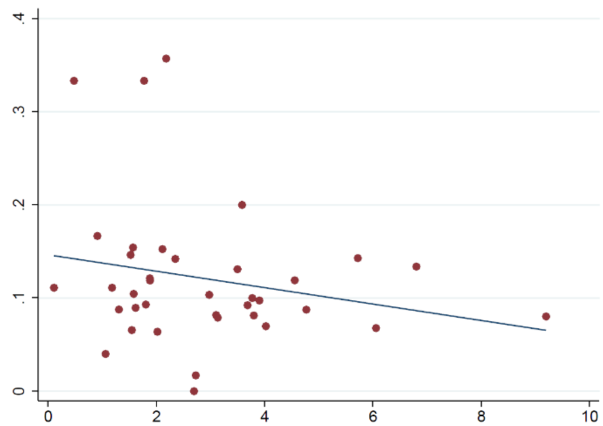
[44] Five matched areas are "Decatur, IL," "Fargo, ND-MN," "Laredo, TX," "Panama City-Lynn Haven-Panama City Beach, FL" and "Pueblo, CO." Honolulu in Hawaii is also one of matched areas satisfying matching process. However, it is not included in final dataset because it is a non-continental area of the U.S.

of households' in each region to total observation in my sample is about 20 percent, 17 percent, 30 percent, and 33 percent, respectively. Furthermore, from 2006 to 2009, the food insecurity rate between the overall U.S. population and the 40 matched areas was virtually identical as 13%.

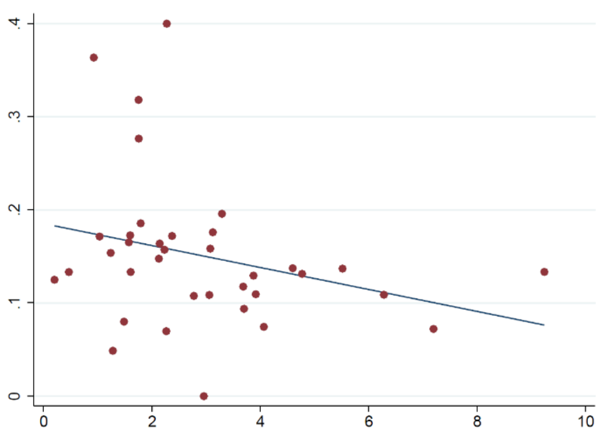
Figures 2.3 displays the relationship between the food insecurity rate and the number of bus-equivalent vehicles in 40 local areas of final dataset from 2006 to 2009. The horizontal axis



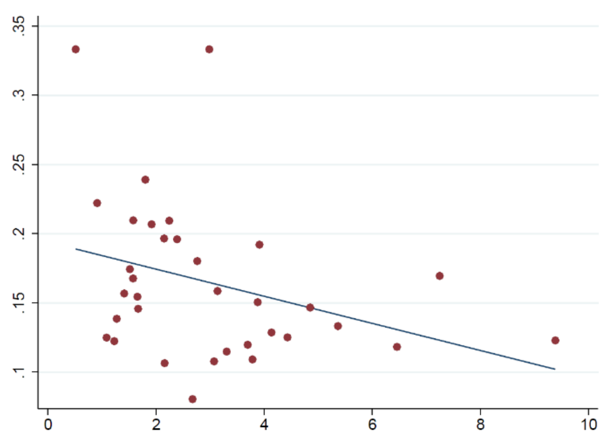
A. year 2006



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.

Figure 2.3 Food insecurity rate versus no. of bus-equivalent vehicles in 40 local areas 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.

2.4.4 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 2.2.

2.5 Results

2.5.1 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 (2.1). 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 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 2.2 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	

Notes: 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. Local (state) variables are calculated at the local area (state) level, and CPS-FSS sampling weights are not applied for mean and standard deviation.

Table 2.3 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%. A failure to take into account the potential endogeneity of public transit accessibility will result in biased estimates. Therefore, I use one-year, two-year, and three-year lagged Urbanized Area Formula (UAF) federal grants as instruments. The first stage coefficients of the instruments are presented at the bottom of Table 2.3 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 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 D.2 in the appendix. These coefficients do not substantively change across measures of food insecurity or regression specifications.

Table 2.3 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)
Dep. var. 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% level; ** at 5% level, and *** at the 1% 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 2.1 and 2.2) in addition to year and state fixed effects.

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 to the poor, as shown in Berube, Deakin, and Raphael (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 2.3 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% 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

[45] According to the Census Bureau, there were 2.59 persons per household from 2006 to 2010.

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 2.3 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 to 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.

[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 U.S." (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 to 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.

Using the same sample used for the IV estimations, I also report OLS estimates in the even-numbered columns of Table 2.3. 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.

2.5.2 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 2.4 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 2.3).[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; i.e. 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

[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

Table 2.4 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	OLS	IV	OLS
	(1)	(2)	(3)	(4)
By using a different cutoff				
Food insecurity = 1, otherwise 0				
1. Using cutoff = 2	-0.0369†	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†	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				
One-year lag of grants	0.0029***		0.0027***	
	(0.0007)		(0.0006)	
Two-year lag of grants	0.0018**		0.0021***	
	(0.0008)		(0.0003)	
Three-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

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 20% level; * at the 10% level, ** at the 5% level, and *** at the 1% 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 2.1 and 2.2) in addition to year and state fixed effects.

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.

et al. 2008),[50] and in car insurance prices (Harrington and Niehaus 1998).[51] 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.

2.5.3 Robustness checks

2.5.3.1 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 2.5 and 2.6 show the analyses for three samples classified by income-to-poverty ratio. Each Panel and Column of Tables 2.5 and 2.6 is a counterpart of Table 2.3. 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)

[50] Using the Survey of Consumer Finances dataset, 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.

Table 2.5 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	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	-0.0043***	-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)
Dep. var. 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

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% level; ** at 5% level, and *** at the 1% 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 2.1 and 2.2) in addition to year and state fixed effects.

Table 2.6 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)
Dep. var. 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

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% level; ** at 5% level, and *** at the 1% 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 2.1 and 2.2) in addition to year and state fixed effects.

in Columns (1) and (3) of Table 2.5 (Table 2.6) 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 2.3, the results in Tables 2.5 and 2.6 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 Appendix Table D.2).

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 2.7 and 2.8 where the significance of coefficients is comparable to that in Table 2.4 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.

2.6. 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 National Transit Database 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 Urbanized Area Formula 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

Table 2.7 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	OLS	IV	OLS
	(1)	(2)	(3)	(4)
By using a different cutoff				
Food insecurity = 1, otherwise 0				
1. Using cutoff = 2	-0.0112†	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†	-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				
One-year lag of grants	0.0102***		0.0106***	
	(0.0026)		(0.0020)	
Two-year lag of grants	0.0059**		0.0077***	
	(0.0024)		(0.0011)	
Three-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

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 20% level; * at the 10% level, ** at the 5% level, and *** at the 1% 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 2.1 and 2.2) in addition to year and state fixed effects.

Table 2.8 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†	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†	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				
One-year lag of grants	0.1508***		0.1440***	
	(0.0449)		(0.0277)	
Two-year lag of grants	0.0955**		0.1146***	
	(0.0392)		(0.0151)	
Three-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

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 20% level; * at the 10% level, ** at the 5% level, and *** at the 1% 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 2.1 and 2.2) in addition to year and state fixed effects.

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.

CHAPTER 3. THE IMPACT OF SNAP VEHICLE ASSET LIMITS ON ASSET ALLOCATION IN LOW-INCOME HOUSEHOLDS

3.1 Introduction

Social assistance programs typically include an 'asset test,' requiring that households own assets worth less than a threshold value in order to be eligible for assistance. This may discourage lower socio-economic status households from accumulating assets. It may also influence households' decisions to hold different types of assets, depending on how the different types of assets are treated in asset tests. At the same time, social assistance programs reduce the need for precautionary savings by providing households with a consumption floor.

Based on these observations, Hubbard et al. (1995) developed a theoretical model that explains the low average savings rate of lower socio-economic status households. Following Hubbard et al. (1995), several empirical papers have investigated the impact of income transfer programs on household behaviors. For example, Neumark and Powers (1998) investigated the impact of Supplemental Security Income (SSI) benefits on savings of individuals nearing retirement age. Gruber and Yelowitz (1999) found a negative effect of Medicaid on savings, and Engen and Gruber (2001) described the negative impact of unemployment insurance on the asset accumulation of workers.

Powers (1998) investigated the impact of asset limits on households receiving Aid for Families with Dependent Children Program (AFDC). Using a first-difference specification for the 1979 and 1983 waves of the National Longitudinal Survey of Young Women, Powers (1998) concluded that relaxing asset limits by one dollar leads to an increase in savings by 25 cents for households headed by single mothers. On the other hand, Hurst and Ziliak (2006) examined changes to the AFDC/TANF [53] asset limits during the 1990s and found little evidence that asset requirements explain savings behavior of poor households.

In addition to setting the maximum total amount of assets that may be held by households, eligibility rules for social assistance programs contain provisions about how different types of assets should be counted towards the asset limit. For example, most forms of retirement wealth are exempt from being counted towards the asset limit in the TANF program and the Supplemental Nutritional Assistance Program (SNAP).[54] Housing wealth is also excluded.

The federal TANF and SNAP program rules describe how the value of a household's vehicle should be treated in the context of asset limits. The consideration of vehicles is particularly important in the context of social support programs for two reasons. First, the value of a vehicle makes up a large proportion of the total wealth of poor households, particularly for single mothers (Sullivan, 2006). Second, if the program rules provide a disincentive for households to own cars, then this affects individuals' mobility, their ability to work, and limits access to grocery stores. Therefore, asset limits may be at odds with U.S. social support policy, which emphasizes individual responsibility.

Several papers investigated changes to the way that vehicles are treated in the asset test for the TANF program. However, there is no consensus in the literature regarding the impact of vehicle asset rules on household savings behavior and asset allocation choice. Sullivan (2006) concluded that a more relaxed TANF vehicle asset policy is positively associated with accumulation of vehicle assets for single mothers. Particularly, he found that excluding vehicles

[53] TANF (Temporary Assistance for Needy Families) is the welfare program that succeeded the AFDC in July 1996.
[54] The "Food Stamp Program" was renamed the "Supplemental Nutrition Assistance Program (SNAP)" in 2008 as part of an effort to reduce the stigma associated with transfer program participation. Although my data pertain to a time period before the program was renamed, I will refer to the Food Stamp Program as well as SNAP synonymously throughout this paper.

from asset tests generates an increase in vehicle equity by around $565. On the other hand, Hurst and Ziliak (2006) found no impact of TANF vehicle policy changes. Most recently, Owens and Baum (2012) found that relaxed TANF vehicle asset rules increase the amount of vehicle assets held by households.

In this paper, I contribute to the literature by examining the impact of relaxing vehicle asset rules in the SNAP program. This paper is the first to analyze the impact of vehicle asset rules in the SNAP program. I use a difference-in-difference specification as well as a household-level fixed effects model. Using household fixed effects allows us to exploit with-household variations to identify an effect of relaxed vehicle policies on household behavior. This is an important improvement over the previous literature. Hurst and Ziliak (2006) used a first difference specification, while Sullivan (2006) relied on repeated cross sections.

I find that liberalizing SNAP asset rules increases vehicle assets of single parents with low education. I focus on this group because of their high ex ante probability of SNAP program participation (Sullivan 2006; Ziliak and Hurst 2006). The magnitude of the impact is large. After the vehicle policy is relaxed, households own a car that is $2,000 more valuable compared to before the policy change. Particularly, I find evidence that low educated single parents who already owned a car before the policy change tend to buy more expensive cars once vehicle asset policies are relaxed. The results also suggest that households take on more debt in order to finance their vehicles. Liberalizing vehicle asset rules has no impact on liquid asset holdings as well as no impact on non-housing wealth and total wealth.

The rest of this paper is structured as follows. In section 3.2, I provide background information on the vehicle assets rules for SNAP eligibility and the policy changes that I investigate. I discuss my empirical strategy in section 3.3 and describe the construction of the data set in section 3.4. I present and discuss results from the empirical estimation in section 3.5, and section 3.6 concludes.

3.2 Background of the vehicle assets rules and policy changes

The Supplemental Nutritional Assistance Program (SNAP) is funded by the Federal Government, but is administered at the state level. Historically, eligibility rules for SNAP benefits were determined at the federal level, and the rules were generally identical across all states.

Federal program rules specify that individuals may have up to $2,250 in countable resources in order to be eligible for SNAP benefits. [55] Countable resources include assets such as checking and savings account balances. Countable resources according to the federal rules also include the fair market value of a household's vehicle, minus the SNAP's standard auto exemption of $4,650. For example, if a household owns a car with a fair market value of $6,000, then $1,350 (= $6,000 - $4,650) are added as a countable resource.[56]

The federal vehicle asset limit was set at $4,500 in 1977. The threshold is not indexed to inflation, and the limit has increased by only $150 since its implementation. The fact that the asset limit has increased so little over time has been criticized in the literature. For example, Super and Dean (2001) show that the vehicle asset limit implemented in 1977 corresponds to about $13,000 in 2000 nominal dollars. Super and Dean (2001) argue that the decline of the real asset limit over time increasingly presents a barrier to SNAP participation for low income households that are car dependent. The SNAP vehicle asset limit has also been criticized as inconsistent with government

[55] The limit for countable resources has increased from $2,000 to $2,250 as of October 2014 for a household without an elderly person (defined as one who is at least 60 years old) or a disabled one. The limit is $3,250 if a household contains at least an elderly or disabled individual. A person is considered to be disabled if he or she receives federal disability payments such as Social Security Disability, Supplemental Security Income or Railroad Retirement payments or general assistance because of disability.

[56] Income-producing vehicles (such as a taxi) or vehicles used as a primary residence are not subject to a vehicle asset test. Also, if vehicle equity (i.e. fair market value minus amount owed for the car) is less than $1,500, the vehicle is considered an inaccessible resource and is excluded from the asset test.

welfare goals encouraging higher employment, since owning a reliable vehicle is crucial for access to jobs and grocery stores for households living in areas with poor public transportation systems (Wemmerus 1993).

As a result of the Hunger Relief Act of 1999, states were given the authority to determine their own eligibility standards for SNAP. Starting in July 2001, states began to align their SNAP vehicle policy with other vehicle policies used for social assistance programs administered at the state level (Super and Dean 2001). Specifically, states had the option to apply the rules of their respective TANF or Maintenance of Effort (TANF/MOE) funded programs to the state's SNAP rules. This, however, was only possible if those programs had more liberal asset requirements compared to the federal SNAP rules. States had the option to implement any vehicle policy they saw fit (for example, raising the asset limit, excluding a vehicle entirely from the asset test, etc.) as long as the state-level policy was at least a generous as the federal rules. The idea behind the changes was to ease the administrative burden of different eligibility tests across different assistance programs, and to extend eligibility to a larger pool of individuals.[57]

Table 3.1 lists vehicle asset policy changes across states. I obtained each state's SNAP vehicle asset policy from the SNAP policy database of the United States Department of Agriculture (USDA). This includes the exact month and year that a particular vehicle asset policy was implemented by state, as well as the nature of the policy. The exact vehicle policies differ slightly between the states. In most cases, states decided to exclude entirely the value of one vehicle in a

[57] Starting with the fiscal year 2001, states were also authorized to offer broad-based categorical eligibility to households if they received any benefit from the state that was paid by TANF funds. Broad based categorical eligibility eliminates the need for any asset tests if individuals received a TANF funded benefit from the state. For example, a TANF funded benefit could be a brochure that was printed using TANF funds and that lists state resources available to low income residents. If an individual meets the state-determined criteria to be eligible to receive this brochure, then the individual is not subject to asset test according to SNAP rules. Since changes in vehicle asset policies apply only to a very small minority of low-income households when broad-based categorical eligibility is implemented in a state, I drop states with broad-based categorical eligibility from my sample.

Table 3.1 State-level vehicle asset rule for the SNAP eligibility

State	After policy change			Included in Subsample of States Used for Household Fixed Effects Specifications?
	Effective date	Vehicle exemption		
Alabama	2001 Sep	Exempt	All vehicles	
Arizona	2003 Jun	Exempt	All vehicles	Yes
Arkansas	2001 Sep	Exempt	One vehicle	
California	2003 Dec	Exempt	One vehicle	Yes
Colorado	2001 Jul	Exempt	One vehicle	
Florida	2001 Sep	More than federal SNAP rule		
Georgia	2005 Dec	Exempt	All vehicles	
Idaho	2007 May	Exempt	One vehicle	
Illinois	2001 Sep	Exempt	One vehicle	
Indiana	2002 Jan	Exempt	All vehicles	Yes
Iowa	2004 Jun	Exempt	One vehicle	
Kansas	2001 Sep	Exempt	All vehicles	
Kentucky	2001 Sep	Exempt	All vehicles	
Louisiana	2001 Sep	Exempt	All vehicles	
Minnesota	2003 Jun	Exempt	All vehicles	Yes
Mississippi	2003 Oct	Exempt	All vehicles	Yes
Missouri	2001 Sep	Exempt	All vehicles	
Montana	1996 Feb	Exempt	One vehicle	
Nebraska	2002 Jan	More than federal SNAP rule		Yes
Nevada	2001 Sep	Exempt	One vehicle	
New Hampshire	2001 Sep	Exempt	One vehicle	
New Jersey	2001 Sep	More than federal SNAP rule		
New Mexico	2002 Jan	Exempt	All vehicles	Yes
New York	2002 Jan	Exempt	One vehicle	Yes
North Carolina	2001 Jul	Exempt	One vehicle	
Ohio	2001 Sep	Exempt	All vehicles	
Oklahoma	2001 Sep	More than federal SNAP rule		
Pennsylvania	2001 Sep	Exempt	One vehicle	
Rhode Island	2003 Jun	Exempt	All vehicles	Yes
Tennessee	2003 Dec	Exempt	All vehicles	Yes
Utah	2001 Sep	More than federal SNAP rule		
Virginia	2002 Sep	Exempt	One vehicle	Yes
Washington	2004 May	Exempt	All vehicles	
West Virginia	2001 Sep	Exempt	All vehicles	
Wisconsin	2001 Sep	Exempt	All vehicles	

Note: Source: SNAP State Policy Database, United States Department of Agriculture. My sample does not include Delaware, Maine, Maryland, Massachusetts, Michigan, North Dakota, Oregon, South Carolina, and Texas because these states implemented broad-based categorical eligibility for SNAP during the sample period. South Dakota, Vermont, and Wyoming are not included in my final sample because the SIPP does not individually identify these states due to small state population. Connecticut is dropped because vehicle asset policies changed multiple times during the sample period. Hawaii and Alaska are not included because federal SNAP program rules, the federal poverty line, and other policies differ for the non-continental United States.

household or the value of all vehicles in a household from the asset limit calculations.[58] Some states chose to significantly raise the exemption value more than the federal SNAP rule. For example, Nebraska increased the exemption value to $12,000 in January 2002.

3.3 Empirical strategy

In this paper I investigate the impact of relaxing vehicle asset rules on vehicle assets and savings behavior for households that have a high probability of receiving food stamps. I focus on single parents with a high school education or less. Around 45 percent of households in this group received SNAP benefits. Of course, not all single parents with low education are eligible for SNAP benefits, and not all eligible households choose to participate in SNAP. However, single parent households with low education have a high *ex ante* probability of participating in SNAP. Consistent with the theoretical model of Hubbard et al (1995), and as discussed in the previous literature, I therefore examine how this group responds changes in vehicle asset rules (Ashenfelter 1983; National Research Council 2001).

I first estimate equations of the form

(3.1) $Y_{ist} = \beta VehiclePolicy_{st} + \gamma X_{ist} + \delta Z_{st} + \tau_t + \mu_s + \epsilon_{ist}$

where Y_{ist} is outcomes of interest for household i living in state s during year t. $VehiclePolicy_{st}$ is a dummy variable that takes a value of one when a vehicle assets policy that was more relaxed than the federal standard was effective in state s at time t. X_{ist} contains a vector of household characteristics such as the sex and race of the head of household, education level of the head of household, the number of household members, and the age of the head of household. In order to control for different savings rates of individuals across the life cycle, I include a polynomial in the age of the head of household as a control (Hubbard et al. 1995). Z_{st} contains a vector of time-varying state characteristics, including SNAP policy rules that capture differences in how the SNAP program was administered in each state, as well as other state-level controls. I discuss these variables in more detail in the data section.

Equation (3.1) contains a full set of year dummies, τ_t, as well as a full set of state dummies, μ_s. The coefficient of interest, β, can therefore be interpreted as a difference-in-difference estimate of implementing a relaxed SNAP vehicle asset policy. In addition, I estimate specifications that make use of the longitudinal nature of the data. I track households over time and estimate the following household fixed effects specification

(3.2) $Y_{ist} = \alpha_i + \beta VehiclePolicy_{st} + \gamma X_{ist} + \delta Z_{st} + \tau_t + \epsilon_{ist}$

α_i is a household level fixed effect, and X_{ist} contains only time-varying characteristics of the household. I do not include state dummies in Equation (3.2) because I include household fixed effects and restrict my sample to households who did not move during the sample period. Including a household level fixed effect in Equation (3.2) allows us to exploit with-household variations to identify an effect of relaxed vehicle policies on household behavior. This removes the effect of any time-invariant unobservable characteristics of households that may otherwise confound the results. This is an important improvement over the previous literature, which relied on first difference specifications (Hurst and Ziliak 2006) or repeated cross sections (Sullivan 2006).

I estimate Equations (3.1) and (3.2) for the at-risk group comprised of single parents with a high school education or less. I focus on this group because of their high ex ante probability of SNAP program participation (Sullivan 2006; Ziliak and Hurst 2006). I also investigate whether the impact of changes to vehicle asset policies on vehicle assets and debt is driven by households that already owned a car before the policy change deciding to buy more expensive vehicles, or whether the impact is driven by households that did not own a car before the policy change deciding to buy a car. Finally, as a falsification test I estimate specifications using the sample of childless individuals. Household without children have a lower ex ante probability of SNAP participation, and are therefore less likely to be affected by the vehicle asset policy changes.

3.4 Data

3.4.1 SIPP

I use household-level panel data from the Survey of Income and Program Participation (SIPP). The SIPP is a series of longitudinal surveys that contains information related to income and wealth from a nationally representative sample of U.S. households. I use the 2001 panel of the SIPP, which covers the years 2001 – 2003. This time period coincides with the implementation dates of the SNAP vehicle exemption policy in several states.[59] Households are interviewed during the same calendar month in each year of the survey, and I am able to track each household over time.

I link the Core SIPP with the SIPP Topical Module. The Core SIPP includes demographic information of household members, while the Topical Module contains information about a household's vehicles, as well as details about other types of assets and debt of the households. Not all SIPP respondents participate in the Topical Module. Information from the Topical Module is available for SIPP surveys conducted in September, October, November, and December in each year of the survey. Since each respondent household takes the survey during their same assigned calendar month each year, the same households participate in the Topical Module each year.

[59] I discuss the timing and nature of changes in states' vehicle policies in the next section.

Therefore, I am able to obtain information regarding vehicle, assets, and debts for about a third of the overall SIPP sample, and I am able to track households' answers over time.[60]

Of particular interests in this paper are car value, or car ownership, the number of cars, and the total amount of money that the household owed for cars, which are available at the household level. Based on the information of a vehicle's make, model, and model year reported by the household, the SIPP imputes the fair market value of the vehicle using Blue Book values. Importantly, states determine the fair market value of a vehicle in the same way for the purpose of SNAP eligibility. The survey also collects information about the amount of debt that is owed on the vehicles owned by a household. Liquid assets are calculated as the sum of dollar amounts in checking and saving accounts, bonds/securities, stocks, and other financial investments (Hubbard et al, 1995). I sum up the liquid assets, IRA accounts, business equity, and vehicle equity to create non-housing net wealth.[61] All dollar amounts in this paper are expressed in constant 2005 values.

Following Hurst and Ziliak (2006), I apply several sample restrictions. I exclude households that moved between states between interviews. I restrict the sample to households where the head of the household was between 18 and 60 years of age in 2001, and I exclude households with elderly or disabled household members because different SNAP assets requirements apply to households with elderly or disabled household members. In my household fixed effects specifications I only include the households that appeared at least twice during the sample period.

I only consider states that did not adopt broad-based categorical eligibility (BBCE) at any time from 2001 to 2003. As explained in the previous section,[62] broad-based categorical eligibility

[60] Appendix C provides a detailed description of the SIPP's complex survey design, including the structure of the waves, rotation groups, and reference month.
[61] Vehicle equity is defined as the car market value less dollar amounts a household owes.
[62] See footnote 57.

eliminates the asset test for all but a very small proportion of SNAP applicants. Nine states adopted BBCE during my sample period, and I exclude these states from my final data set.[63] South Dakota, Vermont, and Wyoming are not included in my final sample. The SIPP does not individually identify these states due to small state population. Connecticut is excluded because vehicle asset rule for SNAP eligibility changed multiple times.[64] Alaska and Hawaii are excluded because SNAP program rules, the federal poverty line, and other policies differ for the non-continental areas of the United States.

Out of the remaining 35 states, 20 implemented their vehicle policy before September 2001 and four states implemented their vehicle policy after December 2003. I include these 24 states when estimating specifications according to Equation (3.1), but I exclude them from my household fixed effects estimations because vehicle policies did not change during the sample period, and my fixed effects specifications exploit within-individual variations.[65] Table 3.1 displays when each state implemented their own vehicle asset policy, as well as a brief description of the new policy.[66]

I match information about states' vehicle asset policies with the SIPP data. In particular, I create a dummy variable that takes a value of one if a relaxed vehicle asset policy was in effect in a household's state of residence at the time of the SIPP interview, and a value of zero otherwise. Exact vehicle policies differ slightly between states, but all policy changes effectively increased the value of a car that a household may have without becoming ineligible for SNAP benefits. Since the primary focus of this paper is the impact of relaxed vehicle asset policies on household behaviors I will use this dummy variable as my primary variable of interest in all specifications.

[63] They are Delaware, Maine, Maryland, Massachusetts, Michigan, North Dakota, Oregon, South Carolina, and Texas.
[64] Specifically, one vehicle was exempted until 2001 August, then exemption rule was dropped, and then the rule was relaxed again in 2002 September.
[65] The final sample for household fixed effects estimation contains households from the following eleven states: Arizona, California, Indiana, Minnesota, Mississippi, Nebraska, New Mexico, New York, Rhode Island, Tennessee, and Virginia.
[66] Appendix Table D.3 presents vehicle policy information for states that are not included in my sample.

3.4.2 State-level control variables

I control for several other policy changes that occurred during my sample period that relate to the way that states administered SNAP (Ratcliffe, Makernan, and Finegold 2008). First, the 1996 welfare reform required states to implement an electronic benefit transfer (EBT) system for distributing SNAP benefits by October 2002. Instead of the paper coupons that were historically used by food stamps recipients to purchase food, the EBT systems provide recipients with an electronic benefit card that works similar to debit cards. The EBT systems were expected to increase SNAP participation due to the decrease in stigma associated with using SNAP benefits, and I control for their effect by including a variable that measures the proportion of the dollar value of SNAP benefits issued by EBT in each state.

I also control for differences in states' outreach activities that aim to inform low-income households about SNAP. I include a variable that measures time-varying outreach spending of each state. Following Ratcliffe, Makernan, and Finegold (2008) I use the dollar value of annual state outreach spending divided by the population below 150 percent of the poverty line that is not receiving SNAP benefits.

Aaronson et al (2012) found that minimum wage workers increase expenditures on durable goods after a minimum wage increase. In particular, they found that the majority of the spending increase goes towards vehicles. If a state increases the state level minimum wage at the same time that SNAP vehicle asset rules change, then this would confound my results. Therefore, I control for the state-level effective minimum wage in all my specifications.

Vehicle owners and operators are subject to vehicle taxes and registration fees collected by states and local governments. Changes in taxes and fees directly impact the cost of owning and operating a vehicle, and therefore it is important that I control for their effect. I obtained historical state tax collections by state from the Census Bureau, and control for per capita state vehicle taxes and fees in all regressions.

I also control for state-level welfare expenditures. Specifically, I include spending on Temporary assistance for Needy Families (TANF), as well as the state-level Maintenance of Effort (MOE) obtained from the Administration for Children and Families, U.S. Department of Health and Human Services. Finally, I control of other time varying state-level characteristics that are related to food security. In particular, I include state-level quarterly manufacturing wages from the Bureau of Economic Analysis, as well as state-level quarterly unemployment rates from the Bureau of Labor Statistics.

3.4.3 Descriptive statistics

I describe all variables used in this study, as well as the summary statistics, in Table 3.2. The first three columns of Table 3.2 contain descriptive statistics for households living in the 35 states used to estimate difference-in-differences specifications according to Equation (3.1). Columns (4)-(6) contain descriptive statistics for the eleven states used to estimate household fixed effects specifications according to Equation (3.2). Some of the states that are included in the 35-state sample had implemented a relaxed vehicle asset policy prior to the start of out sample period. Seventy-seven percent of households in the 35-state sample had a relaxed vehicle asset policy in place at the time of the survey. Since my fixed effects estimates require within-household variations of the vehicle policy, the sample is reduced to those eleven states that changed their vehicle asset policy during the sample period. Fifty percent of observations for households from these eleven states had a relaxed vehicle asset policy in place at the time of the surveys.

Table 3.2 Descriptive statistics for low educated single parents, SIPP from 2001 to 2003

Variable	Definition	Households from 35 States Used in Difference-in-Differences Specifications			Households from 11 States Used in Household Fixed Effects Specifications		
		Mean (SD)	Policy Change Before	Policy Change After	Mean (SD)	Policy Change Before	Policy Change After
		(1)	(2)	(3)	(4)	(5)	(6)
Relaxed Vehicle Asset Policy	=1 if the household lived in a state that had implemented a relaxed vehicle asset policy at the time of the survey interview, 0 otherwise	0.77 (0.42)	0.00 (0.00)	1.00 (0.00)	0.50 (0.50)	0.00 (0.00)	1.00 (0.00)
Savings Variables							
Car Market Value	Fair market value (FMV) of cars that households own (FMV = 0 if no car)	3,566 (4,649)	3,513 (4,556)	3,582 (4,678)	3,116 (4,246)	2,938 (4,013)	3,291 (4,467)
Car Market Value	Fair market value (FMV) of cars that households own, conditional on having a car	5,925 (4,683)	5,947 (4,546)	5,919 (4,725)	5,587 (4,304)	5,300 (4,066)	5,867 (4,524)
Car Equity	The amount of car equity (FMV minus car debt)	1,486 (4,643)	1,581 (4,121)	1,458 (4,788)	1,464 (4,008)	1,397 (3,809)	1,531 (4,203)
Car Debt	The amount of owed on the car	2,080 (5,390)	1,932 (4,845)	2,123 (5,542)	1,652 (4,866)	1,542 (4,413)	1,761 (5,283)
Liquid Assets	The amount of countable resources	1,831 (9,448)	2,445 (14,260)	1,649 (7,454)	1,942 (12,534)	2,096 (15,109)	1,790 (9,363)
Non-housing Wealth	The amount of wealth other than house value	4,160 (15,978)	6,450 (26,077)	3,483 (11,329)	4,500 (20,778)	5,469 (27,080)	3,545 (11,610)
Total Wealth	Sum of Non-housing wealth and house value	7,544 (29,186)	9,397 (31,948)	6,997 (28,310)	5,997 (23,380)	7,206 (29,362)	4,806 (15,348)
Car Ownership	=1 if household owned a car, 0 otherwise	0.60 (0.49)	0.59 (0.49)	0.61 (0.49)	0.56 (0.50)	0.55 (0.50)	0.56 (0.50)
Household Head Variables							
HH Size: 2 Individuals	=1 if household size is 2, 0 otherwise	0.32 (0.47)	0.32 (0.47)	0.33 (0.47)	0.29 (0.45)	0.27 (0.45)	0.30 (0.46)

Table 3.2. continued

HH Size: 3 Individuals	=1 if household size is 3, 0 otherwise	0.36	0.42	0.35	0.34	0.36	0.31
		(0.48)	(0.49)	(0.48)	(0.47)	(0.48)	(0.46)
HH Size: 4+ Individuals	=1 if household size is 4 or more, 0 otherwise	0.31	0.26	0.33	0.38	0.37	0.39
		(0.46)	(0.44)	(0.47)	(0.48)	(0.48)	(0.49)
Less than high school diploma	= 1 if a household head had less than high-school education, 0 otherwise	0.33	0.36	0.33	0.42	0.45	0.39
		(0.47)	(0.48)	(0.47)	(0.49)	(0.50)	(0.49)
High school diploma or GED	= 1 if the head of the household has a high school education, 0 otherwise	0.67	0.64	0.67	0.58	0.55	0.61
		(0.47)	(0.48)	(0.47)	(0.49)	(0.50)	(0.49)
Age	Age of a household head	36.97	36.67	37.06	37.51	36.99	38.02
		(9.09)	(9.18)	(9.07)	(8.71)	(8.84)	(8.57)
Male	=1 if a household head is male, 0 otherwise	0.12	0.16	0.11	0.09	0.09	0.08
		(0.33)	(0.36)	(0.31)	(0.28)	(0.29)	(0.27)
Female	=1 if a household head is female, 0 otherwise	0.88	0.84	0.89	0.91	0.91	0.92
		(0.33)	(0.36)	(0.31)	(0.28)	(0.29)	(0.27)
White	=1 if a household head is white, 0 otherwise	0.57	0.64	0.55	0.63	0.64	0.62
		(0.50)	(0.48)	(0.50)	(0.48)	(0.48)	(0.49)
Black	=1 if a household head is black, 0 otherwise	0.40	0.31	0.43	0.31	0.30	0.32
		(0.49)	(0.46)	(0.49)	(0.46)	(0.46)	(0.47)
Other Race	=1 if a household head is other race, 0 otherwise	0.03	0.05	0.03	0.06	0.05	0.06
		(0.18)	(0.22)	(0.16)	(0.24)	(0.23)	(0.24)
Reduced Lunch	=1 if any children in the household received free/reduced lunch at school	0.69	0.67	0.69	0.74	0.71	0.77
		(0.46)	(0.47)	(0.46)	(0.44)	(0.45)	(0.42)
State-Level Characteristics							
Minimum Wage	Minimum wage	5.24	5.43	5.18	5.39	5.45	5.34
		(0.36)	(0.59)	(0.23)	(0.55)	(0.58)	(0.51)
TANF	Log of expenditure on Temporary Assistance for Needy Families	19.71	19.74	19.71	20.18	19.97	20.38
		(1.17)	(1.29)	(1.13)	(1.53)	(1.51)	(1.51)
MOE	Log of expenditure on Maintenance of Effort	19.06	19.17	19.03	19.59	19.53	19.66
		(1.32)	(1.57)	(1.24)	(1.83)	(1.87)	(1.80)
Unemployment	Unemployment rate	5.53	5.36	5.58	5.65	5.68	5.61
		(0.75)	(1.04)	(0.63)	(0.93)	(0.95)	(0.90)

Table 3.2. continued

Wage	Log of manufacturing wage	9.69 (0.87)	9.71 (0.90)	9.68 (0.86)	9.83 (1.01)	9.84 (1.05)	9.81 (0.97)
Vehicle Tax	Dollar value of per capita state vehicle taxes and fees collected in the quarter of the survey interview (*1000)	21.04 (9.54)	18.23 (9.93)	21.87 (9.27)	16.99 (5.71)	16.58 (6.24)	17.40 (5.13)
State-Level SNAP Policy Rules							
EBT Issuance	Percentage of dollar value of FSP benefits issued by EBT (electronic benefits transfer)	0.92 (0.25)	0.74 (0.41)	0.98 (0.13)	0.79 (0.36)	0.63 (0.44)	0.96 (0.12)
Outreach Spending	Dollar value of outreach spending divided by the population below 150% of the poverty line that are not FSP recipients	27.14 (64.21)	39.97 (89.50)	23.35 (54.02)	51.55 (83.10)	30.69 (43.49)	72.09 (105.00)
N		1,522	347	1,175	407	202	205

Notes: Data are from SIPP panels: Wave 3 in 2001, Wave 6 in 2002, and Wave 9 in 2003. Only includes single parents who have a high school diploma or less education. Vehicles include cars, vans and trucks, but exclude recreational vehicles (RVs) and motorcycles. Values of each vehicle are aggregated if a household owns multiple cars. Liquid assets contain dollar amounts in checking and saving accounts, bonds/securities, stocks, and other financial investments. Non-housing wealth includes liquid assets, IRA accounts, business equity, and vehicle equity. Dollar values are in 2005 dollars.

In my main specification I estimate the impact of state vehicle asset policies on vehicle value, treating the vehicle value as zero if a household did not own a car. Table 3.2 shows that for the sample of 35 states used in the difference-in-differences specification, the mean fair market value of cars is $3,513 before the vehicle policy change, and $3,582 after the policy change.[67] Similarly, the mean car market value increases from $2,938 to $3,291 for the 11-state sample used for household fixed effects model. Conditional on having a car, the mean fair market values of vehicles in the household from the 35-state sample and the 11-state sample are $5,947 and $5,300 before the policy change, respectively. The mean fair market value is above the federal vehicle asset limit of $4,650, and therefore the limit appears to be binding in both samples.[68] After the policy change, the mean fair market value of vehicles decreases to $5,919 in the former sample, but increases to $5,867 in the latter sample. Descriptive statistics of most other variables are very similar between the samples. Once exception is education. Fifty-eight percent of households from the 11-state sample have a high school diploma, while 67 percent of the 35-state sample completed high school.

There are some differences in household characteristics after a vehicle asset policy change compared to before the policy change. As expected, household heads from both samples are slightly older after the policy change. Household heads are also more likely to have a high school diploma or have completed their GED. Since education may be correlated with a household's asset allocation decisions, it is important to control for education in my specifications.

[67] 14.3 percent of households own more than one car. This may be the case when a single parent has a child that is of driving age. In this case I use the sum of the fair market values of all vehicles in the household.

[68] Sullivan (2006) reports an average market value of car of $5,760 in 1996 dollars (about $7,170 in 2005 dollars) for single mothers with at most a high school education for the time period 1992 to 1999. For 2001-2003 I find an average of $5,587 or $5,925, depending on the sample used. The difference in the real car value may be the result of using different samples. My sample includes only 11 or 35 states, while Sullivan used all states.

3.5 Results

3.5.1 Difference-in-differences estimates

Table 3.3 displays the results of estimating specifications according to Equation (3.1), explaining the impact of vehicle asset policies on the value of a household's car, equity in the car, amount owed on the car, as well as the probability of owning a car. All regressions include controls for individual characteristics of the head of the household, family characteristics, state level characteristics and policies, as well as state fixed effects and year dummies. Since each household may appear in multiple years of the survey, I cluster all standard errors at the household level in order to account for within-household correlation of errors. I assign a fair market value of zero for households that did not own a car. I find no statistically significant impact of relaxing vehicle asset policies on the value of a household's car, equity in the car, or the amount owed on the car at conventional levels of statistical significance (Columns 1-3). However, the point estimate from the car value equations is positive and large, with a p-value of 0.15. Column (4) shows that relaxing vehicle asset policies increase the probability of owning a car by seven percentage points. Sixty percent of low educated single parent household own a car in this sample. The results in Column (4) represent a twelve percent increase over this baseline, and therefore the impact is economically significant as well.

Coefficients of all control variables have the expected sign. For example, more education is positively associated with car values and with the probability of owning a car, and females are less likely to own a car compared to males. Similar to Aaronson et al (2012), I find that an increase in the minimum wage is positively associated with the value of a household's car.

Table 3.3 The impact of relaxed SNAP vehicle asset policy on car value, car equity, car debt, and car ownership of low educated single parents – Difference-in-Differences

	(1)	(2)	(3)	(4)
	Car Value	**Car Equity**	**Car Debt**	**Car Ownership**
Relaxed Vehicle Asset Policy	823.2	-183.6	1006.8	0.0740*
	(576.7)	(609.1)	(882.3)	(0.0400)
HH Size: 3 Individuals	208.1	328.8	-120.7	0.00514
	(384.3)	(371.7)	(403.0)	(0.0360)
HH Size: 4+ Individuals	-59.82	252.7	-312.5	-0.0845**
	(396.0)	(417.5)	(480.1)	(0.0403)
High School Education or GED	1633.5***	852.8**	783.9**	0.163***
	(310.6)	(331.4)	(365.9)	(0.0361)
Age	-57.18	-1567.4***	1510.2**	0.0824
	(560.1)	(578.5)	(608.0)	(0.0597)
Age-Square	8.149	43.84***	-35.69**	-0.00152
	(14.80)	(15.34)	(16.62)	(0.00159)
Age-Cube	-0.112	-0.378***	0.266*	0.0000
	(0.124)	(0.129)	(0.144)	(0.0000)
Female	-1305.3**	-55.14	-1250.2	-0.110***
	(596.3)	(715.4)	(902.7)	(0.0420)
Race: Black	-1528.3***	-610.6*	-917.8**	-0.216***
	(354.4)	(346.0)	(383.1)	(0.0374)
Race: Other	-584.7	-780.3^{+}	195.6	-0.123
	(676.2)	(490.7)	(770.5)	(0.0880)
Reduced Lunch	-953.7***	34.83	-988.5**	-0.0750**
	(357.5)	(384.5)	(417.4)	(0.0306)
Min. Wage	4311.7**	3407.5*	904.2	0.0811
	(1805.0)	(2015.6)	(1982.1)	(0.213)
Household Fixed Effect	No	No	No	No
State Fixed Effect	Yes	Yes	Yes	Yes
Year Dummies	Yes	Yes	Yes	Yes
Family Characteristics	Yes	Yes	Yes	Yes
State-Level Characteristics	Yes	Yes	Yes	Yes
State-Level SNAP Policy Rules	Yes	Yes	Yes	Yes
N	1,522	1,522	1,522	1,522

Notes: Standard errors clustered at the household level in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Estimates use data from the Survey of Income Program Participation (SIPP). Sample includes single parents with a high school education or less during the sample period, 2001-2003. State-level characteristics include log of TANF and MOE expenditures, unemployment rate, log of manufacturing wages, and state vehicle taxes and fees. State-level SNAP policy rules are percentage of FSP benefits issued by electronic benefits transfer (EBT) and outreach spending per capita.

Table 3.4 shows specifications estimated according to Equation (3.1) describing the impact of vehicle asset policies on households' liquid assets, non-housing wealth, and total wealth. There is no significant impact of the policy change on the amount of liquid assets that household hold. Liquid assets include checking account balances, savings account balances, and similarly liquid financial assets. Single parents with low education hold on average only about $1,831 in liquid assets, and larger families tend to have more liquid assets. Consistent with the previous literature, I find no evidence of the impact of relaxing vehicle asset policies on liquid (Owens and Baum 2012; Hurst and Ziliak 2006; Sullivan 2006). Non-housing wealth is a broader measure of wealth that includes liquid assets, as well as other financial assets. Table 3.4 shows that relaxing vehicle asset policies does not affect non-housing wealth either. Finally, there is no significant effect of vehicle policy changes on total wealth, which I obtained by adding real estate equity on non-housing wealth.

3.5.2 Fixed effects estimates

My preferred specification exploits within-household variations and includes a household fixed effect in order to track households over time. Results of these household fixed effects specifications according to Equation (3.2) are presented in Table 3.5. All specifications also include controls for time varying characteristics of the head of the household, family characteristics, state level characteristics and policies, as well as year dummies. All standard errors are clustered at the household level.

Column (1) of Table 3.5 shows that vehicle values increase by $2,005 after state vehicle asset policies are relaxed. The effect is statistically significant at the five percent level, and it is highly economically significant as well. The estimated impact of $2,005 for the vehicle policy change represents an increase in vehicle value by about 64% over the mean vehicle value of $3,116.

Table 3.4 The impact of relaxed SNAP vehicle asset policy on wealth of low educated single parents – Difference-in-Differences

	(1)	(2)	(3)
	Liquid Assets	**Non-housing Wealth**	**Total Wealth**
Relaxed Vehicle Asset Policy	1228.4	-2197.2	-2993.7
	(1369.8)	(2608.7)	(3248.6)
HH Size: 3 Individuals	675.8	2571.6*	-1697.8
	(778.6)	(1358.3)	(2395.2)
HH Size: 4+ Individuals	1030.8	1977.1	-1337.8
	(987.8)	(1391.9)	(2279.3)
High School Education or GED	2041.7***	2978.0**	3287.3*
	(742.4)	(1210.6)	(1812.2)
Age	-2289.1*	-3831.9**	7520.4
	(1247.8)	(1752.1)	(8076.9)
Age-Square	60.00*	104.1**	-213.5
	(32.56)	(45.58)	(229.6)
Age-Cube	-0.479*	-0.859**	2.020
	(0.269)	(0.374)	(2.087)
Female	-2940.7^{+}	-5404.9**	-9047.0*
	(1937.5)	(2519.5)	(4824.5)
Race: Black	-1986.0***	-3144.4***	-9854.0***
	(493.1)	(1023.1)	(2351.8)
Race: Other	-1711.6**	-3646.0**	-6027.4**
	(759.6)	(1520.7)	(2473.7)
Reduced Lunch	1057.1	975.7	-1685.5
	(755.4)	(1363.7)	(2605.7)
Min. Wage	-14839.6	-10756.4	-18528.2
	(13314.8)	(13797.3)	(13529.6)
Household Fixed Effect	No	No	No
State Fixed Effect	Yes	Yes	Yes
Year Dummies	Yes	Yes	Yes
Family Characteristics	Yes	Yes	Yes
State-Level Characteristics	Yes	Yes	Yes
State-Level SNAP Policy Rules	Yes	Yes	Yes
N	1,522	1,522	1,522

Notes: Standard errors clustered at the household level in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Estimates use data from the Survey of Income Program Participation (SIPP). Sample includes single parents with a high school education or less during the sample period, 2001-2003. State-level characteristics include log of TANF and MOE expenditures, unemployment rate, log of manufacturing wages, and state vehicle taxes and fees. State-level SNAP policy rules are percentage of FSP benefits issued by electronic benefits transfer (EBT) and outreach spending per capita.

Table 3.5 The impact of relaxed SNAP vehicle asset policy on car value, car equity, car debt, and car ownership of low educated single parents – household fixed effects

	(1)	(2)	(3)	(4)
	Car Value	**Car Equity**	**Car Debt**	**Car Ownership**
Relaxed Vehicle Asset Policy	2005.0**	-735.6	2740.7*	0.0533
	(933.4)	(1099.6)	(1442.9)	(0.0788)
HH Size: 3 Individuals	354.7	390.5	-35.81	0.0869
	(1214.2)	(914.0)	(868.3)	(0.111)
HH Size: 4+ Individuals	2005.0	205.5	1799.6	0.203
	(1507.5)	(1114.1)	(1493.7)	(0.159)
High School Education or GED	2351.0*	314.3	2036.7	0.267
	(1376.5)	(1369.8)	(1732.6)	(0.369)
Age	-4332.1	2134.4	-6466.5	-0.160
	(4346.7)	(4146.3)	(6793.3)	(0.406)
Age-Square	78.02	-1.244	79.26	0.00584
	(103.2)	(92.39)	(141.0)	(0.0116)
Age-Cube	-0.771	-0.175	-0.596	-0.0000602
	(0.881)	(0.766)	(1.187)	(0.000107)
Reduced Lunch	-1403.2	523.3	-1926.6^{+}	-0.0793
	(1032.1)	(1207.5)	(1203.0)	(0.0895)
Min. Wage	9490.2**	2273.7	7216.4^{+}	0.281
	(3827.1)	(3069.0)	(4906.9)	(0.287)
Household Fixed Effects	Yes	Yes	Yes	Yes
State Fixed Effects	No	No	No	No
Year Dummies	Yes	Yes	Yes	Yes
Family Characteristics	Yes	Yes	Yes	Yes
State-Level Characteristics	Yes	Yes	Yes	Yes
State-Level SNAP Policy Rules	Yes	Yes	Yes	Yes
N	407	407	407	407

Notes: Standard errors clustered at the household level in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Estimates use data from the Survey of Income Program Participation (SIPP). Sample includes single parents with a high school education or less during the sample period, 2001-2003. State-level characteristics include log of TANF and MOE expenditures, unemployment rate, log of manufacturing wages, and state vehicle taxes and fees. State-level SNAP policy rules are percentage of FSP benefits issued by electronic benefits transfer (EBT) and outreach spending per capita.

The increase in car value of households does not correspond to an increase in car equity (vehicle market value less amount owed on the vehicle). Column (2) of Table 3.5 shows that there is no statistically significant impact of the vehicle policy changes on the equity that households hold in vehicles. There is a direct accounting relationship between car value, or equity, and debt. If the asset value of the car increases, and at the same time there is no impact on vehicle equity, then the balance must come from increases in debt. Column (3) presents the results of estimating the impact of relaxing vehicle asset polices on the amount of debt on the vehicle. The point estimate ($2,741) of the effect is large, and it is precisely estimated at the 10 percent significance level.

Contrary to the difference-in-difference results presented in Table 3.3, in my household fixed effects estimates I find no statistically significant impact of vehicle asset policies on the probability that households own a car (Column 4 of Table 3.5). The evidence from Table 3.5 suggests that households do respond to policy changes by purchasing more expensive vehicles when vehicle asset policies are liberalized. Moreover, my results show that households use debt in order to purchase the more expensive vehicle. Although low socioeconomic status households are likely to be credit constrained, households may still have access to credit markets, especially when purchasing vehicles (Aaronson et al. 2012). The point estimates of the impact of vehicle policy changes on debt (Table 3.5) suggest that debt on cars increases by a larger amount after vehicle policy changes compared to car values. While this result may seem counterintuitive at first, it is not uncommon for individuals to have negative equity in their vehicle, particularly after trading in one vehicle to buy another (Federal Trade Commission 2012).

Similar to the difference-in-differences estimates, my household fixed effects specifications show that there is no impact of vehicle asset policies on the amount of liquid assets that household hold (Table 3.6). I also find no statistically significant impact of vehicle asset policies on non-housing wealth or total wealth of households.

The results suggesting that households respond to policy changes by purchasing more expensive vehicles after vehicle asset policies are liberalized combine the intensive margin and the extensive margin. This is because I treated vehicle values as zero when households did not own a car. Households that owned a vehicle before the policy change may choose to purchase a more expensive vehicle. At the same time, a household that did not own a vehicle prior to the policy change may choose to buy a vehicle as a result of the relaxed vehicle asset policy. Sullivan (2006), as well as Owens and Baum (2012) found that the probability of vehicle ownership increased as a result of relaxing TANF vehicle rules.

To investigate further, I first estimate car value, car equity, and car debt as a function of vehicle asset policy for the subsample of low educated single parents who owned a car before the policy change. This reduces the sample size by 50 percent compared to the main results from Tables 3.5. Summary statistics for all variables conditional on car ownership before the policy change are available in Appendix Table D.4. The results presented in Table 3.7 show that individuals who owned a car before the policy change own a car that is worth \$2,532 more after the policy change (Column 1). This effect is statistically significant at the ten percent level. Households also increase their vehicle debt by a statistically significant \$3,707 after the policy change (Column 3). There is no statistically significant effect of vehicle policy changes on vehicle equity. Second, I use the subsample of low educated single parents who did not have a car before the policy change and estimate car ownership status as a function of relaxing vehicle asset policies. Column (4) of Table 3.7 shows that the point estimate of the impact of the vehicle policy change is positive, but not statistically significantly different from zero. I conclude that there is no

Table 3.6 The impact of relaxed SNAP vehicle asset policy on wealth of low educated single parents – household fixed effects

	(1)	(2)	(3)
	Liquid Assets	**Non-housing Wealth**	**Total Wealth**
Relaxed Vehicle Asset Policy	3296.5	-1933.8	-5416.5
	(2688.0)	(5456.8)	(5769.5)
HH Size: 3 Individuals	937.6**	2449.7	908.1
	(459.0)	(2878.3)	(2800.0)
HH Size: 4+ Individuals	1075.1	155.6	-3310.1
	(867.4)	(3280.1)	(3172.1)
High School Education or GED	693.5	-4217.5	-2306.0
	(1378.8)	(7159.0)	(6861.7)
Age	-6034.4	-5850.1	-224.2
	(4373.8)	(9230.7)	(12629.8)
Age-Square	59.25	193.1	195.4
	(85.91)	(260.6)	(318.2)
Age-Cube	-0.585	-2.167	-2.260
	(0.727)	(2.271)	(2.666)
Reduced Lunch	-3031.7	2376.8	-64.04
	(2677.3)	(6198.0)	(6287.6)
Min. Wage	-909.2	1543.9	-14990.3
	(5866.4)	(7921.4)	(11636.9)
Household Fixed Effect	Yes	Yes	Yes
State Fixed Effects	No	No	No
Year Dummies	Yes	Yes	Yes
Family Characteristics	Yes	Yes	Yes
State-Level Characteristics	Yes	Yes	Yes
State-Level SNAP Policy Rules	Yes	Yes	Yes
N	407	407	407

Notes: Standard errors clustered at the household level in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Estimates use data from the Survey of Income Program Participation (SIPP). Sample includes single parents with a high school education or less during the sample period, 2001-2003. State-level characteristics include log of TANF and MOE expenditures, unemployment rate, log of manufacturing wages, and state vehicle taxes and fees. State-level SNAP policy rules are percentage of FSP benefits issued by electronic benefits transfer (EBT) and outreach spending per capita.

Table 3.7 The impact of relaxed SNAP vehicle asset policy on outcomes of interest: Samples of low educated single parents who have a car before the vehicle policy change vs. who do not have a car before the vehicle policy change – household fixed effects

	(1)	(2)	(3)	(4)
	Having a Car before the Policy Change			*Not-having a Car* before the Policy Change
	Real Car Value	**Real Car Equity**	**Real Car Debt**	**Car Ownership**
Relaxed Vehicle Asset Policy	2531.7*	-1176.2	3707.9*	0.159
	(1386.8)	(1555.0)	(2059.1)	(0.157)
HH Size: 3 Individuals	-641.8	382.7	-1024.5	0.0991
	(1389.1)	(1159.2)	(848.7)	(0.162)
HH Size: 4+ Individuals	-1955.3	-615.2	-1340.0	0.232
	(1578.2)	(1559.3)	(1832.0)	(0.195)
High School Education or GED	1685.0	-409.0	2094.0	0.776***
	(1602.8)	(2229.7)	(3061.0)	(0.225)
Age	-6760.3	4066.7	-10827.1	-0.435
	(5965.9)	(6180.3)	(9641.6)	(0.451)
Age-Square	107.4	-48.17	155.5	0.0123
	(142.3)	(131.3)	(201.8)	(0.0104)
Age-Cube	-1.033	0.0620	-1.095	-0.0000979
	(1.254)	(1.057)	(1.722)	(0.0000840)
Reduced Lunch	-2271.6+	168.4	-2440.1	-0.00899
	(1484.1)	(1907.2)	(1758.5)	(0.0848)
Min. Wage	14760.8***	5571.0	9189.8	-0.122
	(4978.3)	(4067.0)	(6449.8)	(0.429)
Household Fixed Effect	Yes	Yes	Yes	Yes
State Fixed Effect	No	No	No	No
Year Dummies	Yes	Yes	Yes	Yes
Family Characteristics	Yes	Yes	Yes	Yes
State-Level Char.	Yes	Yes	Yes	Yes
State-Level SNAP Rules	Yes	Yes	Yes	Yes
N	233	233	233	174

Notes: Standard errors clustered at the household level in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Estimates use data from the Survey of Income Program Participation (SIPP). Sample includes single parents with a high school education or less during the sample period, 2001-2003. State-level characteristics include log of TANF and MOE expenditures, unemployment rate, log of manufacturing wages, and state vehicle taxes and fees. State-level SNAP policy rules are percentage of FSP benefits issued by electronic benefits transfer (EBT) and outreach spending per capita.

evidence to suggest that relaxing vehicle asset policies had an impact on car ownership for low educated single parents who did not own a vehicle before the policy change.

I conclude from Tables 3.5 and 3.7 that the increase in vehicle value and vehicle debt is driven by individuals who owned a car before the policy change deciding to purchase a more expensive vehicle. This is an intuitive result because it is unlikely that car dependent households would prefer having no car over having a car that is worth less than the federal asset limit of $4,650. There are several reasons for buying a more expensive car, conditional on already owning one. For example, a household may choose to upgrade their vehicle to a more dependent, safer, or lower mileage model. To the extent that a more reliable vehicle is related to car dependent households' labor market participation and food security, relaxing vehicle asset policies may be a good thing from a policy maker's perspective. However, households may also choose to upgrade their vehicle for other reasons that do not correspond to the policy maker's objectives.

Since I have no information regarding the actual vehicle that a household own, it is difficult to address this question in this paper. However, it may be possible to gain some insight by examining the Blue Book values of vehicles around the sample period. For example, a 1992 Hyundai Elantra in excellent condition and average mileage was valued at $3,225 in 2000. Consumer Reports show that this car had an average reliability rating and an average safety rating.

This suggests that it was possible for households to have reliable and secure transportation to work and to grocery stores with a vehicle valued well below the federal vehicle asset limit of $4,650. The estimated increase by around $2,500 after the vehicle policy change means that by 2002 households could have upgraded to a Toyota Corolla, which is also eight years old, but has a superior safety rating and superior reliability rating.[69]

[69] For the comparison of those two used cars (Elantra vs. Corolla), I use recently produced used cars, instead of the used cars made in 1990s, due to the limited information in Consumer Reports.

Households that receive Temporary Assistance for Needy Families (TANF) or Supplemental Security Income (SSI) are categorically eligible for SNAP, and any changes to the asset rules related to SNAP do not apply to these households.[70] In order words, they are automatically eligible for SNAP without vehicle asset tests. Therefore, the results presented above should not be driven by households that receive TANF benefits. Accordingly, I estimate specifications that exclude households that ever received TANF benefits during the sample period because TANF recipients are categorically eligible for SNAP and the SNAP asset test does not apply.

Table 3.8 shows the results of estimating Equation (3.2) including all controls for the subsample of households that have never received TANF benefits during the sample period. The size of the sample is reduced, and the models were estimated with a sample size of 299 observations. Similar to results from the sample of all single parents with at most a high school diploma, I find that relaxing vehicle asset policy affects car market value and debt for those single parents with at most a high school diploma who never received TANF benefits. Car equity, car ownership, liquid assets, and non-housing wealth are not affected by state vehicle asset policies. Real vehicle value increases by $3,807 as a result of the policy changes. This effect is statistically significant at the 1 percent level, and the point estimate is larger compared to the sample of all single parents.

As an additional robustness check, I estimate specifications according to Equation (3.2) for households that have a significantly lower ex-ante probability of receiving SNAP benefits. I estimated all regression using a sample of individuals with at most a high school education who do not have any children. Despite the similar education level, only around 15 percent of individuals

[70] This is not the same as broad-based categorical eligibility. TANF recipients have also been categorically eligible for SNAP benefits prior to any state-level policy changes.

Table 3.8 The impact of relaxed SNAP vehicle asset policy on all outcomes of interest sample of low educated single parents who never receive tanf – household fixed effects

	(1)	(2)	(3)	(4)	(5)	(6)
	Car Value	**Car Equity**	**Car Debt**	**Car Ownership**	**Liquid Assets**	**Non-housing Wealth**
Relaxed Vehicle Asset Pol.	3807.0***	-224.4	4031.4*	0.121	5022.8	-2106.9
	(1244.6)	(1568.7)	(2161.2)	(0.0927)	(3992.4)	(8264.8)
HH Size: 3 Individuals	751.2	721.0	30.24	0.213*	616.7	5364.2
	(1469.3)	(1237.3)	(980.1)	(0.125)	(763.4)	(3960.8)
HH Size: 4+ Individuals	3046.1*	-141.3	3187.3*	0.389**	1648.4	378.8
	(1743.0)	(1490.3)	(1840.9)	(0.175)	(1293.5)	(4677.6)
High School Education	2497.9*	31.18	2466.7	0.305	1523.3	-9633.7
	(1324.9)	(2049.4)	(2595.4)	(0.340)	(2267.3)	(11800.3)
Age	-4660.4	5597.9	-10258.3	-0.440	-8731.7	-2689.4
	(5012.3)	(6556.7)	(8708.9)	(0.493)	(6328.0)	(12994.7)
Age-Square	53.96	-90.43	144.4	0.0115	79.57	134.7
	(116.0)	(141.8)	(168.6)	(0.0135)	(122.5)	(331.4)
Age-Cube	-0.659	0.440	-1.099	-0.000111	-0.756	-1.838
	(0.962)	(1.084)	(1.339)	(0.000120)	(0.986)	(2.796)
Reduced Lunch	-1760.9	669.1	-2430.0*	-0.162*	-3724.9	3299.3
	(1219.7)	(1390.1)	(1423.9)	(0.0862)	(3312.5)	(8014.6)
Min. Wage	13501.2**	4180.5	9320.7	0.276	-3534.1	-305.0
	(5275.2)	(4428.8)	(6658.2)	(0.280)	(10588.3)	(13908.9)
HH Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes
State Fixed Effect	No	No	No	No	No	No
Year Dummies	Yes	Yes	Yes	Yes	Yes	Yes
Family Char.	Yes	Yes	Yes	Yes	Yes	Yes
State-Level Char.	Yes	Yes	Yes	Yes	Yes	Yes
State-Level SNAP Policy Rules	Yes	Yes	Yes	Yes	Yes	Yes
N	299	299	299	299	299	299

Notes: Standard errors clustered at the household level in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Estimates use data from the Survey of Income Program Participation (SIPP). State-level characteristics include log of TANF and MOE expenditures, unemployment rate, log of manufacturing wages, and state vehicle taxes and fees. State-level SNAP policy rules are percentage of FSP benefits issued by electronic benefits transfer (EBT) and outreach spending per capita.

without children received food stamps, compared to 45 percent of single parents. Therefore, individuals without children are less likely to be affect by the vehicle policy changes. Singles without children own similar valued vehicles to ones of single parents, but have higher car equity. Real car equity of single individuals without children is around $2,200, compared to $1,500 of single parents.

Table 3.9 shows that vehicle policy changes do not affect the value of vehicles, vehicle equity, vehicle debt, or the probability of having a car for single individuals without children.[71] The point estimates are smaller compared to the point estimates from the specifications using single parents, and the standard errors are large. The number of observations is also larger for the sample of household of individuals without children compared to the households headed by single parents. Therefore, I conclude that the statistical insignificance of the results is not driven by smaller sample size.

3.6 Conclusion

In this paper, I used data from single parents with low education obtained from the Survey of Income and Program Participation to examine the effects of state vehicle asset rules on vehicle assets and debts, car ownership, liquid assets holdings, as well as non-housing wealth. I used a difference-in-differences specification, as well as a fixed effects estimator that exploits within-household variations in the timing of state vehicle asset policy changes to identify the effect of state vehicle asset rules on the outcomes of interest.

Liberalizing vehicle asset rules results in a significant increase in the value of households' vehicles. In particular, after the vehicle asset policy is relaxed, households own cars that are around

[71] Since this sample consists of non-married individuals without children, I do not control for family size or children receiving reduced lunch in any of the specifications.

Table 3.9 The impact of relaxed SNAP vehicle asset policy on all outcomes of interest. low educated individuals without children – household fixed effects

	(1)	(2)	(3)	(4)	(5)	(6)
	Car Value	**Car Equity**	**Car Debt**	**Car Ownership**	**Liquid Assets**	**Non-housing Wealth**
Relaxed Vehicle Asset Pol.	-93.12	-391.4	298.3	0.0188	-3592.0	44471.3
	(949.3)	(967.7)	(1554.6)	(0.0658)	(5639.7)	(34843.9)
High School Education	547.7	-4474.6	5022.4	0.0199	-1829.0	-1834.6
	(440.2)	(3598.2)	(3862.4)	(0.0369)	(5537.4)	(15837.7)
Age	-558.8	588.4	-1147.2	-0.309	3366.4	-77104.5^{+}
	(2287.9)	(3001.9)	(3442.4)	(0.260)	(20291.3)	(52491.9)
Age-Square	4.138	-6.841	10.98	0.00590	-226.8	641.6
	(46.03)	(70.41)	(77.79)	(0.00526)	(570.6)	(998.0)
Age-Cube	0.0331	0.0115	0.0216	-0.0000372	2.637	-3.382
	(0.348)	(0.545)	(0.587)	(0.0000387)	(5.316)	(8.109)
Min. Wage	-1185.7	1588.3	-2774.0	-0.0910	-11934.0	44835.0
	(2749.2)	(2776.3)	(3676.9)	(0.195)	(23822.3)	(46377.8)
HH Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes
State Fixed Effect	No	No	No	No	No	No
Year Dummies	Yes	Yes	Yes	Yes	Yes	Yes
Family Char.	Yes	Yes	Yes	Yes	Yes	Yes
State-Level Char.	Yes	Yes	Yes	Yes	Yes	Yes
State-Level SNAP Policy Rules	Yes	Yes	Yes	Yes	Yes	Yes
N	555	555	555	555	555	555

Notes: Standard errors clustered at the household level in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Estimates use data from the Survey of Income Program Participation (SIPP). State-level characteristics include log of TANF and MOE expenditures, unemployment rate, log of manufacturing wages, and state vehicle taxes and fees. State-level SNAP policy rules are percentage of FSP benefits issued by electronic benefits transfer (EBT) and outreach spending per capita.

$2,000 more expensive compared to the time prior to the policy change. This increase corresponds to an increase in vehicle asset by 64 percent at the mean. I find evidence to suggest that households use credit in order to finance the more expensive car. I also find evidence that the increase in vehicle market values after SNAP vehicle policies are relaxed stems from households who already owned a car before the policy change buying a more expensive vehicle. There is no impact of the vehicle asset policy changes on the propensity of households to own a car. Liberalizing vehicle asset rules has no impact on liquid asset holdings and no impact on non-housing wealth.

The results of this paper contribute to the literature on the effects of asset tests used to determine eligibility for social assistance programs. This paper is the first to analyze the impact of vehicle asset rules in the SNAP program. The literature does not agree about the effect of vehicle asset policies in other social assistance programs, and I provide additional evidence suggesting that individuals do respond to liberalized asset policies.

Since I observe only the fair market value and debt associated with households' vehicles, but not the actual vehicle owned by the households, it is difficult to assess whether the effect of the vehicle asset policy changes is desirable from a policy maker's perspective. The increase in vehicle values and debt I report here may be the result of households upgrading their vehicles to more dependable and safer models, which has the potential to improve labor market outcomes and food security. However, the current data do not allow us to test this hypothesis directly, and further research is needed.

CHAPTER 4. THE IMPACT OF AIR QUALITY NOTIFICATIONS ON INFANT HEALTH: EVIDENCE FROM KOREA

4.1 Introduction

It has been documented that health at birth, specifically birth weight, has long term effects. For example, Currie (2011) and the papers she cites show that infants with higher birth weights are taller, have greater IQ scores, attain higher education levels and earn more when they are adults. Because of birth weight's importance in shaping future outcomes, it is important from both scientific and public policy perspectives to investigate its determinants (Almond and Currie 2011). In this paper, I focus on the impact of air quality and the effectiveness of public air quality warnings on infant health.

The Asian yellow sand (called Hwang-sa in Korean) is a weather phenomenon, that is generated in the arid lands of northern China and the desert regions of Mongolia plateau "under the conditions of high temperature, low humidity, and high wind velocity" (Chun et al. 2001). Winds with abnormally high speed, particularly the Westerlies,[72] pick up dust and sand particles and carry them towards the Korean peninsula. Then, these particles of dust and sand gradually settle in Korea's territory, and this event is called a yellow sand outbreak (event). The events occur "most frequently during spring from March to May, but irregularly during winter" (Chun et al. 2001). Summer (called monsoon season in Korea) has no Asian dust due to heavy rainfalls. Figure 4.1 displays the average daily particulate matter levels (PM10, a proxy of yellow dust) by month and illustrates this phenomenon.[73]

[72] The Westerlies, winds blowing from the west to the east, occur in "the temperate zones, in the middle latitudes between 30 and 60 degrees latitude, in the Earth."
[73] PM10 consists of particles such as ash and dust that are less than $10\mu m$ in diameter.

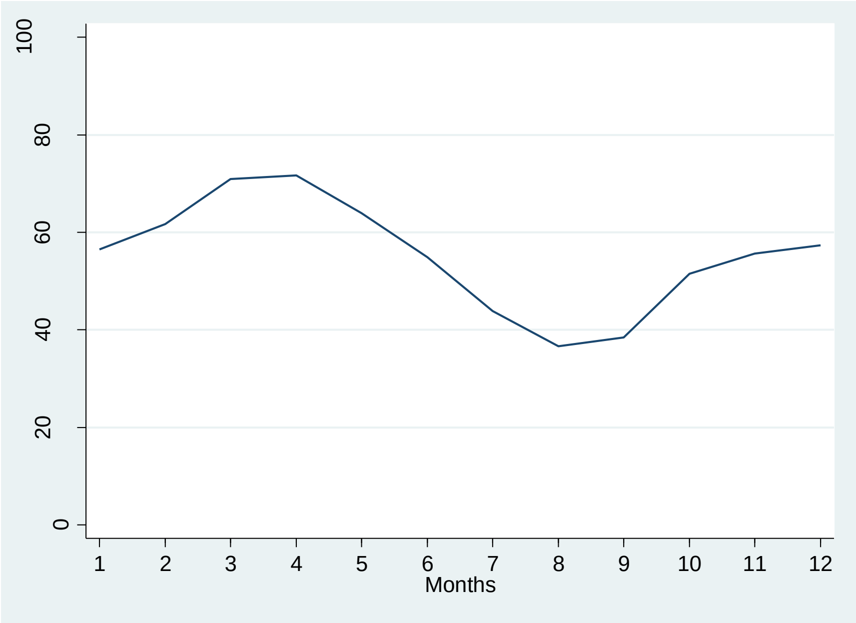


Figure 4.1 Average daily PM10 concentrations in my sample between years 2003 and 2011

The dust and sand particles carried to Korea by winds are believed to harm human health and to cause adverse respiratory health effects, particularly in children and the elderly (Ministry of Environment of Korea 2002). Dust concentrations are more harmful to pregnant women who are likely to retain a lower level of immunity (National broadcast newspaper in Korea 2011). Epidemiological literature has also found negative health consequences of yellow sand (Park et al. 2005; Lee et al. 2007).

Due to these detrimental effects, in order to reduce the risk of dust exposure, Korea has developed a warning system with behavioral guidelines. Since 2002, Korean Meteorological Administration (KMA) releases notifications to the public based on the PM10 levels. In the areas that are affected by yellow sand events, concentration of PM10 is elevated. An advisory and a warning is issued when PM10 level rise above 400 and 800 $\mu m/\mathrm{m}^3$ for over 2 hours in a day, respectively. These public notifications advise individuals, especially children, the elderly, and people with respiratory illnesses to reduce outdoor activities. During yellow dust warning days, staying indoors is recommended. Pregnant women are suggested to refrain from outdoor activities and to wear protective masks if necessary. Individuals do follow these behavioral guidelines. For example, in 2002, in response to high density yellow dust, elementary schools are closed, and plants in some industries, such as semiconductor manufacturing temporarily are shut down (KMA).

Using data obtained from about 1.5 million birth certificates of infants born between 2003 and 2011 in Korea, I investigate the effect of dust notifications issued by the KMA on birth weight. The mechanisms through which these notifications may affect birth outcomes are twofold. First, when a notice is issued, if pregnant women comply with the advisory by staying indoors, they avoid exposure to the pollutants. Therefore, their babies are born healthier. Consider the following hypothetical example of two identical pregnant women Annie and Barbie who live in cities A and B, respectively. A yellow dust event hits both cities, increasing PM10 levels to 400 and 399 $\mu m/\mathrm{m}^3$ in cities A and B, respectively. Because of the warning issue rule mentioned above, city A warns its residents, while city B does not. Consequently, unlike Barbie, Annie takes precautionary action by staying indoors and avoids exposure to elevated levels of pollution. Therefore, Annie's baby is more likely to be born healthier compared to Barbie's baby.

The second mechanism involves an unintended consequence of the dust warnings. Specifically, the warnings may reduce the risk that a pregnant woman catches infectious diseases such as the flu which influences infant health negatively (Rasmussen, Jamieson and Uyeki 2012). During a yellow sand outbreak, when a warning is issued, Koreans respond by wearing preventive masks. This is documented in the popular media.[74] Such masks not only provide protection against the dust, but also against airborne infectious diseases (Cowling et al. 2009; MacIntyre et al. 2008). Similarly, if individuals stay indoors more, when a dust warning is issued, in effect, they isolate

[74] New York Times, April 12th, 2002, p.3. "China's Growing Deserts Are Suffocating Korea" http://events.nytimes.com/2002/04/14/international/asia/14KORE.html?pagewanted=print&position=top&_r=0

themselves and become less likely to get infected or spread diseases. When the majority of the population undertakes such preventive actions, even the individuals who do not protect themselves are likely to be protected. This positive externality is known as the Community (or Herd) Effect in the epidemiology literature (John and Samuel 2000).[75] Thus, mothers who have experienced more dust warnings are less likely to catch infectious diseases, and their babies are less likely to suffer negative consequences of these diseases.

This paper is the first to investigate the effectiveness of public air quality warnings on birth outcomes. Previous papers by Moretti and Neidell (2011), Neidell (2009) and Neidell (2004) also consider public warnings, but these papers focus on smug alerts' effect on respiratory illnesses such as the asthma in general population, rather than birth outcomes. Additionally, in this paper, I exploit a natural experiment to estimate the effect of air quality warnings. Yellow sand storms occur naturally and are blown mostly in the spring from northern China and Mongolia. The deterioration in air quality due to these exogenous storms gives rise to public warnings. Thus, the identification of the effect of air quality warnings comes from the exogenous geographical and temporal variation in pregnant women's experience of dust notifications.

Controlling for the air quality during pregnancy (measured by the average exposure to PM10), I find that dust notifications have statistically significant effect on fetal health. If a pregnant mother experiences an additional advisory or a warning during her pregnancy, her baby's birth weight increases by about 10 grams. I also provide evidence for an unintended consequence of these notifications. Specifically, I show that a baby is more likely to be born with lower weight if their mother's risk of catching an infectious disease, particularly the flu, during pregnancy is higher. However, the detrimental effect of the flu on newborns' health gets smaller if their mothers

[75] Herd Effect is defined as the indirect protection observed in the unprotected or unimmunized segment of a population in which a large proportion is immunized or protected (John and Samuel 2000).

experienced air quality notifications. My findings are robust to inclusion of weather controls. Taken together, my results provide evidence for the effectiveness of warning systems in promoting public health. My results also underline the importance of taking into account individual's avoidance behavior when estimating the impact of air quality on birth outcomes, a confounding factor which is not explicitly taken into consideration when estimating the effect of pollution on infant health.

The rest of this paper is organized as follows. In section 4.2, I provide an empirical specification. Section 4.3 describes data construction and section 4.4 presents the estimated results. Section 4.5 concludes.

4.2 Empirical specification

In order to investigate the role of the dust notifications on infant health outcomes, I estimate the equation depicted below:

(4.1) $Health_{ict} = \alpha + \beta PM10_{ict} + \gamma Notices_{ict} + X_{ic}\rho + \mu_c + \theta_t + \epsilon_{ict}$

where $Health_{ict}$ indicates birth outcomes of an infant i born to a mother residing in region c at time t. I consider four outcome variables: a continuous measure of birth weight, a binary indicator of low birth weight (indicating whether the infant's birth weight is less than 2,500 grams), gestation weeks and fetal growth (birth weight per gestation week).[76] $PM10_{ict}$ measures the air quality. Specifically, $PM10_{ict}$ is the average hourly PM10 to which infant i's mother is exposed during her pregnancy. $Notices$ stands for the number of days the mother experienced an advisory or a warning in her pregnancy. Because the exposure to pollution in different developmental stages of the fetus may have differential impact on birth outcomes, in another specification, I use the

[76] Studies, such as Coneus and Spiess (2012), also used fetal growth as a birth outcome measure.

exposure of mothers to PM10 and notices in each trimester of pregnancy instead of their exposure during the whole pregnancy.

X in Equation (4.1) is a vector of control variables that include parental characteristics, such as both parent's age, education, marital status and employment status. Omission of such variables could bias my estimates. For example, it is possible that mothers who have certain attributes (such as more education or more experience) could be more aware of the potential negative health effects of yellow sand. If these mothers time their pregnancy to avoid the months in which there are frequent yellow sand outbreaks or when the density of the dust is high, and if these educated mothers have babies with higher birth weights due to better nutrition, etc., then I might incorrectly attribute a difference in birth weight between highly-educated and low-educated mothers to air quality or dust warnings, when in fact part of the difference might be due to the mother's education. Similarly, family affluence can determine infant health (Currie 2011), so it is important to control for family income level. In this paper, I use parental education and employment status as proxies of family income, as the income itself is not available in the data source.[77]

Vector X also contains variables that are believed to have an effect on infant birth weight (Currie 2011). Such variables include infant's gender, an indicator of whether the infant was part of a multiple birth and birth parity. In the regressions, I include indicators for the region of residence, μ_c, to account for unobserved time-invariant characteristics of the regions. For example, there could be a disparity in economic development across regions, and the more urbanized areas are likely to have greater access to health care. Equation (4.1) also contains a vector of year dummies, θ_t. Standard errors in all specifications are clustered at the city level.

[77] Solon (1992) considered father's years of education as a good proxy of permanent income.

4.3 Data

My data set is composed of two different data sets: 1) Korean birth certificates and 2) Hourly PM10 observations. Korean birth certificates data are obtained from Vital Statistics-Natality Files provided by Statistics Korea Micro Data Service System. These files cover all of birth certificates issued across Korea. The birth certificate data set contains infant-level variables such as gender, birth weight, gestational length, whether the infant was singleton, and birth order, as well as parental demographics such as age, education level, employment status, and marital status. Following Knittel, Miller, and Sanders (2011), I restrict my sample to infants whose gestational age is between 27 and 42 weeks in order to sufficiently determine three trimesters.

PM10 data are obtained from National Institute of Environmental Research (NIER) in Korea. Hourly PM10 measure is available at the monitor station level. Some districts contain multiple monitor stations, and in total there are roughly 250 such weather stations across Korea. In case of multiple monitoring stations in a region, I used the average of their measures. I calculated the average hourly PM10 exposure of every mother during their pregnancy according to their city of residence, gestation length and their baby's date of birth listed in the birth certificates.[78] My measure of air pollution is the average hourly PM10 concentration in the city of residence of the mother during her pregnancy. Figure 4.2 shows the average daily PM10 concentrations in each region across Korea between years 2003 and 2011 in my sample.[79] As shown, the PM10 concentration is relatively higher in the northeast, close to northern China and the Mongolia

[78] The birth certificates data set only includes month and year of birth, but not day of birth. In my analysis, I assumed that infants are born on the 15th day of the month reported in the certificate. I were also unable to identify children born from the same mother and twins as the birth certificate data set does not include mother's name and residential street address.

[79] Although PM10 concentrations are available at the weather station level in a region, for eight regions (Seoul, Busan, Daegu, Incheon, Gwangju, Daejeon, Ulsan, and Gyeonggi-do) I report the average PM10 levels in a region in this map due to the lack of space.

plateau. For example, it was 58.6 $\mu m/m^3$ in Seoul between 2003 and 2011, whereas Geoje-si, the most southeastern region used in my sample, had 36.3 Geoje-si $\mu m/m^3$.

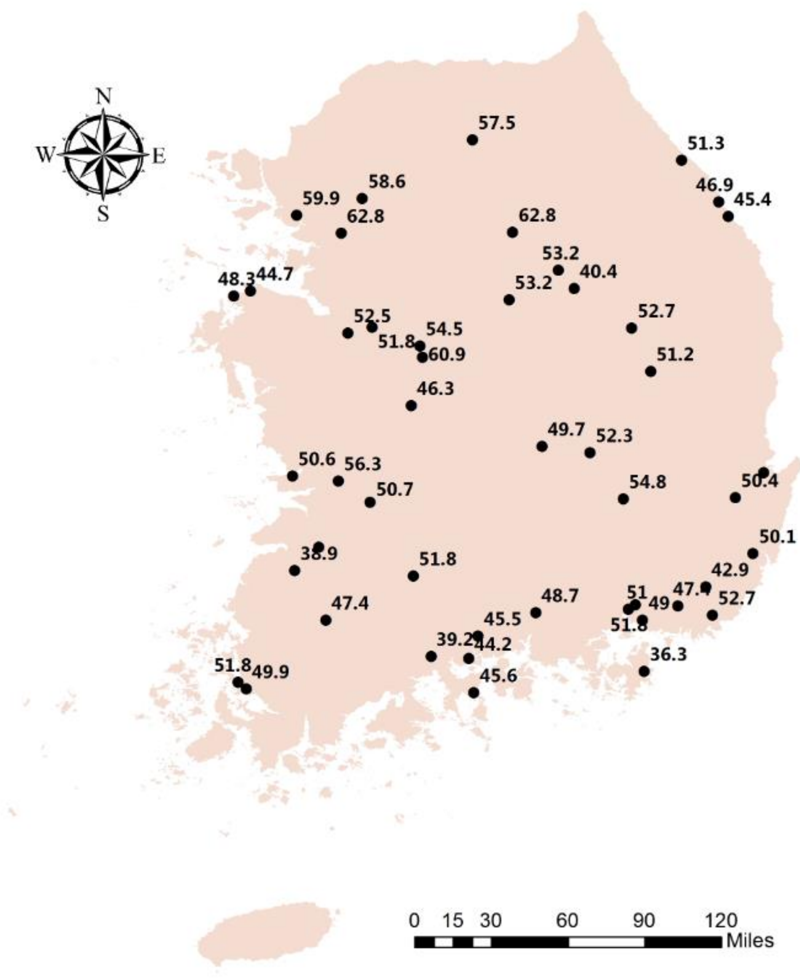


Figure 4.2 Average daily PM10 concentrations in each region across Korea between years 2003 and 2011

Since 2002, the KMA has been issuing advisories and warnings to the residents based on the PM10 levels in the area. These notices provide information to the residents and advise them to take protective action against air pollution. The thresholds of PM10 above which *advisories* and *warnings* are issued are 400 and 800 $\mu m/m^3$ for two consecutive hours, respectively. To construct my measure of advisories and warnings, I counted the number of pregnancy days in which observed PM10 level was greater than 400 and 800 $\mu m/m^3$ for at least two hours. That is, the variables *Advisory* and *Warning* denotes the number of corresponding notices by the KMA a mother experiences during her pregnancy.

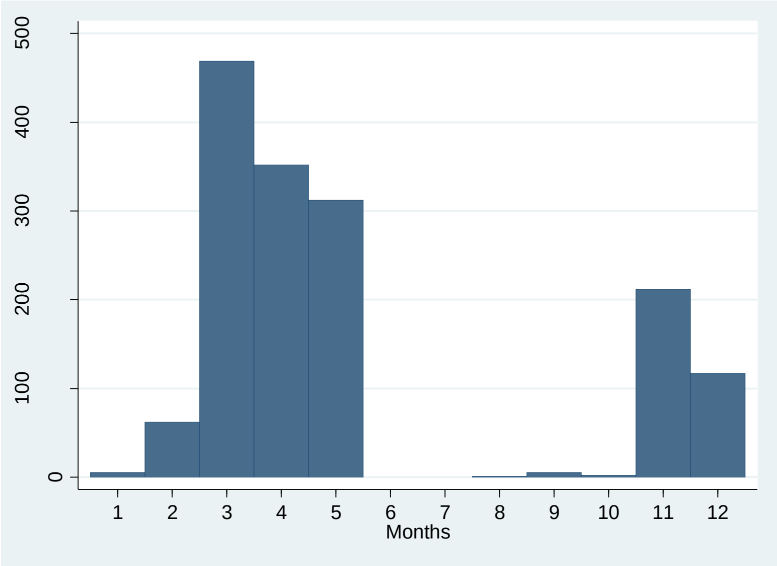
My final data set is composed of about 1.5 million infants born to mothers in Korea between 2003 and 2011.[80] The descriptions and the summary statistics of the variables I use in my analysis are presented in Table 4.1. The average Korean infant was born just above 3,200 grams with gestational age of 39 weeks. Approximately, five percent of Korean infants weighed less than 2,500 grams at birth. An average Korean mother is not employed, is in her late 20s or early 30s, and she has a college degree or more. She is also married. An average Korean father is employed, in his early to mid 30s with a college degree or more. A comparison of Korean infants' characteristics to those of American infants born in New Jersey reveals that the incidence of low birth weight is about twice as much in New Jersey compared to Korea (Currie et al. 2009). This difference could be partially due to the difference in parents' education levels: the average American mother has a high school diploma.

Average hourly PM10 exposure of a mother in my sample is about 56 $\mu m/m^3$. Due to yellow dust breaks, mothers experienced 1.1 advisories and 0.46 warnings during their pregnancies (issued when PM levels greater than 400 and 800 $\mu m/m^3$ for two consecutive hours during a day, respectively). Number of advisories (warnings) during pregnancy ranges between 0 and 7 (0 and 3) in my sample. Figures 4.3 and 4.4 depict the total numbers of advisories and warnings in all 123 regions in my sample between years 2003 and 2011, and they show similar patterns to Figure 4.1.

[80] My sample starts from 2003 since dust alert systems have been established during the middle of the year 2002. In the data set I obtained from the Statistics Korea, there are about 4 million birth certificates between 2003 and 2011. However, I lose observations since the PM10 data is not available for some Korean cities.

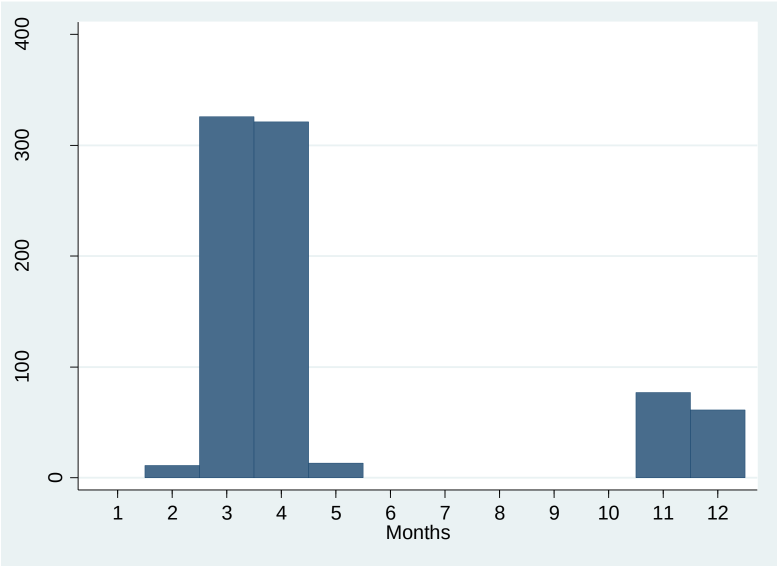
Table 4.1 Descriptions and summary statistics for Korean babies born between 2003 and 2011

Variable	Description	Mean	(SD)
Outcome variables			
Birth Weight	Birth weight of the infant in grams	3,233.30	(454.36)
Low Birth Weight	=1 if birth weight is less than 2,500 grams	0.05	(0.21)
Gestation	Gestational age of the infant in weeks	38.85	(1.59)
Fetal Growth	Birth weight/Gestation	83.11	(10.63)
Air quality and Notice variables			
Advisory	Number of pregnancy days in which PM10 levels were above 400 two consecutive hours	1.10	(1.26)
Warning	Number of pregnancy days in which PM10 levels were above 800 two consecutive hours	0.46	(0.74)
PM10	Average hourly PM10 exposure during pregnancy	55.62	(9.33)
Infant variables			
Singleton	=1 if the infant is singleton (as opposed to twin or triplet)	0.97	(0.16)
Girl	=1 if the infant is a girl	0.48	(0.50)
Birth order 2	=1 if the infant is the second child to a mother	0.39	(0.49)
Birth order 3+	=1 if the infant is the third child to a mother or higher	0.09	(0.29)
Parent variables			
Married	=1 if the parents of the infant are married	0.99	(0.09)
Mother working	=1 if mother is employed	0.28	(0.45)
Mother's age 20-29	=1 if mother's age is between 20 and 29	0.41	(0.49)
Mother's age 30-39	=1 if mother's age is between 30 and 39	0.57	(0.50)
Mother's age 40+	=1 if mother's age is at least 40	0.02	(0.12)
Mother HS	=1 if the mother's highest completed degree is high school	0.35	(0.48)
Mother College	=1 if the mother's highest completed degree is college or more	0.63	(0.48)
Father working	=1 if father is employed	0.96	(0.20)
Father's age 20-29	=1 if father's age is between 20 and 29	0.19	(0.39)
Father's age 30-39	=1 if father's age is between 30 and 39	0.74	(0.44)
Father's age 40+	=1 if father's age is at least 40	0.07	(0.25)
Father HS	=1 if the father's highest completed degree is high school	0.31	(0.46)
Father College	=1 if the father's highest completed degree is college or more	0.67	(0.47)
Observations		1,472,978	



Note: Figure illustrates the total number of advisories in all 123 cities in my sample between years 2003 and 2011.

Figure 4.3 Number of advisories in my sample between years 2003 and 2011



Note: Figure illustrates the total number of warnings in all 123 cities in my sample between years 2003 and 2011.

Figure 4.4 Number of warnings in my sample between years 2003 and 2011

4.4 Results

Results obtained from estimation of Equation (4.1) are presented in Table 4.2. In addition to the variables listed, all regressions include city and year fixed effects. Outcome variables are the birth weight in grams (column 1), and indicator for whether the birth weight is less than 2,500 grams (column 2), gestational age in weeks (column 3), and ratio of birth weight to gestational age in grams per week (column 4). Standard errors reported in parentheses are clustered at the city level.

Column 1 in Table 4.2 shows that babies of the mothers who were exposed to worse air quality during their pregnancy are born with lower weights. Specifically, a one $\mu m/m^3$ increase in the average exposure to PM10 during pregnancy leads to about 1 gram reduction in the newborn's birth weight. This implies a 10 percent increase in the average hourly PM10 exposure reduces birth weight by about 0.2% (from the baseline of 3,200 grams). Column 1 also indicates that each additional advisory and warning that mother experiences during her pregnancy improves birth weight by 10 and 14 grams, respectively. These effects are statistically different from zero. A warning's effect is larger than an advisory's effect. The p-value for the equality of coefficients is less than 0.01. This could be because a warning signals greater dust levels and greater risk than an advisory, and therefore a warning may prompt a greater response.

Advisories and warnings are issued based on the measurements of PM10. Specifically, when there is a spike of pollutants for two hours during one day, an advisory or warning is issued. Notice that a spike in PM10 concentrations during two hours has a minimal effect on the average PM10 exposure during pregnancy (typically 39 weeks). For example, during a yellow dust event, if PM10 levels increased to 400 $\mu m/m^3$ for two hours, the average hourly exposure will increase to 56.11 $\mu m/m^3$ from 56 $\mu m/m^3$. According to my estimates in column 1, such a change in the

Table 4.2 The effect of dust notifications on infant health

	(1)	(2)	(3)	(4)
	Birth Weight	Low Birth Weight	Gestational Age	Fetal Growth
Advisories	9.913***	-0.004***	0.076***	0.113***
	(0.700)	(0.000)	(0.005)	(0.012)
Warnings	14.037***	-0.006***	0.106***	0.164***
	(1.446)	(0.001)	(0.008)	(0.027)
PM10	-0.943***	0.000***	-0.006***	-0.012***
	(0.136)	(0.000)	(0.001)	(0.003)
Singleton	844.850***	-0.491***	2.836***	17.103***
	(5.026)	(0.004)	(0.025)	(0.100)
Girl	-96.495***	0.009***	0.137***	-2.765***
	(0.672)	(0.000)	(0.003)	(0.015)
Birth Order 2nd	27.760***	-0.009***	-0.394***	1.581***
	(1.236)	(0.000)	(0.004)	(0.029)
Birth Order 3+	57.712***	-0.011***	-0.396***	2.353***
	(1.966)	(0.001)	(0.006)	(0.048)
Married	32.477***	-0.014***	0.120***	0.611***
	(4.784)	(0.002)	(0.015)	(0.115)
Mother employed	5.911***	0.000	-0.002	0.151***
	(1.041)	(0.000)	(0.003)	(0.025)
Mother’s Age 20-29	62.534***	-0.008**	0.057**	1.478***
	(5.960)	(0.003)	(0.023)	(0.140)
Mother’s Age 30-39	60.916***	-0.001	-0.025	1.589***
	(5.904)	(0.003)	(0.023)	(0.141)
Mother’s Age 40+	17.866**	0.019***	-0.289***	0.997***
	(6.830)	(0.004)	(0.027)	(0.166)
Mother HS	43.073***	-0.010***	0.045***	1.022***
	(3.361)	(0.002)	(0.013)	(0.078)
Mother College	49.545***	-0.015***	0.108***	1.070***
	(3.457)	(0.002)	(0.013)	(0.080)
Father employed	10.228***	-0.005***	0.008	0.268***
	(1.724)	(0.001)	(0.007)	(0.038)
Father’s Age 20-29	20.831	-0.004	0.045	0.474
	(12.742)	(0.007)	(0.048)	(0.310)
Father’s Age 30-39	22.673*	-0.004	0.046	0.518
	(12.983)	(0.007)	(0.047)	(0.318)
Father’s Age 40+	11.855	0.003	-0.041	0.403
	(12.714)	(0.007)	(0.047)	(0.310)
Father HS	20.278***	-0.007***	0.027**	0.470***
	(3.256)	(0.001)	(0.011)	(0.076)

Table 4.2 continued

Father College	26.175***	-0.012***	0.081***	0.518***
	(3.318)	(0.001)	(0.011)	(0.080)
Observations	1,472,978	1,472,978	1,472,978	1,472,978

Notes: Outcome variables are the birth weight in grams (1), and indicator for whether the birth weight is less than 2,500 grams (2), gestational age in weeks (3), and ratio of birth weight to gestational age in grams per week (4). Regressions include indicators for cities and years. Standard errors reported in parentheses are clustered at the city level. *, ** and *** indicate significance at 10%, 5% and 1% levels, respectively.

PM10 levels will reduce the baby's birth weight by about 0.11 grams. However, because an advisory is issued, baby's birth weight will improve by about 10 grams. The net effect of the rise in PM10 levels on birth weight will be an increase of 9.9 grams. My results suggest that the effect of a smaller spike of PM10 is detrimental, because it does not trigger an advisory. For example, an increase of PM10 levels to 350 $\mu m/m^3$ for two hours will raise the average hourly PM10 exposure to 56.09 $\mu m/m^3$, which will reduce the birth weight by about 0.09 grams.

Similar to those in column 1, results presented in columns 2 to 4 in Table 4.2 provide evidence for a negative effect of average PM10 exposure and a positive effect of notifications on birth outcomes. Each additional advisory and warning that a pregnant woman experiences reduces the probability of low birth weight by 0.4 and 0.6 percentage points (from the baseline of 5 percentage points). More advisories and warnings increase the gestational age and average fetal growth, while PM10 exposure reduces them.

The signs of the control variables in Table 4.2 are as expected. Girls, twins or triplets and babies born to mothers who have not previously given birth weigh less at birth compared to boys, singletons and babies born to mothers who have given birth to at least one baby, respectively. Prime age for best birth outcomes are 20s for mothers and 30s for fathers. Babies whose parents are employed and have attained higher education levels are born healthier.

Previous papers have provided evidence for differential effect on the birth outcomes of external factors in different developmental stages of a fetus (Currie 2011). To investigate this possibility, in the regressions, I include exposure to PM10 and number of notices against poor air quality in first, second and third trimesters, instead of the overall exposure during the whole pregnancy. For example, instead of the variable *Advisories*, I include *Advisories – trimester 1*, *Advisories – trimester 2* and *Advisories – trimester 3* that measure the number of advisories a pregnant women has experienced during her first, second and third trimesters, respectively.

The results presented in Table 4.3 are similar to those in Table 4.2. Number of advisories experienced in any trimester has a positive and significant impact on the birth weight. These effects are not statistically different from each other. While the effect of warnings in the first trimester is not statistically different from zero, the warnings in the second and third trimesters improve birth

Table 4.3 The effect of dust notifications on infant health in trimesters

	(1)	(2)	(3)	(4)
	Birth Weight	Low Birth Weight	Gestational Age	Fetal Growth
Advisories – trimester 1	9.905***	-0.004***	0.078***	0.111***
	(0.865)	(0.000)	(0.005)	(0.017)
Advisories – trimester 2	11.844***	-0.005***	0.080***	0.158***
	(1.113)	(0.000)	(0.007)	(0.018)
Advisories – trimester 3	12.115***	-0.004***	0.087***	0.145***
	(0.856)	(0.000)	(0.005)	(0.016)
Warnings – trimester 1	-0.076	-0.000	0.004	-0.010
	(1.712)	(0.001)	(0.008)	(0.034)
Warnings – trimester 2	6.871***	-0.002***	0.038***	0.109***
	(1.374)	(0.001)	(0.007)	(0.029)
Warnings – trimester 3	3.576**	-0.002***	0.037***	0.026
	(1.507)	(0.001)	(0.008)	(0.032)
PM10 – trimester 1	-0.128**	0.000***	-0.002***	-0.000
	(0.058)	(0.000)	(0.000)	(0.001)
PM10 – trimester 2	-0.742***	0.000***	-0.003***	-0.013***
	(0.061)	(0.000)	(0.000)	(0.001)
PM10 – trimester 3	0.089	0.000	-0.001*	0.004***
	(0.064)	(0.000)	(0.000)	(0.001)

Table 4.3 continued

Singleton	844.679***	-0.491***	2.835***	17.100***
	(5.027)	(0.004)	(0.025)	(0.100)
Girl	-96.501***	0.009***	0.137***	-2.765***
	(0.671)	(0.000)	(0.003)	(0.015)
Birth Order 2nd	27.651***	-0.009***	-0.395***	1.579***
	(1.237)	(0.000)	(0.004)	(0.029)
Birth Order 3+	57.689***	-0.011***	-0.397***	2.353***
	(1.968)	(0.001)	(0.006)	(0.048)
Married	32.424***	-0.014***	0.119***	0.610***
	(4.766)	(0.002)	(0.015)	(0.115)
Mother employed	6.050***	0.000	-0.001	0.153***
	(1.039)	(0.000)	(0.003)	(0.025)
Mother's Age 20-29	62.393***	-0.008**	0.057**	1.475***
	(5.954)	(0.003)	(0.023)	(0.139)
Mother's Age 30-39	60.819***	-0.001	-0.025	1.587***
	(5.902)	(0.003)	(0.023)	(0.141)
Mother's Age 40+	17.868***	0.019***	-0.289***	0.997***
	(6.826)	(0.004)	(0.026)	(0.166)
Mother HS	43.053***	-0.010***	0.045***	1.022***
	(3.365)	(0.002)	(0.013)	(0.078)
Mother College	49.581***	-0.015***	0.108***	1.070***
	(3.460)	(0.002)	(0.013)	(0.080)
Father employed	10.342***	-0.005***	0.009	0.270***
	(1.715)	(0.001)	(0.007)	(0.038)
Father's Age 20-29	20.802	-0.004	0.045	0.473
	(12.734)	(0.007)	(0.047)	(0.310)
Father's Age 30-39	22.602*	-0.004	0.046	0.516
	(12.975)	(0.007)	(0.047)	(0.318)
Father's Age 40+	11.866	0.003	-0.041	0.403
	(12.705)	(0.007)	(0.047)	(0.310)
Father HS	20.328***	-0.007***	0.027**	0.471***
	(3.255)	(0.001)	(0.011)	(0.076)
Father College	26.218***	-0.012***	0.081***	0.519***
	(3.316)	(0.001)	(0.011)	(0.080)
Observations	1,472,978	1,472,978	1,472,978	1,472,978

Notes: Outcome variables are the birth weight in grams (1), an indicator for whether the birth weight is less than 2,500 grams (2), gestational age in weeks (3), and ratio of birth weight to gestational age in grams per week (4). trimester 1, trimester 2 and trimester 3 variables indicate the number of advisories, warnings and average PM10 level during trimesters 1, 2 and 3, respectively. Regressions include indicators for cities and years. Standard errors reported in parentheses are clustered at the city level. *, ** and *** indicate significance at 10%, 5% and 1% levels, respectively.

outcomes significantly. Average PM10 exposure in early stages of pregnancy (first and second trimesters) has a negative impact on the birth outcomes.

Samet et al. (1998) and Deschênes and Moretti (2009) show that weather conditions influence newborns' health outcomes. If weather conditions also have an effect on air quality and dust warnings, omission of weather controls will bias my estimates (Currie et al. 2009; Lleras-Muney 2010; Moretti and Neidell 2011). To avoid the potentially confounding effect of weather conditions, in the regressions, I include *Average Temperature* and *Average Precipitation* during the mother's pregnancy. Results presented in Table 4.4 suggest that my findings are not sensitive to inclusion of weather variables.

Table 4.4 The effect of air dust notifications on infant health (with weather controls)

	(1)	(2)	(3)	(4)
	Birth Weight	Low Birth Weight	Gestational Age	Fetal Growth
Advisories	10.419***	-0.004***	0.076***	0.127***
	(0.827)	(0.000)	(0.006)	(0.014)
Warnings	14.329***	-0.006***	0.106***	0.174***
	(1.664)	(0.001)	(0.010)	(0.032)
PM10	-1.113***	0.000***	-0.007***	-0.016***
	(0.191)	(0.000)	(0.001)	(0.004)
Average Temperature	-0.599**	0.001***	-0.004**	-0.010*
	(0.281)	(0.000)	(0.002)	(0.006)
Average Precipitation	-0.045**	-0.000	-0.000	-0.001**
	(0.020)	(0.000)	(0.000)	(0.000)
Singleton	842.156***	-0.491***	2.827***	17.042***
	(6.106)	(0.005)	(0.029)	(0.120)
Girl	-96.797***	0.009***	0.137***	-2.772***
	(0.809)	(0.000)	(0.003)	(0.018)
Birth Order 2nd	29.311***	-0.009***	-0.393***	1.616***
	(1.303)	(0.000)	(0.005)	(0.031)
Birth Order 3+	58.546***	-0.010***	-0.398***	2.374***
	(2.364)	(0.001)	(0.007)	(0.058)
Married	30.891***	-0.013***	0.108***	0.593***
	(5.298)	(0.003)	(0.017)	(0.130)
Mother employed	5.853***	-0.000	-0.004	0.154***
	(1.154)	(0.000)	(0.003)	(0.028)

Table 4.4 continued

Mother's Age 20-29	67.529***	-0.007*	0.066**	1.573***
	(7.629)	(0.004)	(0.030)	(0.185)
Mother's Age 30-39	65.354***	-0.001	-0.015	1.667***
	(7.666)	(0.004)	(0.030)	(0.189)
Mother's Age 40+	24.510***	0.018***	-0.266***	1.112***
	(8.434)	(0.005)	(0.033)	(0.211)
Mother HS	44.841***	-0.011***	0.051***	1.060***
	(4.159)	(0.002)	(0.013)	(0.099)
Mother College	50.269***	-0.016***	0.113***	1.083***
	(4.305)	(0.002)	(0.014)	(0.103)
Father employed	10.143***	-0.005***	0.008	0.265***
	(2.010)	(0.001)	(0.009)	(0.044)
Father's Age 20-29	41.924***	-0.018**	0.056	1.016***
	(14.032)	(0.009)	(0.060)	(0.329)
Father's Age 30-39	44.003***	-0.018**	0.060	1.058***
	(14.056)	(0.009)	(0.058)	(0.333)
Father's Age 40+	32.526**	-0.011	-0.030	0.934***
	(13.654)	(0.009)	(0.059)	(0.319)
Father HS	17.139***	-0.006***	0.013	0.405***
	(3.336)	(0.002)	(0.012)	(0.079)
Father College	23.157***	-0.010***	0.063***	0.466***
	(3.512)	(0.002)	(0.011)	(0.085)
N	1,082,004	1,082,004	1,082,004	1,082,004

Notes: Outcome variables are the birth weight in grams (1), and indicator for whether the birth weight is less than 2,500 grams (2), gestational age in weeks (3), and ratio of birth weight to gestational age in grams per week (4). Regressions include indicators for cities and years. Standard errors reported in parentheses are clustered at the city level. *, ** and *** indicate significance at 10%, 5% and 1% levels, respectively. Average Temperature and Average Precipitation measure the weather conditions mothers were exposed to during their pregnancy.

If pregnant mothers take preventive action against worse air quality (for example, by wearing protective masks and staying indoors) when an advisory or a warning is issued, then they are also less likely to catch an infectious disease such as the flu that harms the fetus. Therefore, during an outbreak of a disease, the effect of notifications on infant health should be amplified. Alternatively, the detrimental effect of diseases should be offset when a notification is issued. To test this hypothesis, as an extension, I estimate a specification depicted below:

$$(4.2)\quad Health = \gamma Notices + \delta Disease + \alpha Notices \times Disease + \beta PM10 + \rho X + \epsilon$$

where *Disease* is a measure of how spread-out a disease is during a mother's pregnancy. I consider the flu since this disease is very common and harmful to the fetus, if caught by the pregnant mother (Rasmussen, Jamieson and Uyeki 2012).

I do not have data on the actual flu infection rate in Korea. Instead, I use Google Trends' monthly index for keywords "flu" and "influenza". Google Trends' monthly index ranges between 0 and 100, and it is based on the number of searches of keywords in the Google search engine. The month with the highest number of searches of a specific keyword is assigned a 100. The other index values are determined based on the ratio of the number of searches in a month to that in the month with highest number of searches. For example, if the number of a keyword's searches in a month, say January 2000, is 10% of the number of searches of that keyword in the highest month, say July 2010, then the index value of January 2000 is 10.

Higher index values for keywords "influenza" and "flu" in a month implies higher actual incidence of the disease. This is because, an individual's interest in searching the keywords "flu" or "influenza" is likely to rise when they or other people they know are infected. Thus, during an outbreak of flu, keywords about flu are searched for more times in the internet. Put differently, during the actual flu outbreaks, Google Trends' index values must be higher. Cho et al. (2013) reports that Google Trends indices are highly correlated with the infection rate using flu surveillance data in Korea between years 2007 and 2012. Using the Google Trend's indices for keywords "flu" and "influenza", I constructed variables *Influenza* and *Flu*. These variables are the average of the index values of the corresponding keyword during the mothers' pregnancy, and I use them as proxies for flu infection rates during the mother's pregnancy. Larger values of *Flu* and *Influenza* indicate a greater risk for the mother to catch the flu during her pregnancy.[81]

Results obtained from estimating Equation (4.2) over the sample of infants born between 2007 and 2011 are presented in Table 4.5.[82] In the regressions, I include all control variables employed in Equation (4.1). The effect of advisories and warnings on birth outcomes is positive

Table 4.5 The effect of notifications on infant health during flu outbreaks

	(1)	(2)	(3)	(4)
	Birth Weight	Low Birth Weight	Birth Weight	Low Birth Weight
Advisories	7.606***	-0.004***	11.332***	-0.005***
	(1.403)	(0.001)	(1.334)	(0.001)
Warnings	8.947***	-0.005***	12.478***	-0.007***
	(2.292)	(0.001)	(2.080)	(0.001)
PM10	-1.782***	0.001***	-1.677***	0.001***
	(0.298)	(0.000)	(0.293)	(0.000)
Influenza	-0.243**	0.000**		
	(0.121)	(0.000)		
Advisories× Influenza	0.443***	-0.000***		
	(0.100)	(0.000)		
Warnings × Influenza	0.384***	-0.000***		
	(0.085)	(0.000)		
Flu			-0.092	0.000
			(0.098)	(0.000)
Advisories× Flu			0.428***	-0.000***
			(0.084)	(0.000)
Warnings × Flu			0.393***	-0.000***
			(0.070)	(0.000)
N	724,520	724,520	724,520	724,520

Notes: Outcome variables are the birth weight in grams (1), and indicator for whether the birth weight is less than 2,500 grams (2). Regressions include indicators for cities and years. Standard errors reported in parentheses are clustered at the city level. *, ** and *** indicate significance at 10%, 5% and 1% levels, respectively. In addition to the variables listed, all control variables are included in the regressions. Flu and Influenza are proxies of how spread-out the disease flu is during the mother's pregnancy.

[81] Markowitz, Nesson and Robinson (2010) also use similar Google Trends data for US in their paper where they investigate the effect of employment rates on flu incidence. They report that Google Trends data tracks the actual flu surveillance very well.

[82] I consider only this subsample of infants because the analysis of Cho et al. (2013) indicates a strong correlation between the Google Trends indices and the actual surveillance data during this period (2007-2011). In addition, internet use has become more wide-spread in Korea in late 2000s.

significant. Coefficients of *Influenza* and *Flu* are negative (though only the former is statistically significant). This implies mothers who had greater risk of catching flu during their pregnancy gave birth to babies with lower birth weights. The interactions of *Advisories* and *Warnings* with proxies of the extent of flu outbreaks during a mother's pregnancy are positive and significant for birthweight. In other words, the detrimental effect of flu on newborn's health is diminished when the mother experiences an advisory or a warning. This could be an evidence for an unintended consequence of advisories and warnings. Taking protective action against high PM10 levels such as wearing masks or staying indoors also protects mothers against infectious diseases such as the flu. They become less likely to catch a disease, and as a result, their babies are born healthier.

My results show that each dust notification increases an infant's weight at birth by about 0.3% (10 grams from the baseline of 3,200 grams). Black, Devereux and Salvanes (2007) reports that a one percent rise in birth weight increases future earnings by about 0.13%. Therefore, one warning's effect on the future earnings of a newborn is about 0.04%. Assuming the average newborn will earn as much as the per capita income in Korea (about $25,000), the effect of each dust warning is $10 per year for each new born for the rest of their lives.[83] Assuming that individuals start working at age 25 and retire at age 60 (the minimum official retirement age in Korea), the present value of the stream of $10 annually is about $36 at interest rate 6% (the average lending rate in Korea). If the life time earnings of all 470,000 babies born in 2010 increase by $36, the total benefit to Koreans of a dust notification is about $17 million. Despite their benefits for the infants, dust notifications may be costly to the Korean mothers. For example, if a pregnant woman skips work due to a dust notification, she suffers a loss of income. Assuming each mother earns as much as the average income in Korea, $25,000 per year, the loss of a day's income due

[83] Korea's per capita GDP was $22,151 in 2010.

to a dust notification is about $100. In my sample 28% of the mothers are employed. If all working mothers skip a day of work due to dust notifications, the total loss of income will be about $13 million. Thus, the benefit of a dust notification in excess of its cost is about $4 million.

4.5 Conclusion

Previous papers have demonstrated that infant health, particularly weight at birth, is an important predictor of future outcomes. In this paper, using a data set composed of about 1.5 million infants born between 2003 and 2011 in Korea, I investigate the impact of air quality warnings on birth weight. Air quality in Korea is affected by yellow dust outbreaks, naturally-formed dust storms blown from China and Mongolia to Korea. Specifically, these storms increase the PM10 concentrations in the air. As a measure against yellow sand outbreaks, Korean Meteorological Administration watches PM10 levels and issues notifications when PM10 levels rise above certain thresholds. These notifications advise individuals to take preventive action by avoiding outdoor activities. Controlling for the air quality mothers are exposed to during their pregnancy (average PM10 concentration), I find a positive and statistically significant effect of dust notifications on birth outcomes. Specifically, each additional warning increases birth weight by about 10 grams from a baseline of 3,200 grams.

My finding could be indicative of two mechanisms. First, when warnings are issued, if pregnant women avoid outdoors, they are less likely to be exposed to harmful particles in the air. This will result in a smaller amount of harmful pollutants to be transmitted to the fetus. Thus, babies of mothers who experienced more warnings are less likely to have low birth weight. The second mechanism could be an unintended consequence of warnings. The preventive actions (staying indoors, and wearing protective masks) undertaken by the pregnant women and the public in general could reduce the spread of infectious diseases such as the flue. Since a mother who experienced warnings is less likely to be infected by diseases, their babies will have better birth outcomes. I provide evidence that PM10 warnings reduce the negative impact of flu outbreaks on infant health.

Back of the envelope calculations suggest that dust notifications are economically beneficial to Korea. Each additional dust notification increases future earnings of an average Korean infant by $10 annually for the rest of their lives. Present value of such a 35-year annuity is about $36 per infant, or about $17 million for all 470,000 infants born in 2010. Because of a dust warning, mothers may skip work and consequently suffer an income loss of $100 per day. Since 28% of the 470,000 mothers are employed, the total productivity loss due to a dust notification is $13 million. Therefore, the net benefit of a dust warning is about $4 million to the Koreans.

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APPENDIX A: 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

APPENDIX B: HOW IS MSA-LEVEL MATCH 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.[84] 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

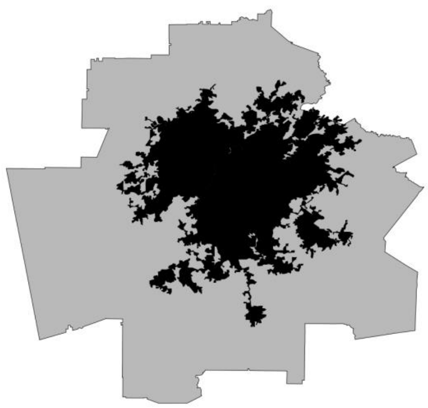
[84] Based on name comparison, there is one more case in which two UAs occupy an MSA: an example is an MSA "Beaumont-Port Arthur, TX," and two UAs, "Beaumont, TX" and "Port Arthur, TX." However, these 9 MSAs are eventually not in my final sample.

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.

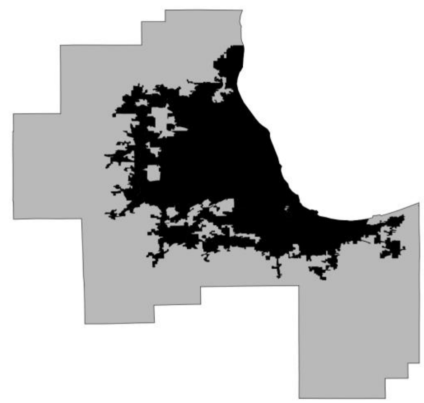
An MSA consists of one or more whole counties, whereas a UA may consist of portions of counties. Therefore, in the second step, I calculate the population in 2000 in overlapped areas between an MSA and a UA. The population of county portions in a UA is obtained from the U.S. Environmental Protection 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%. 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%. 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 dataset due to the availability of transportation data.

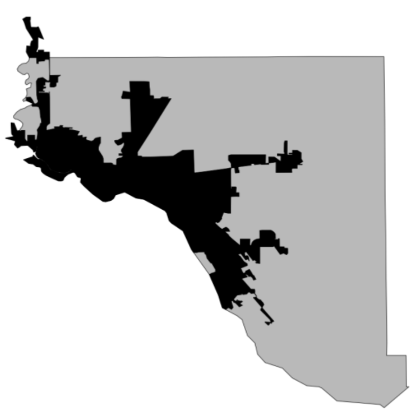
Appendix Figure A.1 presents four matched area examples out of the final 40 local areas, and belong to South, Midwest, South, and Northeast, respectively. Gray areas indicate an MSA area, while black regions are a UA. In Appendix Figure A.1.,A., whole areas of the UA named "Atlanta, GA" is contained in the MSA named "Atlanta-Sandy Springs-Marietta, GA." In Appendix Figure A.1.,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



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

Figure A.1 Example of comparison of an MSA (Gray) and a UA (Black) this area is negligible.[85] 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 dataset 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.

[85] Population of the portion of a county "Dona Ana" occupies 3.9 percent of the population of the UA "El Paso, TX-NM."

APPENDIX C: SIPP DATA DETAILS

The sample in each SIPP panel randomly but equally breaks down into four rotation groups, and each rotation group started interviewing at a different time in each following month. Each rotation group is mutually exclusive and the composition does not change over time within the same panel. For example, in the 2001 panel, rotation group-1 had a survey every month from October 2000 through September 2003, while rotation group-4 began in January 2001 and ended in December 2003. The 2001 panel consists of nine waves, where one wave is composed of four monthly interview responses from household members about demographics, labor force participation, and government program participation.

Households were first interviewed about financial assets and debts of a household in the third wave in 2001. The same questions were asked again during the sixth and the ninth waves of the survey in 2002 and 2003. This allows up to trace the changes in assets and liabilities for the households in each rotation group between 2001, 2002, and 2003. Since the month of the SIPP interview is known, we match the implementation of the month to the SIPP. This SIPP sample design enables us to employ the monthly level Food Stamp vehicle exemption rules across states in a panel format. The sample period of this paper is from September to December in 2001, 2002 and 2003.

APPENDIX D: TABLES

Table D.1 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 D.2 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	OLS	IV	OLS	IV	OLS
	(1)	(2)	(3)	(4)	(5)	(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)

Table D.2 continued

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

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% level; ** at 5% level, and *** at the 1% 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.

Table D.3 State-level vehicle asset rule for the SNAP eligibility
for states not included in my estimation sample

State	After policy change		
	Effective date	Vehicle exemption	
Alaska	2001 Sep	Exempt	One vehicle
Delaware	2000 Feb	Exempt	All vehicles
Hawaii	2002 Sep	Exempt	All vehicles
Maine	2000 Sep	Exempt	All vehicles
Maryland	2001 Mar	Exempt	All vehicles
Massachusetts	2001 Sep	Exempt	All vehicles
Michigan	2000 Oct	Exempt	All vehicles
North Dakota	2000 Oct	Exempt	All vehicles
Oregon	2000 Dec	Exempt	All vehicles
South Carolina	2001 Apr	Exempt	All vehicles
South Dakota	2001 Sep	Exempt	One vehicle
Texas	2001 Sep	More than federal SNAP rule	
Vermont	2001 Sep	Exempt	One vehicle
Wyoming	2001 Sep	More than federal SNAP rule	

Notes: Source: SNAP State Policy Database, United States Department of Agriculture
Connecticut is not listed above because vehicle asset rule for SNAP eligibility changed multiple times. Specifically, one vehicle was exempted until 2001 August, then exemption rule was dropped, and then the rule was relaxed again since 2002 September.

Table D.4 Summary statistics for low educated single parents from 11-state sample used for household fixed effects specifications, *conditional on owning a car* before the policy change SIPP from 2001 to 2003

Variable	Mean (SD)	Policy Change	
		Before	After
	(1)	(2)	(3)
Relaxed Vehicle Asset Policy	0.46	0.00	1.00
	(0.50)	(0.00)	(0.00)
Saving Variables			
Car Market Value	4,821	4,749	4,904
	(4,443)	(4,176)	(4,751)
Car Equity	2,278	2,257	2,303
	(4,700)	(4,643)	(4,786)
Car Debt	2,542	2,491	2,601
	(5,805)	(5,402)	(6,265)
Liquid Assets	2,116	1,930	2,331
	(11,809)	(11,960)	(11,684)
Non-housing Wealth	6,034	6,988	4,929
	(22,933)	(28,363)	(14,343)
Total Wealth	8,228	9,712	6,511
	(27,051)	(32,530)	(18,836)
Car Ownership	0.88	0.90	0.86
	(0.33)	(0.31)	(0.35)
Household(HH) Head Variables			
HH Size: 2 Individuals	0.31	0.29	0.34
	(0.46)	(0.45)	(0.48)
HH Size: 3 Individuals	0.37	0.38	0.36
	(0.48)	(0.49)	(0.48)
HH Size: 4+ Individuals	0.32	0.34	0.30
	(0.47)	(0.47)	(0.46)
Less than high school degree	0.32	0.36	0.27
	(0.47)	(0.48)	(0.45)
High School Degree or GED	0.68	0.64	0.73
	(0.47)	(0.48)	(0.45)
Age	38.93	38.78	39.10
	(8.24)	(8.26)	(8.24)
Age-Square	1,583	1,571	1,596
	(640)	(642)	(640)
Age-Cube	66,816	66,141	67,596
	(39,371)	(39,461)	(39,435)

Table D.4 continued

Male	0.15	0.15	0.15
	(0.36)	(0.36)	(0.36)
Female	0.85	0.85	0.85
	(0.36)	(0.36)	(0.36)
White	0.67	0.69	0.65
	(0.47)	(0.47)	(0.48)
Black	0.25	0.24	0.27
	(0.44)	(0.43)	(0.45)
Other Race	0.08	0.07	0.08
	(0.27)	(0.26)	(0.28)
Reduced Lunch	0.68	0.66	0.71
	(0.47)	(0.48)	(0.45)
State-Level Characteristics			
Minimum Wage	5.47	5.51	5.42
	(0.61)	(0.61)	(0.59)
TANF	19.80	19.73	19.88
	(1.50)	(1.52)	(1.48)
MOE	19.14	19.21	19.07
	(1.80)	(1.84)	(1.75)
Unemployment	5.54	5.68	5.38
	(1.01)	(1.04)	(0.97)
Wage	9.67	9.73	9.61
	(1.10)	(1.12)	(1.08)
Vehicle Tax	17.83	17.20	18.55
	(5.93)	(6.30)	(5.42)
State-Level SNAP Policy Rules			
EBT Issuance	0.75	0.58	0.94
	(0.39)	(0.45)	(0.13)
Outreach Spending	23.86	16.25	32.66
	(51.81)	(29.84)	(68.14)
N	233	125	108

Notes: Data are from SIPP panels: Wave 3 in 2001, Wave 6 in 2002, and Wave 9 in 2003. Vehicles include cars, vans and trucks, but exclude recreational vehicles (RVs) and motorcycles. Values of each vehicle are aggregated if a household owns multiple cars. Liquid assets contain dollar amounts in checking and saving accounts, bonds/securities, stocks, and other financial investments. Non-housing wealth includes liquid assets, IRA accounts, business equity, and vehicle equity. Dollar values are in 2005 dollars. Car ownership is not 100 percent before the policy change because there are 13 households who had different car ownership status for two time periods before the vehicle policy relaxed.

VITA

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