Essays in Food Security in Latin America and the United States

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Dedication

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Abstract

This dissertation comprises three essays related with the problem of food insecurity (i.e., lack of access to enough and varied food required by households for their daily activities) in middle and high-income countries. The first chapter, "Subsidized Health Care and Food Insecurity: Evidence from Colombia", suggests that participation in a public-funded health care insurance for the poor is associated with a reduction on the probability of being food insecure. This result principally holds for rural households. The second chapter, "The Effects of Rising Staple Prices on Food Insecurity: The Case of Tortilla in Mexico" provides evidence on how increases in the price of tortilla, the most important staple in the country, is related with higher household food insecurity rates in Mexican states. Moreover, these price surges are more relevant when they take place in grocery stores—that sell low-quality tortillas—rather than locally-owned, small-scale tortillerías, specialized in selling freshly-made tortillas. The third chapter, "Food Price Fluctuations and Household Food Insecurity in the United States, 2005–2010" studies the association between food prices and household food insecurity in this country, showing that the price of grain and dairy-based products has the greatest association with higher food insecurity rates among American households during the Great Recession.

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Chapter 1

Introduction

The International Covenant on Economic, Social and Cultural Rights from the United Nations "recognize(s) the right of everyone to an adequate standard of living for himself and his family, including adequate food, clothing and housing, and to the continuous improvement of living conditions".[1] Nevertheless, as stated by the Food and Agriculture Organization (FAO), "There is more than enough food produced in the world to feed everyone, yet 815 million people go hungry".[2] Although hunger is a problem that mostly strikes the least developed nations, the lack of access to enough and varied food for daily activities—i.e., food insecurity—is also a problem that affects the most developed countries in the world.

By following a *behavioral approach*, this dissertation analyzes the problem of household food insecurity for two middle-income countries and one high-income nation: Colombia, Mexico, and the United States, respectively. As explained by Barrett (2010), Headey and Ecker (2013), and Maxwell, Vaitla, and Coates (2014), this behavioral approach to food insecurity uses self-reported answers from questionnaires that address daily-life situations when households struggle to have enough and varied food for their activities.

In Chapter 2, "Subsidized Health Care and Food Insecurity: Evidence from Colombia", I use data from the 2008 Colombian Living Standards Survey to estimate the association between participation in the publicly-funded Subsidized Regime (SR) of health care for the poor and a set of Foster-Greer-Thorbecke-like (FGT) measures of food insecurity (incidence, gap, and severity). Enrollment into the SR is not exogenous due to self-selection from potentially eligible households, discretionary municipality-level policies that affect eligibility, and manipulation of the assignment process for electoral purposes. Therefore, I use the proportion of lifetime the household head has resided in the current municipality as an instrumental variable. Taking the uninsured population as the comparison group, the two-stage least squares regression estimates reveal that participation in the SR is associated with a reduction of the probability of being food insecure and

[1] `http://www.ohchr.org/EN/ProfessionalInterest/Pages/CESCR.aspx`, consulted on May 30/18
[2] `http://www.fao.org/state-of-food-security-nutrition/en/`, consulted on May 30/18

the food insecurity gap (how far, on average, are households to overcome food insecurity), but does not have any correlation with the severity of food insecurity. These results principally hold in rural areas.

Chapters 3 and 4 evaluate the relationship between food prices and household food insecurity over time. For both essays, the data available do not track households across time, impeding to control for potential time-invariant unobserved heterogeneity and measurement error that might bias the parameters from the regression estimates. Therefore, I follow Deaton (1985) by constructing a series of panel data sets (i.e., pseudo-panels), that aggregate household-level data into greater units of information (e.g., metropolitan areas or states).

In Chapter 3, co-authored with Mariana Urbina-Ramirez, we study the association between rising prices of tortilla—the Mexican staple par excellence—and household food insecurity between 2008 and 2014, a period in which global food prices experienced dramatic increases. In this essay, we use a unique combination of household-level data (the Mexican National Survey of Household Income and Expenditure) that allows identifying the place where households bought their tortillas, with official information on prices. Usually, Mexican households buy tortillas in two places: local and independent stores that sell freshly-made tortillas (i.e., tortillerías), or grocery stores that acquire the product from large-scale factories. The regression estimates suggest that tortilla prices from grocery stores have a greater association with higher food insecurity rates. This result principally holds for households in the lowest income quintiles, as well as for households in urban areas.

Finally, in Chapter 4 I analyze the association between food prices and food insecurity in the United States for the period 2005–2010, which covers the Great Recession. Matching official household-level data on food insecurity from the Current Population Survey (CPS) and aggregated UPC and random-weighted data on food prices from the Quarterly Food-at-home Price Database (QFHPD), I find that price surges—as well as unexpected increases—from grains and dairy products have a positive association with higher food insecurity rates.

Chapter 2

Subsidized Health Care and Food Insecurity: Evidence from Colombia

2.1 Introduction

Before the new constitution of 1991 stipulated that health care should be a universal right for all citizens, Colombia's health care system consisted of a fragmented set of insurance packages, depending on employment category and status. Public employees and the military had their own separate health regimes. Private workers, the unemployed, and those not in the labor force could use either public or private providers, but all expenses should be covered from their own pockets. Therefore, in 1993, the Colombian government undertook a major reform of its health care system. The current health care system can be described as a two-tiered regime. The Subsidized Regime (SR), mostly publicly funded, targets the poorest households, where eligibility is given through a proxy means test.[1] The middle and upper classes are intended to belong to the Contributive Regime (CR), which is funded through payroll taxes from formal employment. Despite the efforts of the government in providing universal health care coverage, there still exists a significant proportion of the population—mostly poor—that remains uninsured.

The structure and characteristics of the SR intend to reduce the price of health care for the poorest (substitution effect), making its access more affordable. At the same time, it will leave households with more disposable income to spend on other goods (income effect). Indeed, several articles have addressed the positive effect of the SR on health care utilization in Colombia (Bitrán, Giedion, and Muñoz, 2004; Camacho and Conover, 2013; Gaviria, Medina, and Mejía, 2006; Miller, Pinto, and Vera-Hernández, 2013; Panopoulus and Vélez, 2001; Trujillo, Portillo, and Vernon, 2005). There is little evidence, however, on the effects of the SR on household consumption of other goods. Moreover, no previous

[1] According to Grosh and Baker (1995), administrative data was initially used for targeting social programs for the poor. Based on that information, it was possible to categorize potential recipients according to their wealth level, but respondents underreported their income. To overcome this problem, governments started using data from living standards surveys or national household surveys in order to determine eligibility. Instead of using only information about income, they also took data about the materials used to build dwellings, ownership of durable goods, employment status, and schooling level of the household members, in order to calculate a proxy score that ranks households according to those characteristics. A threshold determines which observations are eligible.

work has addressed the impact of participation in the SR on achieving the minimum level of food consumption required for daily activities—i.e., food security—.

By comparing with households under the SR with the uninsured population, I use the Colombian Living Standards Survey of 2008 (LSS) to estimate the association between enrollment in the SR on household food security. Literature has addressed food insecurity using a diverse set of indicators, ranging from calorie availability and dietary diversity, monetary poverty, to subjective responses from questions that aim to capture behavioral and psychological aspects of this problem (Barrett, 2010; Headey and Ecker, 2013; Maxwell, Vaitla, and Coates, 2014). In this paper, I follow the behavioral approach, measuring food insecurity as a binary indicator (i.e., one if food insecure, zero otherwise), based on self-reported answers from a questionnaire that addresses daily-life situations when households fell into food insecurity episodes during a certain period of time. This categorization helps to identify the incidence of food insecurity based on the number of affirmative answers, but is not informative about how deep this situation is among those who suffer it (i.e., how far are they to overcome food insecurity), and, moreover, the inequality within this group. Following Gundersen (2008), I calculate and use FGT-like measures of food insecurity based on Foster, Greer, and Thorbecke (1984) to estimate the association between participation in the SR and the incidence of food insecurity, as well as its gap and severity.

As will be explained further, there are two important caveats that limit the scope of standard regression analysis. First, enrollment into the SR is not exogenous, is subject to measurement error, and selectivity is contingent on discretionary policies and political manipulation (Bitrán, Giedion, and Muñoz, 2004; Camacho and Conover, 2011; Jaramillo, 2001; McGee, 1999; Miller, Pinto, and Vera-Hernández, 2013; Panopoulus and Vélez, 2001; Trujillo, Portillo, and Vernon, 2005). Second, the researcher only observes households' health care insurance status, not the original score from the proxy means test that determines participation. As a consequence, OLS-based estimates on the impact of participation on the SR may be biased. Using data from the 2003 LSS, Miller, Pinto, and Vera-Hernández (2013) estimate a synthetic eligibility score and conduct a fuzzy regression discontinuity (RD) approach in order to minimize endogeneity issues.[2] But for the data used in this paper, the synthetic score cannot be properly assigned. Since its inception, the score has been subject to several changes in its calculation methodology, the first one taking place in 2003. Furthermore, those changes are not public.[3]

Given these constraints, this paper follows Gaviria, Medina, and Mejía (2006) in relying on an instrumental variables (IV) approach that uses as an exclusion restriction the proportion of lifetime that the household head reports having resided in the current municipality at the time of the survey. This IV aims to capture the extent of political and social networks within households that may help to increase the probability of enrollment to the SR. As I present below, enrollment to the SR is associated with a reduction of both food insecurity incidence and gap, but it has no correlation with its severity. These results principally prevail in rural areas, and are robust to several econometric specifications.

The remainder of this chapter is organized as follows: Section 2.2 provides background about the current health care system in Colombia, as well as for the definition of food insecurity used in this work. Section 2.3 describes the data used for this work, whereas Section 2.4 explains the identification strategy. Section 2.5 reports and analyzes the estimates and robustness checks, and Section 2.6 presents the conclusions.

[2] Lee and Lemieux (2010) argue that RD has become a credible and transparent tool for estimating the causal effect of a program intervention in the absence of experimental data. In the same way, Hahn, Todd, and Van der Klaauw (2001) formally recognize that this approach requires looser assumptions compared to other non-experimental approaches (e.g., difference-in-differences or instrumental variables).

[3] Castañeda (2005) explains in detail the first algorithm of the score, that lasted between 1993 and 2003.

2.2 Background

2.2.1 The Colombian Health Care System

Law 100 of 1993 established and currently regulates the health care system in Colombia. This legislation aimed to expand health care coverage, improve the efficiency and equity in service delivery, and to increase funding. According to Miller, Pinto, and Vera-Hernández (2013), this system is a typical case of a "managed competition" model of health care (Enthoven, 1978a,b), in which the nature of the competition is determined by the different sizes of the medical networks (composed of hospitals, clinics, and primary care centers) and the quality of the services that each provider can offer. Providers always have to ensure the provision of the basic package of benefits and services indicated by the law. In the main cities, it is usual to find a variety of large-size networks, but in small municipalities and in rural areas is more likely to find only one provider.

Table 2.1 summarizes the current organization of the Colombian health care system since 1993. Three pillars hold this structure, which is based on targeting and eligibility criteria, funding sources, and benefits. On one side, the subsidized regime (SR)—fully publicly funded throughout general taxes and contributions from formal workers via payroll taxes—aims to cover the poorest and most vulnerable population, as well as the unemployed. On the other hand, all non-poor families and formal workers are intended to belong to the contributive regime (CR), totally funded by payroll taxes from employers and employees. Pubic workers and those serving the military have their own special regimes, with unique health care plans.

Despite the efforts made during the last years to increase health care coverage in Colombia through both the SR and CR, a significant fraction of the population is still not covered by any formal type of insurance. These are called *vinculados* (associated), and, according to the law, they have the right to use public clinics and hospitals for emergency assistance. According to Miller, Pinto, and Vera-Hernández (2013), in 1993, just 25 percent of the Colombian population had formal health insurance. That proportion grew to 80 percent in 2007.

As described by Miller, Pinto, and Vera-Hernández (2013), beneficiaries from both the CR and SR have to pay out of pocket for some services. The system provides free access to a limited package of medicines (mostly generic) and preventive medical care. Usage of curative services and visits to specialists require a co-payment. These costs are lower for the users of the SR (10 percent of the full price), and in the case of curative services they are capped at half the monthly minimum wage. With respect to the uninsured, co-payments correspond to 30 percent of the total cost, but capped six times greater than for those under the SR. Both CR and SR were designed to cover and provide the same type of benefits and services. Nevertheless, Agudelo et al. (2011) estimate that the content of the health care package of the SR is about 60 percent of the total package of the CR.

Eligibility for the SR is determined by the *Sistema de Identificación de Beneficiarios* (SISBEN), a proxy means test composed of a series of variables that capture the main characteristics of households in terms of wellbeing, such as housing features (quality of the construction materials of the dwelling and access to utilities), ownership of durable goods (e.g., TV, car, washing machine), demographic composition, educational attainment, and labor force participation. The Registry of the Poor is the corresponding survey that collects that information. This survey is conducted by local authorities through door-to-door interviews in the poorest areas. The first version of the SISBEN score came in 1993, with subsequent changes in 2003 and 2011.[4] The score ranges from 0 (poorest) to 100 (least poor). Initially, urban households with scores of 47 or less were eligible for the SR, whereas in rural areas the threshold was set at 30 points. Since 2003, due to the changes in methodology, thresholds changed to 22 and 32, respectively. The SISBEN score is also used to determine eligibility for other welfare programs, like access to a social pension

[4] In 2017, the Colombian government announce the implementation of a new version of the SISBEN score, which would be ready by 2019.

for retired persons who did not make contributions to social security during their time as active workers, unemployment insurance, or nutrition and social assistance for children—conditional on school attendance—(known as *Familias en Acción*).[5]

It is important to remark that budgetary and political reasons have altered eligibility criteria. For example, as explained by Panopoulus and Vélez (2001), Bitrán, Giedion, and Muñoz (2004), and Trujillo, Portillo, and Vernon (2005), municipalities that are not able to guarantee the minimum funding to cover all of the eligible population should give priority to the poorest households, and, also, to those located in rural zones or with pregnant women, children under the age of five, elderly, female heads, indigenous population, or disabled members. Likewise, as described by Camacho and Conover (2011), local politicians used to manipulate the SISBEN score for electoral purposes. To minimize the risk of score manipulation, in 2003 the national government, in addition to the introduction of changes to the algorithm, stipulated that the new version and any further revision would not be publicly available.

Likewise, using a random sample for Bogota—the capital city of Colombia—from the 2003 LSS, Gaviria, Medina, and Mejía (2006) find cases of neighborhood blocks with at least one insured and one uninsured household. Additionally, after using the whole sample of the 2003 LSS, they find poor households not enrolled to the SR and non-poor households receiving the benefits. According to the authors, these results support the fact that discretionary policies and political manipulation of the SISBEN score for electoral purposes have influenced eligibility to the SR. Moreover, the results also provide evidence that municipalities have faced problems in targeting the potentially eligible population.

2.2.2 The Latin American and Caribbean Food Security Scale

The Latin American and Caribbean Food Security Scale (ELCSA for its acronym in Spanish) is a joint effort between academics from several countries and the Food and Agri-

[5]Cuesta and Olivera (2014) explain in more detail the eligibility to these additional welfare programs.

culture Organization of the United Nations (FAO) to construct a harmonized measure that identifies food insecurity across the region. The ELCSA was based on the Food Security Supplement of the Current Population Survey of the United States (FSS-CPS), as well as from other nationally-based measures of food insecurity (e.g., Brazil, Colombia, and Venezuela). Like the United States Department of Agriculture (USDA), the ELCSA defines food insecurity as the household-level condition of limited or uncertain access to sufficient and adequate food products.[6]

The original questionnaire of the ELCSA consists of 15 questions—eight for households without children—addressing situations in which households would have experienced problems with having balanced and enough food due to the shortage of money, during a given period of time. All questions are constructed in such a way that each household answers either "yes" or "no". The cutoff points that determine food insecurity under the ELCSA slightly differ these of the USDA. Table 2.2 displays that households between zero and two affirmative answers on the FSS-CPS—with or without children— are categorized by the USDA as food secure, whereas for the ELCSA only households with zero affirmative questions fall into this category. Moreover, the USDA only disaggregates food insecurity into two categories: low and very low (severe) food insecurity. On the other hand, the ELCSA divides food insecurity into three categories—low, moderate, and severe—.

2.2.3 An FGT Approach for Measuring Food Insecurity

As described in the introduction section, this paper categorizes food insecurity as a binary variable that is equal to one if the household is food insecure, zero otherwise. That indicator is not capable of reflecting the differences in the depth and severity of the problem. Thus, I follow Gundersen (2008) constructing FGT-like measures of food insecurity, as in Foster, Greer, and Thorbecke (1984). The incidence (FGT_0), gap (FGT_1), and severity (FGT_2) indicators of food insecurity as a whole are a useful tool for providing policy rec-

[6] Comité Científico de la ELCSA (2012) describes in more detail the construction of the ELCSA.

ommendations. Together, they are able to identify the proportion of households that fall under this condition, how far on average are the affected households to overcome food insecurity, and how unequal are these affected households among themselves, respectively.

Based on Foster, Greer, and Thorbecke (1984) and Haughton and Khandker (2009), I define the FGT family of food insecurity measures as:

$$FI_\alpha = \frac{1}{N}\sum_{i=1}^{H}\left(\frac{G_i}{z}\right)^\alpha \tag{2.1}$$

where N denotes total population, H represents the food insecure population, z is the food insecurity threshold, x_i is the number of affirmative answers from household i, $G_i = z - x_i$ indicates household i's food insecurity gap (how far is the household to overcome food insecurity), and $\alpha \geq 0$ is the measure of sensitivity of the index to food insecurity. When $\alpha = 0$, $FI_0 = H/N$ corresponds to the food insecurity incidence. If $\alpha = 1$, FI_1 is the food insecurity gap, and when $\alpha = 2$, FI_2 is the food insecurity severity index.

What is the intuition behind these measures? Following the reasoning proposed by Haughton and Khandker (2009) for poverty, FI_0, the food insecurity incidence, just captures the proportion of households that affirmatively answered more questions than the established threshold. This indicator, however, does not say anything about how food insecure the food insecure households are. For example, consider 4 different households, whose number of affirmative questions regarding food insecurity are 0, 0, 3, and 5. Assuming a food insecurity threshold of two affirmative answers, the total incidence is 50 percent. But it is clear that food insecure households would need different levels of effort to overcome this problem—if we consider that more affirmative questions imply more food insecurity—and the incidence does not capture this situation. The food insecurity gap, represented by FI_1, measures the average distance food insecure households are to overcome the food insecurity threshold. On the other hand, the food insecurity severity,

FI_2, which is the weighted sum of the poverty gaps, where the weights correspond to the gaps themselves. Both food insecurity gap and severity are very useful measures when comparing this condition among different groups.

2.2.4 A Theoretical Framework on the Effects of Participation in the SR on Household Food Security

Following Tuttle (2013)—which estimates the effects of energy price shocks on household food insecurity in the United States—this section illustrates a simple theoretical framework that addresses the effects of participation in the SR on food expenditure and, consequently, food insecurity.

Consider a household with no access to a formal health care insurance, whose utility is derived from the utilization of health care services or goods and food consumption ($U(H, F)$), and maximize such that utility subject to its budget constraint ($m = p_h H + p_f F$). The combination of health care utilization and food consumption that maximizes household's utility is given by the point in which the marginal rate of substitution (MRS)—the ratio between the marginal utility of health care utilization and food consumption—equalizes the relative prices.

In addition, suppose a critical level of food consumption required by the members of this household for their daily activities (f_{min}). Any food consumption below f_{min} categorizes the household as food insecure. Therefore, a reduction in the relative prices or an increase in its disposable income, while holding their consumption preferences constant, would help to raise food consumption and, consequently, to overcome food insecurity. This theoretical framework is described by Figure 2.1.

As explained in section 2.2.1, the purpose of the SR is to increase the access to health care to the poor, as well as to improve participants' health condition, by offering products and services at no cost or at subsidized prices. Thus, for a food insecure household without insurance (represented by point A of figure 2.1), enrollment to the SR has two main implications: on one side, assuming no change in the price of food, it relaxes the budget constraint, since the price of health care is lower. On the other hand, it would increase household income by having healthier and, consequently, more productive working-age members. The overall shift of the budget constraint generates two effects: first, the reduction of the price of health care would induce the household to increase the utilization of health care products and services provided by the SR. This is the *substitution effect*. Second, the household faces more disposable income, and would increase the consumption of food, which is the *income effect*. That increase on food consumption would be enough that household overcomes f_{min} and, therefore, becomes food secure. This situation is represented by point B of Figure 2.1.

Previous works have already addressed the effects of participation in the SR on a wide set of health and labor-related variables in Colombia. These studies have used different methodologies in order to assess the endogeneity of enrollment in the SR: instrumental variables (Panopoulus and Vélez, 2001; Gaviria, Medina, and Mejía, 2006), propensity score matching (Trujillo, Portillo, and Vernon, 2005), or regression discontinuity (Camacho and Conover, 2013; Miller, Pinto, and Vera-Hernández, 2013). In summary, these articles have found a positive effect of the SR on utilization of medical services (e.g., preventive care, outpatient visit, hospital utilization) and a reduction on inpatient spending. Also, the SR reduces the absence of children from normal activities. With respect to labor-related outcomes, these previous articles have found that enrollment to the SR decreases labor force participation. On the other hand, this paper aims to evaluate if there is evidence of an income effect of the enrollment on the SR, and if that effect helps to reduce food insecurity in Colombian households. But, as described in section 2.2.1, the SISBEN scores also determines participation in other public-funded programs beyond the SR, and such those programs could have a more direct effect on food consumption, and, consequently, food insecurity. This "participation" effect is not addressed by the theoretical framework described in this section.

2.3 Data

In 1997, under the guidance of the World Bank, the National Administrative Department of Statistics of Colombia (DANE, in Spanish) started collecting new socio-demographic data following the guidelines of the Living Standards Measurement Surveys, in order to follow up a set of variables that helped in designing and implementing the necessary policies to achieve the Millennium Development Goals. Unlike the traditional Continuous Household Survey, focused principally on the measurement of the labor force trends, the Living Standards Survey (LSS) aims to capture additional information about participation in social programs and household wealth. In this paper, I use the 2008 version of the LSS.

Before 2008, the LSS was conducted only twice (1997 and 2003). After this year, the Colombian government decided to undertake the data collection process on a yearly basis. The survey provides very detailed information about monthly household expenditures in food and non-food goods. Additionally, the LSS includes an annual supplement regarding different topics, like child care, personal safety, or use of information technologies. For 2008, the supplement refers to food security for the first time. The food security questionnaire consists of 17 questions, 10 for households without children, that address daily life episodes where the households could have experienced lack of enough and varied alimentation due to the lack of monetary resources. This questionnaire follows the guidelines for the Latin American Food Security Scale (ELCSA), with some changes: the battery of questions is greater (17 questions instead of 16), and the period of reference is shorter (last 30 days instead of the last three months). For the purposes of this paper, a household is categorized as food insecure if affirmatively answered more than two questions. This is the same threshold used in the United States with the FSS-CPS. I take this threshold due to the lack of consensus on the usage of the ELCSA, as explained in Section 2.2.2.

The LSS is statistically representative at the national level, in rural and urban zones, and for the thirteen principal metropolitan areas (including Bogota, the capital and largest city of the nation). The 2008 sample comprises 50,542 individuals in 13,611 households. More than half of the households in the survey report being enrolled in the SR, whereas 37.1 percent belong to the CR. Adding up the households that are part of any of the special health care regimes (3.3 percent), almost 92 percent of the households in the 2008 LSS have any type of formal insurance. This number is higher than the reported by Miller, Pinto, and Vera-Hernández (2013) for 2007 (about 80 percent).

After removing households with missing values in at least one of the controls or outcomes of interest, the final sample used in this paper comprises 8,027 observations, including 6,942 households under the SR—the treatment group—and 1,085 from the uninsured—the comparison group—. As described in Section 2.2.1, it is likely to expect that uninsured households and those enrolled under the SR share similar socio-economic characteristics. Thus, they might differ principally in the treatment status (participation in SR), due to inadequate targeting or budget constraints from the local authorities.

Table 2.3 presents the descriptive statistics of the household-level characteristics of interest by health care insurance status. The estimates display some relevant differences in the mean values among several categories (e.g., average years of education, presence of either children or elderly members, self-reported health conditions, some dwelling unit's characteristics, and income quintile position). According to these statistics, uninsured households tend to be wealthier than those under the SR. The potential presence of outliers would be the result of measurement error from the LSS. In Section 2.5.3, I provide the results of the econometric models that control by these atypical observations, using the methodology proposed by Verardi, Dehon et al. (2010). Similarly, Table 2.4 provides descriptive statistics for the outcomes of interest—the FGT-like measures of food insecurity, in addition to the number of affirmative questions in the food security supplement of the LSS—comparing households between the SR and the uninsured. According to these numbers, households in the SR are more likely to be food insecure and, thus, their food insecurity gap, severity, and the number of affirmative answers are greater compared with uninsured households. However, mean differences are statistically significant only for the food insecurity incidence, as indicated by the corresponding t-statistics and p-values.

2.4 Empirical Framework

2.4.1 Identification Strategy

Consider the following linear equation which describes household food security status as a function of a set of observed characteristics and a zero-mean error term that captures unobserved factors:

$$Y_i = \alpha' X_i + \beta S_i + u_i \tag{2.2}$$

where Y_i represents the FGT-like measure of food insecurity (incidence, gap, or severity) or the number of affirmative questions in the food security supplement of the LSS; X_i is a vector of household-level controls; S_i is a binary indicator variable of enrollment to the subsidized regime (SR), and u_i is a zero-mean error term that captures unobserved characteristics that may affect the outcome variable.

In Equation 2.2, the parameter of interest is β, which captures the average difference on the outcomes between households in the SR and the uninsured, after controlling for observable household characteristics. As previously explained, eligibility to the SR is determined by the SISBEN score, which is not observed by the econometrician.[7] Regardless whether the score is observed, S_i is subject to measurement error and unobserved heterogeneity. All this implies the estimation of Equation 2.2 through ordinary least squares (OLS) cannot provide unbiased estimators.

[7]Neither the LSS nor any other household survey include that information. Only the Registry of the Poor, which is not available to the public, contains the SISBEN score, and only for the interviewed households.

More specifically, there are four aspects that undermine the exogeneity of S_i. First, households can manipulate the SISBEN score—and, therefore, participation into the SR—by providing inaccurate information to the interviewers when filling out the Census of the Poor. Households that are just slightly better off than those that are categorized just below the eligibility threshold, have the incentives to lie about their socio-economic conditions to increase the probability of enrollment. Second, score manipulation can also come from political authorities seeking electoral benefits. Third, participation into the SR is also determined by discretionary policies due to budget constrains, when municipalities are not capable to cover the totality of the eligible population into the SR. Thus, they have to limit their scope of action by covering some specific groups, leaving the rest uninsured. Last, but not least, targeting issues (e.g., providing enrollment to non-poor households) also affect the exogeneity of S_i.

Given the endogeneity of the control variable of interest, I follow Gaviria, Medina, and Mejía (2006) by using the ratio between the time the household head has been residing in the current municipality and her age as an instrumental variable (IV). This IV seeks to correct for unobserved heterogeneity and measurement error. It helps to explain the variation in Y_i that cannot be attributed to S_i after controlling for observed household characteristics (X_i) that also affect enrollment to the SR, like participation due to administrative, budgetary, or political issues.

The authors build the argument that supports the IV on two pillars. First, municipalities manage the SR by targeting the potentially eligible population, selecting the beneficiaries, and making the payments (premiums) to the intermediary companies that provide the services. Second, enrollment to the SR is also related with political connections and social networks within the municipalities. Previous articles and studies cited by Gaviria, Medina, and Mejía (2006) have provided qualitative and quantitative evidence regarding how these networks work. For example, Ruiz et al. (1999) describes for a small municipality by the Pacific Coast how the authorities selected some of the beneficiaries by personal whims, or just because they were public workers, of the hospital, or the insurance company. Likewise, BDO International and CCRP (2000), based on a series of surveys, report that beneficiaries tend to not knowing their rights from participation to the SR. Additionally, beneficiaries report that selection of the intermediary company was based following recommendations from friends, relatives, politicians, or social leaders, or was just determined by the municipality. Therefore, according to Gaviria, Medina, and Mejía (2006), longer residence spells at the current municipality (as a proportion of lifetime) expands the extent of political connections and social networks within the community, that should increase the probability of enrolment to the SR.

In this paper, the two-stage equations to estimate are the following:

$$S_i = \gamma' X_i + \delta Z_i + v_i \tag{2.3}$$

$$Y_i = \theta' X_i + \omega \hat{S}_i + u_i \tag{2.4}$$

where Z_i corresponds to the instrumental variable.

2.4.2 Validity of the Instrumental Variable

The IV should fulfill three properties in order to be valid: exclusion restriction, relevance, and monotonicity. If these hold, the parameter of interest—ω—can be interpreted as a local average treatment effect (LATE), which captures the effect of participation in the SR on food insecurity for those households in which the instrument induced them into treatment. Unlike OLS, in which the parameter of interest identifies the average treatment effect (ATE) for all treated observations, ω captures the ATE only for households in which their own extent of political and social networks had a key role in determining enrollment in the SR (i.e., the compliers). In the context of this paper, the IV is continuous. Therefore, I assume that higher values of Z increase the probability of enrollment in the SR by having greater networks.

First, the IV is assumed to fulfill the exclusion restriction, which means that Z_i affects Y_i only through S_i. Additionally, it implies that Z_i is not correlated with u_i. Technically, this assumption is hard to test and, at the same time, is the most complicated to support using theoretical arguments.[8] Some issues will put under risk the validity of the exclusion restriction. First, the household decision of remaining at the same municipality may be influenced by location-specific characteristics that might also affect food insecurity status (e.g., job opportunities, housing conditions, quality of education, access to utilities, health conditions of the household members). The variables in X_i intend to capture the aforementioned features. For those that are unobserved, the inclusion of municipality-level fixed effects becomes an optimal solution. Unfortunately, due to data anonymity policies from the Colombian Statistics Department, the public version of the LSS does not include municipality identifiers. Given the available data, I interact department identifiers with an indicator variable that is equal to one whether the household resides in an urban area, zero otherwise.

Additionally, greater political or social connections may help to reduce the likelihood of food insecurity, not through participation into the SR, but, for example, via in-kind donations. Figure 2.2 displays the probability of receiving in-kind donations, conditional on the instrumental variable, indicating a negative association between the variables, as illustrated by the slope of the locally weighted scatter plot smoothing line. Moreover, the correlation coefficient is negative (-0.017) and statistically insignificant. Therefore, it is possible to rule out the influence of the instrumental variable on household food insecurity throughout food donations.

At the same time, longer residence spells at the municipality may be the result of

[8] In the case when the number of endogenous control variables is equal to the number of instruments ($K = L$), it is not possible to test the exogeneity of the IV's. When $K < L$, Hansen's J-statistic (Hansen (1982), based on an extension of a test proposed by Sargan (1958)) helps to test whether all instruments are exogenous, but assuming that at least one of them is exogenous. Thus, rejecting H_0 indicates that at least one of the instruments is not valid, but failing to reject H_0 does not mean that all the instruments are valid.

owning or working at well-established grocery neighborhood stores, or having more experience with farming the land. Therefore, these households could take food products from their own business or harvest, reducing the probability of being food insecure. Figure 2.3 illustrates the probability that households take food from their own business or harvest, conditional on the instrumental variable. For households with short spells at the current municipality, the association between the two variables is negative. But, when that spell is greater than 0.5, is possible to observe a positive slope of the locally weighted scatter plot smoothing line. Thus, households that have been residing in the current municipality for a relevant proportion of their lifetime are more likely to take food products from their own business of harvest. Although small in magnitude (0.059), the correlation coefficient between the two variables is positive and statistically significant at one percent or less. Therefore, the IV could not only reduce household food insecurity by having greater political and social networks that increase the probability of enrolment in the SR, but also by increasing the chances of obtaining food from their own business or harvest. In this case, the $2SLS$ estimates between participation in the SR and household food insecurity could not be able to represent a full causal effect. Consequently, the regression estimates should be interpreted as a representation of the association between the two variables of interest.

Second, the IV is expected to be relevant. As stated in Angrist and Pischke (2009), a weak instrument might reduce the precision of the IV estimator in the second stage, even worse than the estimates under OLS. This is easily evaluated during the first-stage estimation, computing the F-statistic for testing $H_0 : \delta = 0$. The results reported in Section 2.5 will rule out the possibility of having a weak instrument, robust on different specifications.

Third, the IV should fulfill the monotonicity property. This condition assumes that the instrument would not have any effect on the treatment status for some observations, but requires the instrument to impact in the same direction on those who are effectively affected by it. This assumption implies to rule out the existence of defiers (e.g., individuals that did not participate into treatment after being induced to participation throughout the IV). But, as explained by DiNardo and Lee (2011), when the instrumental variable is continuous, for any given value of Z, it is possible to allow the treatment status to be probabilistic. In other words, conditional on unobserved factors, it is possible to allow the probability of participation to increase as the value of the instrument goes up. Consequently, the proportion of compliers has to outnumber the proportion of defiers, as the value of Z rises. This assumption is known as *probabilistic monotonicity*. In the context of this paper, the assumption implies that as the residence spell at the same municipality increases, the probability of enrollment to the SB should also rise. Figure 2.4 illustrates such that probability for the sample used in this paper, conditional on the instrumental variable. As seen, the locally weighted scatter plot smoothing line exhibits a positive slope for all values of Z_i.

2.5 Results

2.5.1 First Stage

Table 2.5 provides the results of the estimates of Equation 2.3, corresponding to the first stage of the IV system. This stage characterizes the determinants of enrollment in the SR, according to a set of household characteristics (X_i), fixed effects that capture heterogeneity at the state-urban level, and the proposed instrumental variable (Z_i) that aims to correct for the endogeneity of S_i. All the standard errors were corrected for heteroskedasticiy using the estimator proposed by White (1980).

The results display the coefficient associated with the fraction of lifetime the household head has been residing in the current municipality is positive and statistically significant. Since this variable is defined in the range $[0, 1]$, the regression coefficient can been directly interpreted as the percentage-point difference in the probability of enrollment to the SR between a household head that has been living the entire life in the current municipality and a newcomer, holding other characteristics constant. For example, in column 4, a life-long resident is $0.121 \times 100 = 12.1$ percentage points more likely to be part of the SR than a newcomer. This parameter, for all the specifications displayed in Table 2.5, is close to the estimated by Gaviria, Medina, and Mejía (2006), which is 0.119.

Regarding the relevance of the instrument, the F-statistic is greater than the accepted threshold ($F \geq 23$), for all specifications. Under the presence of robust standard errors, Montiel-Olea and Pflueger (2013) and Pflueger and Wang (2014) encourage econometricians to use a larger threshold for rejecting the null hypothesis $H_0 : \delta = 0$, unlike the general rule of thumb ($F \geq 10$), based on Stock and Yogo (2002), which is for conditionally homoscedastic and serially uncorrelated errors. Therefore, a weak instrumental variable is not a concern here. Henceforth, the remaining econometric estimations will correspond to the model in column 4, which includes both the observable household-level characteristics and department-urban-level fixed effects.

2.5.2 Second Stage

Table 2.6 presents the results of the second stage, which estimates the association between enrollment in the SR on the set of FGT-like measures of food insecurity—incidence, gap, and severity—and the number of affirmative answers in the food security supplement of the LSS, after correcting for the endogeneity of the treatment variable (S_i). The results provide evidence that participation in the SR has a significant association in reducing the food insecurity incidence and gap by 20.2 and 13.1 percentage points, respectively, and almost by 2 the number of affirmative answers, for those households in which the instrument had an implication in program participation (recall, a household is considered food insecure if affirmatively answered 3 or more questions from the Food Security Supplement of the LSS). However, the coefficient regarding the food insecurity severity—which measures the degree of inequality among food insecure households—is not statistically significant.

Additionally, it is important to remark that the coefficient associated with the dummy variable that indicates whether the household takes food from their own harvest, fishing, or business is negative and statistically significant for all the four regression models. This finding suggests that food insecurity is associated with households that own a business or farm their fields and take food from these activities, contrary to the initial prior explained in section 2.4.2. With respect to the reception of food via in-kind transfers, the estimated coefficient is positive and statistically significant for all the different regressions.[9] Given the positive correlation between this variable and the outcomes of interest, the exclusion restriction would be seriously compromised, since the IV might be affecting food insecurity status throughout other variables rather than just the treatment indicator.

Third row from Table 2.6 illustrates the estimates of the reduced-form equations, mostly supporting the previous findings. These models correspond to the regression of the outcomes of interest on the set of observed household-level characteristics and the instrumental variable. As explained by Angrist and Pischke (2009), the coefficients associated with the reduced form estimates reflect a proportional impact of the causal effect in study. The parameters of interest from the reduced-form estimates display the same sign and statistical significance as those from the $2SLS$ estimations. Last, but not least, notice the OLS parameters (fourth row of Table 2.6) are smaller in absolute terms compared with their $2SLS$ counterparts.

2.5.3 Robustness Checks

The econometric specification used for these estimations (Equations 2.3 and 2.4) assumes a homogeneous effect of participation in the SR for all individuals. Nevertheless, the association could be different among different types or groups of observations. This section provides some robustness checks in order to identify heterogeneity in the correlation by splitting the sample into different sub-samples that group observations under certain observed characteristics.

[9] These results are not displayed in Table 2.6, but are available upon request.

As described in section 2.4, the extent of social and political networks—captured by the instrumental variable—is expected to have a greater impact in enrollment to the SR in small municipalities and rural areas. Additionally, it is important to remark the visible differences in wellbeing between urban and rural areas in Colombia. In 1960, almost 55 percent of the population in Colombia lived in rural areas. In 2008, that proportion falls to 25.5 percent.[10] Improvements in job conditions and opportunities in greater cities, and, most important, the persistence of a 50-year armed conflict—which impact has mostly taken place in the countryside—have propitiated a gap in living conditions between rural and urban areas. Due to the lack of municipality indicators (which would allow to split the sample into small and big municipalities), I estimate separate regression models for rural and urban areas, as displayed by Tables 2.7 and 2.8. First-stage estimates on the effect of the instrument on SR participation display the same sign and statistical significance for both sub-samples, but the coefficient is greater for rural households (0.147, compared with 0.104 for the urban sub-sample). The second-stage estimates display that enrollment to the SR has an impact in mitigating both food insecurity incidence and gap, but these effects take place only in rural households. More precisely, it reduces on average the probability that a rural household is food insecure by 51.4 percentage points, and shortens the food insecurity gap by 18.2 percentage points. Additionally, the number of affirmative answers is cut down by 3. For both sub-samples, there is no effect of the SR on the severity of food insecurity.

Income, as a proxy of wellbeing, is another aspect to consider. As displayed by Table 2.4, almost 22 percent of households under the SR belong to the richest national income quintiles (4 and 5). For the uninsured, more than 37 percent fall into this category.[11] Considering the fact that the SR aim to cover poor households, these proportions seem to be greater than expected. Measurement error on the income variable or the presence of self-selection might be driving these results. Additionally, it is likely to expect that

[10] The World Bank (2016)

[11] The income distribution was estimated using the complete LSS sample, that is, including the remaining households that belong either to the contributive regime or the special health care regimes.

participation into the SR would have a small or no impact in mitigating food insecurity in richer households. Tables 2.9, 2.10, and 2.11 display the regression estimates for the sub-sample of households between income quintiles 1 to 3, and disaggregating by rural and urban households. In summary, participation in the SR is associated with less food insecurity only in rural households, resembling the results from Table 2.7. More precisely, the estimated parameter indicates that enrollment to the SR reduces the incidence of food insecurity by more than 58 percentage points, considering an average food insecurity rate of 69.6 percent for uninsured poor households in rural areas.

Additionally, I follow Verardi, Dehon et al. (2010) to identify outliers from the LSS sample in a less arbitrary fashion. The authors propose a robust approach for calculating the mean and covariance matrix drawn from the distribution of the Mahalanobis distances for a single variable of a set of controls. For this case, I use the inverse hyperbolic sine (IHS) transformation of the per capita household income as the control variable. Figure 2.5 displays the distribution of the IHS transformation of the per capita household income. The proportion of zero and high-income households is greater for the uninsured relative to those under the SR. This situation could be the result of measurement error from the LSS. Tables 2.12, 2.13, and 2.14 report the $2SLS$ estimates for the full sample, as well as for rural and urban sub-samples, after controlling for outliers. The results from Tables 2.12 and 2.13 are very similar to the findings reported in Tables 2.6 and 2.7 in magnitude and statistical significance—i.e., a positive association between participation in the SR and mitigation of both food insecurity incidence and gap—. But, unlike the regression estimates from Table 2.8, in which enrollment to the SR does not have a correlation with any of the FGT-like measures of food insecurity, the results from Table 2.14 suggests that, after the removal of the outliers, the treatment variable is associated with a reduction of the food insecurity gap in urban households by 17.6 percentage points. The intuition behind this result is that participation in the SR would not enough to overcome food insecurity, but might help to reduce the average distance from the threshold for those food insecure households.

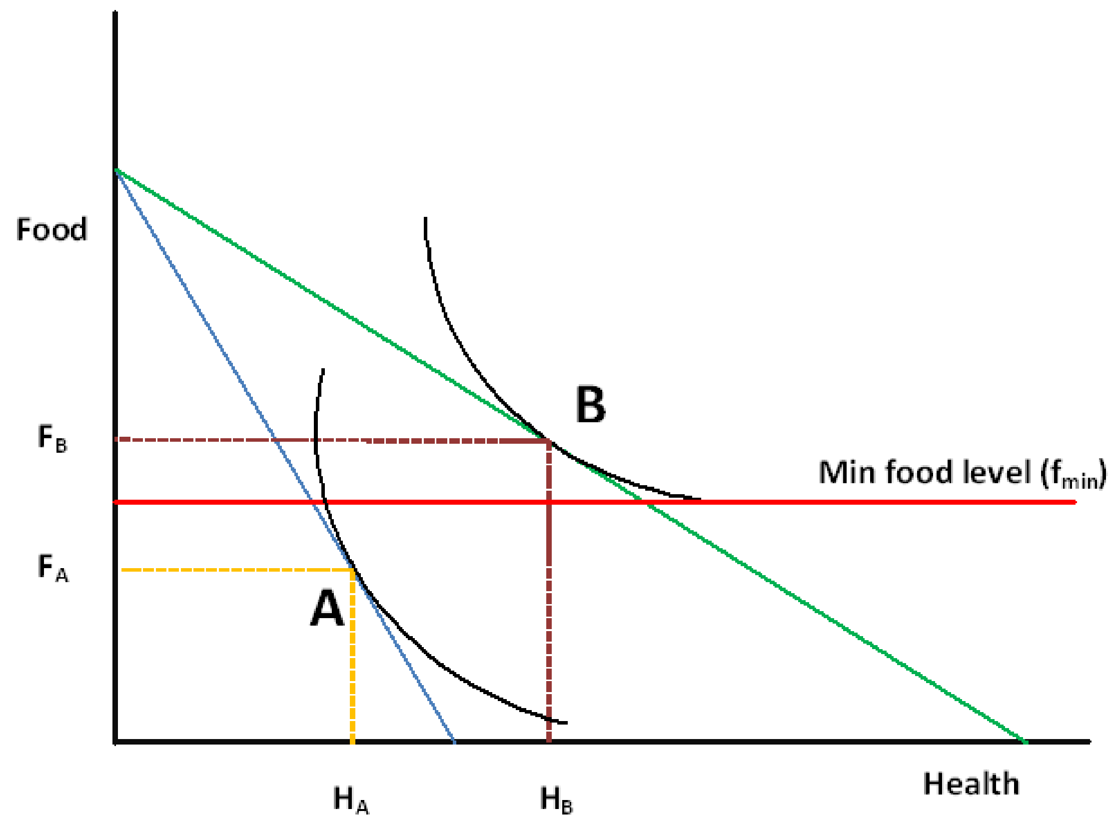
2.6 Conclusions

This paper addresses whether the Colombian subsidized health regime is associated with an income effect in household food expenditure and plays a role on mitigating food insecurity. Enrollment in the SR is determined by a proxy means test (the SISBEN score). Nevertheless, this score is not available for the econometrician. Additionally, there is evidence that the SISBEN score and, thus, participation to the SR, is subject to self-selection, municipality-level discretionary policies that affect eligibility, and manipulation for political purposes. Therefore, standard OLS estimates are biased due to measurement error and unobserved heterogeneity. To correct for such endogeneity, I use the fraction of lifetime the head of the household has been residing in the current municipality as an instrumental variable. The logic behind this instrument is that longer spells in the current place increases the probability of enrollment to the SR, due to extent of political and social networks that households can develop.

Using data from the Colombian 2008 LSS, I find that enrollment in the SR has an association with mitigating food insecurity among households, mostly occurring in rural households. The results display that households with this public-funded health care insurance might reduce the probability of being food insecure between 21 and 28 percentage points, comparing with their uninsured counterparts. On the other hand, the correlation between participation in the SR and the reduction of the food insecurity gap is positive (an average reduction of 13 percentage points). These results mostly happen in rural areas. When considering only this sub-sample, the regression estimates of the coefficients of interest indicates an average reduction of 50 and 16 percentage points on both food insecurity incidence and gap, respectively. For urban households, participation in the SR is only associated with reduction of the food insecurity gap, just after controlling for atypical observations.

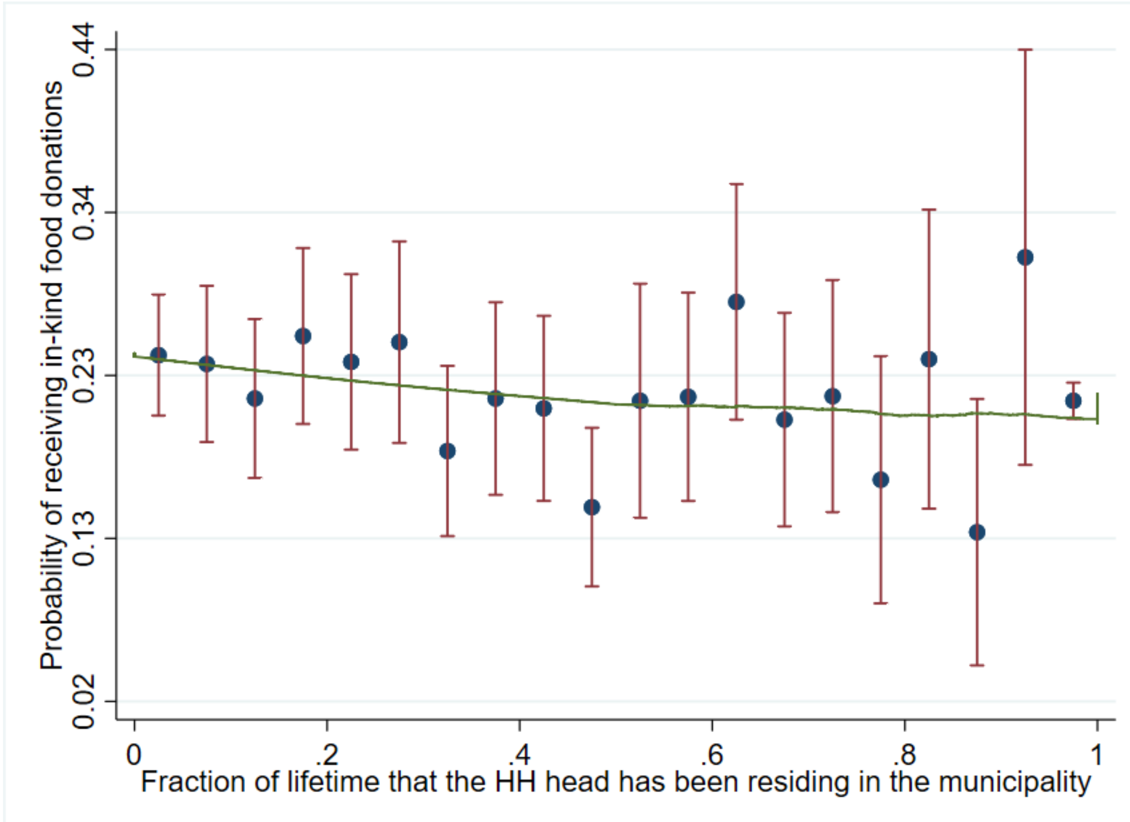
In summary, the estimates provide evidence of a association between participation in the SR and a income effect by allowing rural households to use the disposable income—as a result of facing lower prices on health care services—to achieve or overcome the minimum level of food expenditure that satisfies their daily needs. Presumably, the SR is acting as the main gate for participation to other SISBEN-eligible programs that can affect household food consumption, and, thus, will help to reduce the probability of being food insecure. For example, *Familias en Acción* is a cash transfer program for very poor households that also provides supplemental nutrition to children, conditional on school attendance and regular medical check-ups. Attanasio and Mesnard (2006) and Lopez-Arana et al. (2016) provide evidence that this program has a positive effect on food consumption. In other words, this paper has only described the (potential) causal relationship between participation on a welfare program and household food insecurity, but it not yet indicative of the mechanisms in which such that participation works towards that mitigation.

Figure 2.1: **The Effects of Participation in the Subsidized Regime on Household Food Security**



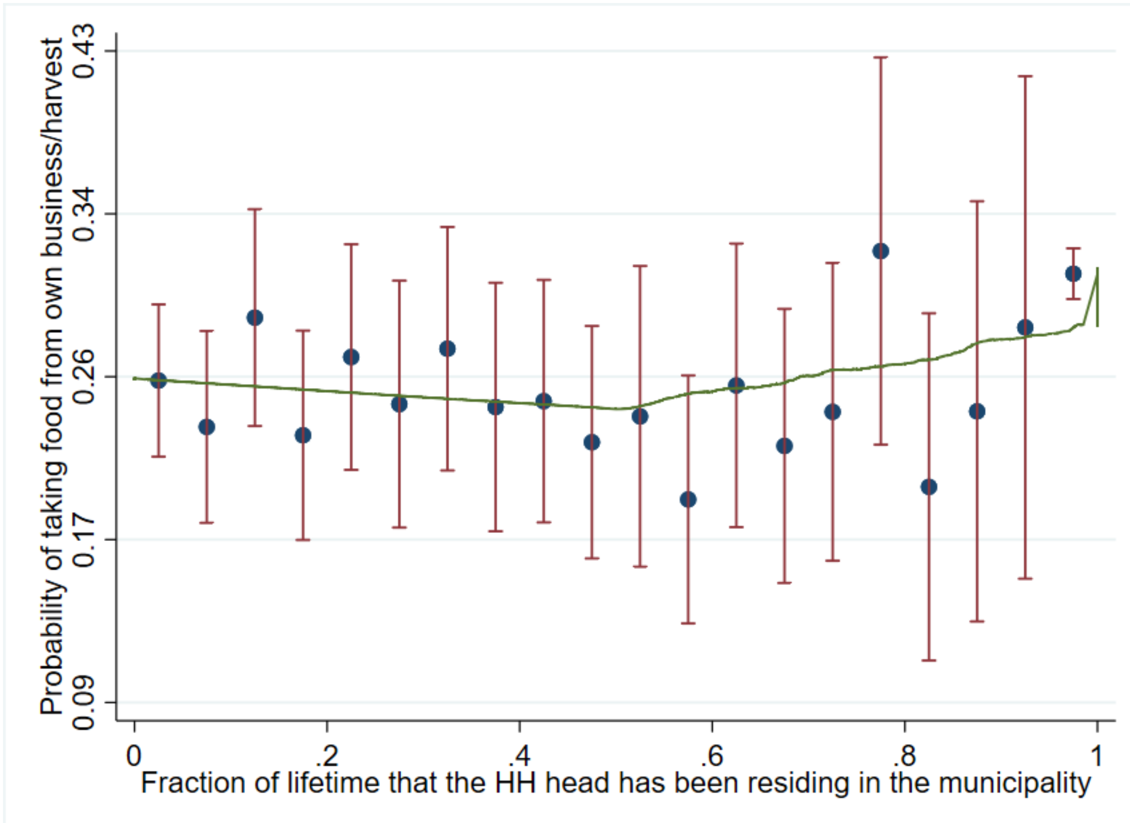
Based on Tuttle (2013).

Figure 2.2: **Probability of Receiving In-kind Food Donations, Conditional on Instrumental Variable**



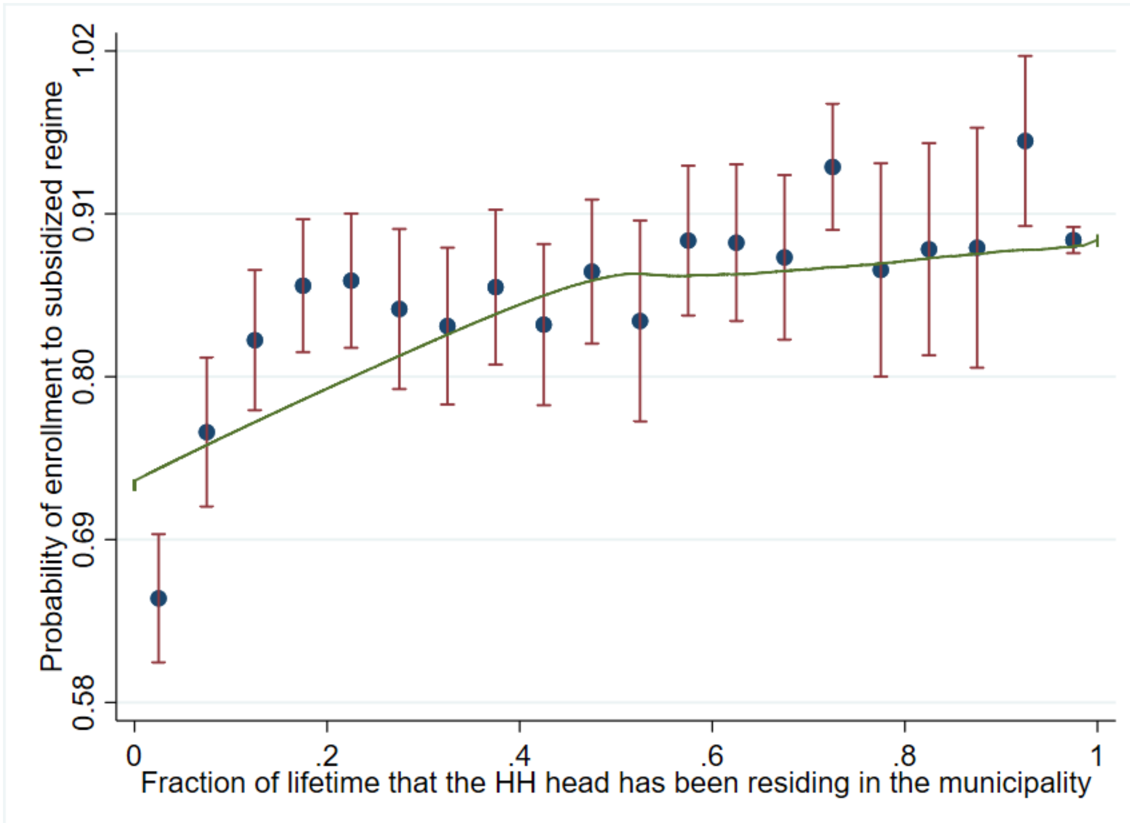
Vertical lines represent 95% confidence intervals. Source: 2008 Colombian LSS.

Figure 2.3: **Probability of Taking Food From Own Business/Harvest, Conditional on Instrumental Variable**



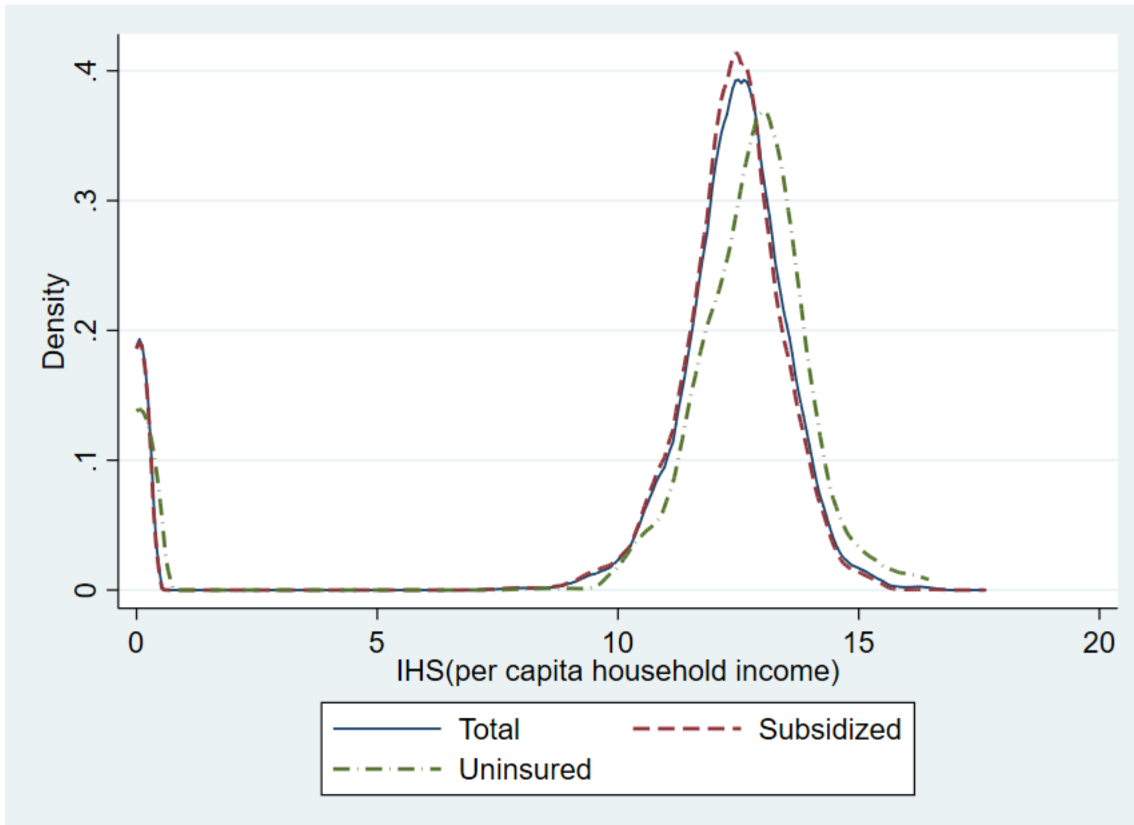
Vertical lines represent 95% confidence intervals. Source: 2008 Colombian LSS.

Figure 2.4: **Probability of Enrollment to Subsidized Regime, Conditional on Instrumental Variable**



Vertical lines represent 95% confidence intervals. Source: 2008 Colombian LSS.

Figure 2.5: **Distribution of the IHS Transformation of Per Capita Household Income**



Source: 2008 Colombian LSS.

Table 2.1: **Current Health Care System in Colombia (since 1993)**

Regime	**Uninsured**	**Subsidized**	**Contributive**	**Special**
Target		Poorest and vulnerable (unemployed, working with no written contract, displaced)	Middle and upper classes	Public workers, military
Funding	Public		Private	By own institution
Eligibility		SISBEN score	All formal workers, self-employed earning more than 1 minimum wage	
Benefits	Emergency/basic services in public hospitals	Full access to the Obligatory Health Plan. Equal benefits (at least, mandated by law)		Case-wise

Table 2.2: **Cutoff Points for Determining Food Insecurity**

	USDA cutoffs		ELCSA cutoffs	
Type of household	**With children**	**Without children**	**With children**	**Without children**
Food Secure	0-2	0-2	0	0
Low food insecurity	3-7	3-5	1-5	1-3
Moderate food insecurity	Not defined	Not defined	6-10	4-6
Severe food insecurity	8+	6+	11+	7+

Table 2.3: **Descriptive Statistics, Household Characteristics**

	Total				Subsidized				Uninsured			
Controls	**Mean**	**SD**	**Min**	**Max**	**Mean**	**SD**	**Min**	**Max**	**Mean**	**SD**	**Min**	**Max**
= 1 if household head is male	0.687	0.464	0.000	1.000	0.682	0.466	0.000	1.000	0.724	0.447	0.000	1.000
= 1 if household head is single	0.112	0.315	0.000	1.000	0.103	0.303	0.000	1.000	0.171	0.376	0.000	1.000
Years of education of HH head	4.509	3.625	0.000	21.000	4.361	3.518	0.000	19.000	5.455	4.123	0.000	21.000
= 1 if employed	0.770	0.421	0.000	1.000	0.765	0.424	0.000	1.000	0.797	0.402	0.000	1.000
Household size (persons)	3.882	2.098	1.000	20.000	3.959	2.088	1.000	20.000	3.389	2.094	1.000	15.000
HH median age	31.080	18.649	1.000	96.000	31.003	18.715	1.000	96.000	31.569	18.223	3.000	92.000
Squared HH median age	1313.690	1525.329	1.000	9216.000	1311.393	1531.741	1.000	9216.000	1328.387	1484.257	9.000	8464.000
= 1 if at least one child member in HH	0.712	0.453	0.000	1.000	0.726	0.446	0.000	1.000	0.617	0.486	0.000	1.000
= 1 if at least one elder member in HH	0.207	0.405	0.000	1.000	0.217	0.412	0.000	1.000	0.146	0.353	0.000	1.000
= 1 if HH lives in urban area	0.635	0.482	0.000	1.000	0.627	0.484	0.000	1.000	0.682	0.466	0.000	1.000
= 1 if at least one HH member reports regular/bad health cond.	0.616	0.486	0.000	1.000	0.631	0.483	0.000	1.000	0.523	0.500	0.000	1.000
= 1 if at least one HH member reports chronical disease	0.303	0.460	0.000	1.000	0.313	0.464	0.000	1.000	0.236	0.425	0.000	1.000
1 if at least one HH member had minor problems in last 30 days	0.366	0.482	0.000	1.000	0.375	0.484	0.000	1.000	0.308	0.462	0.000	1.000
= 1 if HH took food products from harvest/fishing, or own business for consumpti	0.287	0.453	0.000	1.000	0.295	0.456	0.000	1.000	0.236	0.425	0.000	1.000
= 1 if HH received food products from in-kind donations	0.217	0.412	0.000	1.000	0.218	0.413	0.000	1.000	0.212	0.409	0.000	1.000
= 1 if primary walls are made of brick, stone, or smooth wood	0.670	0.470	0.000	1.000	0.663	0.473	0.000	1.000	0.711	0.454	0.000	1.000
= 1 if floor material is not sand or soil	0.850	0.357	0.000	1.000	0.847	0.360	0.000	1.000	0.865	0.342	0.000	1.000
= 1 if HH gets water for consumption and cooking from direct aqueduct	0.467	0.499	0.000	1.000	0.456	0.498	0.000	1.000	0.539	0.499	0.000	1.000
= 1 if HH has sewerage or connection to septic tank	0.752	0.432	0.000	1.000	0.751	0.433	0.000	1.000	0.760	0.427	0.000	1.000
= 1 if HH has garbage collection service	0.515	0.500	0.000	1.000	0.504	0.500	0.000	1.000	0.582	0.494	0.000	1.000
IHS of per capita household income	11.195	3.822	0.000	17.631	11.161	3.789	0.000	17.631	11.413	4.025	0.000	16.455
= 1 if household belongs to quintile 2	0.249	0.432	0.000	1.000	0.258	0.437	0.000	1.000	0.190	0.392	0.000	1.000
= 1 if household belongs to quintile 3	0.221	0.415	0.000	1.000	0.226	0.418	0.000	1.000	0.190	0.392	0.000	1.000
= 1 if household belongs to quintile 4	0.161	0.368	0.000	1.000	0.152	0.359	0.000	1.000	0.220	0.415	0.000	1.000
= 1 if household belongs to quintile 5	0.078	0.269	0.000	1.000	0.067	0.250	0.000	1.000	0.152	0.359	0.000	1.000
Number of observations	8,027				6,942				1,085			

Own estimates. Source: 2008 Colombian LSS

Table 2.4: **Descriptive Statistics, Outcomes of Interest**

	Total		Subsidized		Uninsured		Diff. Means	
Outcomes	**Mean**	**SD**	**Mean**	**SD**	**Mean**	**SD**	**t-stat**	**P-value**
Food insecurity incidence	0.524	0.499	0.528	0.499	0.496	0.500	−1.977	0.048
Food insecurity gap	0.220	0.292	0.221	0.292	0.216	0.293	−0.510	0.610
Food insecurity severity	0.134	0.246	0.134	0.246	0.133	0.247	−0.161	0.872
Number of affirmative answers regarding food insecurity	4.634	4.935	4.654	4.925	4.500	4.994	−0.956	0.339
Number of observations	8,027		6,942		1,085			

Own estimates. Source: 2008 Colombian LSS

Table 2.5: **First Stage Estimates (determinants of enrollment to the SR)**

Controls	(1)	(2)	(3)	(4)
Fraction of life HH head has been residing in the municipality	0.131***	0.130***	0.119***	0.121***
	(0.012)	(0.012)	(0.012)	(0.012)
= 1 if household head is male			−0.033***	−0.033***
			(0.009)	(0.009)
= 1 if household head is single			−0.043***	−0.044***
			(0.014)	(0.014)
Years of education of HH head			−0.006***	−0.006***
			(0.001)	(0.001)
= 1 if employed			−0.000	−0.001
			(0.011)	(0.011)
Household size (persons)			0.004*	0.005**
			(0.002)	(0.002)
HH median age			0.001	0.002*
			(0.001)	(0.001)
Squared HH median age			−0.000	−0.000
			(0.000)	(0.000)
= 1 if at least one child member in HH			0.057***	0.058***
			(0.013)	(0.013)
= 1 if at least one elder member in HH			0.017	0.017
			(0.011)	(0.011)
= 1 if at least one HH member reports regular/bad health cond.			0.012	0.009
			(0.009)	(0.009)
= 1 if at least one HH member reports chronical disease			0.019**	0.022**
			(0.008)	(0.008)
1 if at least one HH member had minor problems in last 30 days			0.015*	0.017**
			(0.008)	(0.008)
= 1 if HH took food products from harvest/fishing, or own business for consumpti			0.009	0.006
			(0.009)	(0.009)
= 1 if HH received food products from in-kind donations			−0.012	−0.013
			(0.009)	(0.009)
= 1 if primary walls are made of brick, stone, or smooth wood			−0.010	−0.002
			(0.008)	(0.009)
= 1 if floor material is not sand or soil			0.016	0.010
			(0.011)	(0.011)
= 1 if HH gets water for consumption and cooking from direct aqueduct			−0.027***	−0.018*
			(0.010)	(0.010)
= 1 if HH has sewerage or connection to septic tank			0.025***	0.025**
			(0.010)	(0.010)
= 1 if HH has garbage collection service			0.002	0.010
			(0.010)	(0.011)
IHS of per capita household income			0.002	0.002
			(0.001)	(0.001)
= 1 if household belongs to quintile 2			0.001	0.001
			(0.011)	(0.011)
= 1 if household belongs to quintile 3			−0.002	−0.002
			(0.012)	(0.012)
= 1 if household belongs to quintile 4			−0.052***	−0.052***
			(0.015)	(0.015)
= 1 if household belongs to quintile 5			−0.097***	−0.098***
			(0.021)	(0.021)
Number of observations	8,027	8,027	8,027	8,027
R-squared	0.019	0.038	0.055	0.071
Weak Identification F-statistic	120.638	117.799	99.094	101.477
Socio-demographic Controls			YES	YES
Department x Urban Fixed Effects		YES		YES

Significant at *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Robust standard errors in parentheses

Own estimates. Source: 2008 Colombian LSS

Table 2.6: **Second Stage Estimates**

	(1)	(2)	(3)	(4)
Outcomes	**Food insecurity incidence**	**Food insecurity gap**	**Food insecurity severity**	**Number of affirmative answers**
Second-stage estimates	-0.202^{*}	-0.121^{*}	-0.071	-1.940^{*}
	(0.119)	(0.067)	(0.058)	(1.129)
Reduced-form estimates	-0.024^{*}	-0.015^{*}	-0.009	-0.234^{*}
	(0.014)	(0.008)	(0.007)	(0.136)
OLS estimates	-0.040^{***}	-0.038^{***}	-0.029^{***}	-0.614^{***}
	(0.015)	(0.008)	(0.007)	(0.141)
Number of observations	8,027	8,027	8,027	8,027
Average outcome for the uninsured	0.496	0.216	0.133	4.500
Department x Urban Fixed Effects	YES	YES	YES	YES

Significant at *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Robust standard errors in parentheses

Own estimates. Source: 2008 Colombian LSS

Table 2.7: **Second Stage Estimates, Rural Households Only**

	(1)	(2)	(3)	(4)
Outcomes	**Food insecurity incidence**	**Food insecurity gap**	**Food insecurity severity**	**Number of affirmative answers**
Second-stage estimates	-0.514^{***}	-0.182^{**}	-0.090	-3.232^{**}
	(0.175)	(0.089)	(0.074)	(1.500)
First-stage estimates	0.147^{***}	0.147^{***}	0.147^{***}	0.147^{***}
	(0.020)	(0.020)	(0.020)	(0.020)
Reduced-form estimates	-0.076^{***}	-0.027^{**}	-0.013	-0.477^{**}
	(0.025)	(0.013)	(0.011)	(0.219)
OLS estimates	-0.079^{***}	-0.047^{***}	-0.032^{**}	-0.823^{***}
	(0.026)	(0.015)	(0.013)	(0.242)
Number of observations	2,932	2,932	2,932	2,932
Weak Identification F-statistic	54.702	54.702	54.702	54.702
Average outcome for the uninsured	0.586	0.235	0.138	4.951
Department Fixed Effects	YES	YES	YES	YES

Significant at *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Robust standard errors in parentheses

Own estimates. Source: 2008 Colombian LSS

Table 2.8: **Second Stage Estimates, Urban Households Only**

	(1)	(2)	(3)	(4)
Outcomes	**Food insecurity incidence**	**Food insecurity gap**	**Food insecurity severity**	**Number of affirmative answers**
Second-stage estimates	−0.005	−0.130	−0.096	−1.908
	(0.172)	(0.100)	(0.087)	(1.676)
First-stage estimates	0.104***	0.104***	0.104***	0.104***
	(0.015)	(0.015)	(0.015)	(0.015)
Reduced-form estimates	−0.000	−0.014	−0.010	−0.199
	(0.018)	(0.010)	(0.009)	(0.174)
OLS estimates	−0.009	−0.027***	−0.024***	−0.393**
	(0.018)	(0.010)	(0.009)	(0.172)
Number of observations	5,095	5,095	5,095	5,095
Weak Identification F-statistic	47.162	47.162	47.162	47.162
Average outcome for the uninsured	0.454	0.207	0.130	4.291
Department Fixed Effects	YES	YES	YES	YES

Significant at *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Robust standard errors in parentheses

Own estimates. Source: 2008 Colombian LSS

Table 2.9: **Second Stage Estimates, Income Quintiles 1 to 3 Only**

	(1)	(2)	(3)	(4)
Outcomes	**Food insecurity incidence**	**Food insecurity gap**	**Food insecurity severity**	**Number of affirmative answers**
Second-stage estimates	−0.123	−0.110	−0.072	−1.665
	(0.162)	(0.097)	(0.086)	(1.616)
First-stage estimates	0.104***	0.104***	0.104***	0.104***
	(0.013)	(0.013)	(0.013)	(0.013)
Reduced-form estimates	−0.013	−0.011	−0.007	−0.173
	(0.017)	(0.010)	(0.009)	(0.169)
OLS estimates	−0.046**	−0.044***	−0.032***	−0.708***
	(0.018)	(0.011)	(0.010)	(0.187)
Number of observations	6, 102	6, 102	6, 102	6, 102
Weak Identification F-statistic	61.525	61.525	61.525	61.525
Average outcome for the uninsured	0.617	0.288	0.183	5.800
Department x Urban Fixed Effects	YES	YES	YES	YES

Significant at *** p<0.01, ** p<0.05, * p<0.1

Robust standard errors in parentheses

Own estimates. Source: 2008 Colombian LSS

Table 2.10: **Second Stage Estimates, Rural Households, Income Quintiles 1 to 3 Only**

	(1)	(2)	(3)	(4)
Outcomes	**Food insecurity incidence**	**Food insecurity gap**	**Food insecurity severity**	**Number of affirmative answers**
Second-stage estimates	-0.582^{**}	-0.191	-0.079	-3.480^{*}
	(0.231)	(0.122)	(0.104)	(2.051)
First-stage estimates	0.132^{***}	0.132^{***}	0.132^{***}	0.132^{***}
	(0.022)	(0.022)	(0.022)	(0.022)
Reduced-form estimates	-0.077^{***}	-0.025	-0.010	-0.460^{*}
	(0.029)	(0.016)	(0.014)	(0.271)
OLS estimates	-0.100^{***}	-0.064^{***}	-0.043^{***}	-1.076^{***}
	(0.030)	(0.018)	(0.016)	(0.304)
Number of observations	2,312	2,312	2,312	2,312
Weak Identification F-statistic	35.045	35.045	35.045	35.045
Average outcome for the uninsured	0.696	0.296	0.177	6.063
Department Fixed Effects	YES	YES	YES	YES

Significant at *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Robust standard errors in parentheses

Own estimates. Source: 2008 Colombian LSS

Table 2.11: **Second Stage Estimates, Urban Households, Income Quintiles 1 to 3 Only**

	(1)	(2)	(3)	(4)
Outcomes	**Food insecurity incidence**	**Food insecurity gap**	**Food insecurity severity**	**Number of affirmative answers**
Second-stage estimates	0.213	−0.108	−0.115	−1.268
	(0.251)	(0.152)	(0.136)	(2.506)
First-stage estimates	0.086***	0.086***	0.086***	0.086***
	(0.017)	(0.017)	(0.017)	(0.017)
Reduced-form estimates	0.018	−0.009	−0.010	−0.109
	(0.021)	(0.013)	(0.012)	(0.215)
OLS estimates	−0.007	−0.026*	−0.023*	−0.384*
	(0.023)	(0.014)	(0.013)	(0.232)
Number of observations	3,790	3,790	3,790	3,790
Weak Identification F-statistic	26.332	26.332	26.332	26.332
Average outcome for the uninsured	0.574	0.283	0.186	5.660
Department Fixed Effects	YES	YES	YES	YES

Significant at *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Robust standard errors in parentheses

Own estimates. Source: 2008 Colombian LSS

Table 2.12: **Second Stage Estimates, Excluding Outliers**

	(1)	(2)	(3)	(4)
Outcomes	**Food insecurity incidence**	**Food insecurity gap**	**Food insecurity severity**	**Number of affirmative answers**
Second-stage estimates	-0.272^{**}	-0.145^{**}	-0.087	-2.362^{**}
	(0.127)	(0.071)	(0.061)	(1.183)
First-stage estimates	0.121^{***}	0.121^{***}	0.121^{***}	0.121^{***}
	(0.013)	(0.013)	(0.013)	(0.013)
Reduced-form estimates	-0.033^{**}	-0.017^{**}	-0.011	-0.285^{**}
	(0.015)	(0.008)	(0.007)	(0.142)
OLS estimates	-0.045^{***}	-0.044^{***}	-0.035^{***}	-0.716^{***}
	(0.015)	(0.009)	(0.008)	(0.149)
Number of observations	7,196	7,196	7,196	7,196
Weak Identification F-statistic	92.413	92.413	92.413	92.413
Average outcome for the uninsured	0.491	0.216	0.133	4.486
Department x Urban Fixed Effects	YES	YES	YES	YES

Significant at *** p<0.01, ** p<0.05, * p<0.1

Robust standard errors in parentheses

Own estimates. Source: 2008 Colombian LSS

Table 2.13: **Second Stage Estimates, Excluding Outliers, Rural Households Only**

	(1)	(2)	(3)	(4)
Outcomes	**Food insecurity incidence**	**Food insecurity gap**	**Food insecurity severity**	**Number of affirmative answers**
Second-stage estimates	-0.465^{**}	-0.155^{*}	-0.083	-2.643^{*}
	(0.182)	(0.091)	(0.077)	(1.548)
First-stage estimates	0.146^{***}	0.146^{***}	0.146^{***}	0.146^{***}
	(0.021)	(0.021)	(0.021)	(0.021)
Reduced-form estimates	-0.068^{***}	-0.023^{*}	-0.012	-0.385^{*}
	(0.026)	(0.013)	(0.011)	(0.226)
OLS estimates	-0.072^{***}	-0.049^{***}	-0.036^{***}	-0.840^{***}
	(0.027)	(0.015)	(0.013)	(0.251)
Number of observations	2,682	2,682	2,682	2,682
Weak Identification F-statistic	50.227	50.227	50.227	50.227
Average outcome for the uninsured	0.569	0.233	0.138	4.875
Department Fixed Effects	YES	YES	YES	YES

Significant at *** p<0.01, ** p<0.05, * p<0.1

Robust standard errors in parentheses

Own estimates. Source: 2008 Colombian LSS

Table 2.14: **Second Stage Estimates, Excluding Outliers, Urban Households Only**

	(1)	(2)	(3)	(4)
Outcomes	**Food insecurity incidence**	**Food insecurity gap**	**Food insecurity severity**	**Number of affirmative answers**
Second-stage estimates	−0.135	−0.175*	−0.117	−2.784
	(0.183)	(0.106)	(0.092)	(1.775)
First-stage estimates	0.105***	0.105***	0.105***	0.105***
	(0.016)	(0.016)	(0.016)	(0.016)
Reduced-form estimates	−0.014	−0.018*	−0.012	−0.291
	(0.019)	(0.011)	(0.010)	(0.184)
OLS estimates	−0.017	−0.035***	−0.030***	−0.516***
	(0.019)	(0.011)	(0.010)	(0.183)
Number of observations	4,514	4,514	4,514	4,514
Weak Identification F-statistic	42.365	42.365	42.365	42.365
Average outcome for the uninsured	0.454	0.208	0.130	4.298
Department Fixed Effects	YES	YES	YES	YES

Significant at *** p<0.01, ** p<0.05, * p<0.1

Robust standard errors in parentheses

Own estimates. Source: 2008 Colombian LSS

Chapter 3

The Effects of Rising Staple Prices on Food Insecurity: The Case of Tortilla in Mexico

with Mariana Urbina-Ramirez[1,2]

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3.1 Introduction

Increasing food prices have adverse effects on the demand for food, and households that are poor, less educated, landless or farming at a small scale, or living in urban areas, are among the most vulnerable to this problem (Brinkman et al., 2010; Headey and Fan, 2008; Ruel et al., 2010; Zezza et al., 2008). Households follow different coping strategies to mitigate the effects on their wellbeing, like purchasing lower-quality products, reallocating intra-household resources, using different ingredients and implementing cooking methods, or reducing the consumption of other basic goods or services (Green et al., 2013; Ruel et al., 2010). According to Hadley et al. (2012), households first change the quality of the food purchased, and, when the situation deteriorates, they apply reversible strategies (e.g., borrowing) to alleviate food insecurity, and then switch to irreversible strategies such as selling productive assets. Otherwise, households are forced to reduce overall food intake.

Since 2006, global food prices have increased, following a volatile trajectory, reaching their peak between 2008 and 2011 (FAO, 2017). Several works have analyzed the effects of these changes in food prices on household wellbeing, particularly on poverty, food consumption, nutrition, and food insecurity (Brinkman et al., 2010; Hadley et al., 2012; Ruel et al., 2010). In developing countries, many grains and tubers, which also experienced significant price surges during the global food price crisis, are considered as food staples, representing a large proportion of households diets. According to Melgar-Quinonez et al. (2006), food staples represent more than 10 percent of food-at-home expenditure in developing countries.

In this paper, we address how household food insecurity is affected by the recent price surge of a very important staple in Mexico: the maize tortilla, a product that accounts for more than 9 percent of total food-at-home expenditure. Tortilla is a thin, flat bread, made from maize or wheat, that has been part of its culinary culture for centuries (Corona, 2016;

EcuRed, 2008), and commonly used with products such as beef, chicken, pork, vegetables, or cheese to make traditional Mexican dishes.

Using a unique combination of household-level data with official prices, we estimate the association between rising tortilla prices and food insecurity in Mexico between 2008 and 2014. During this period—which coincides with the global food price crisis—the price of Mexican maize tortillas surged between 8.7 and 35.8 percent, depending on the place of purchase. Tortillas are generally purchased from *tortillerías*—local and independent stores that produce and freshly sell the product to the public—or grocery stores that sell tortillas produced by large-scale factories. Tortilla production in tortillerías differs from large-scale factories. Tortillerías use *nixtamalized* flour or combine fresh maize dough with nixtamalized flour to make tortillas.[3] In addition to using nixtamalized flour, factories add chemical preservatives to conserve their characteristics (e.g., flexibility, humidity, and whitening) for longer periods of time (Vazquez Carrillo et al., 2011). The data used in this paper include the place where households bought their tortillas, which allows to investigate whether they decided to purchase lower-quality tortillas in order to maintain their consumption level, one of the main coping strategies discussed in the literature. Additionally, the estimations in this paper account for differences in income among Mexican households, in order to determine whether the observed price surge has heterogenous effects among different groups, based on their per capita income level.

As explained later in this paper, we do not count with household-level panel data for Mexico that simultaneously tracks food consumption and food insecurity conditions. Therefore, we follow Deaton (1985) by constructing a series of panel data sets, based on aggregating data by categories of household types. The construction of these pseudo-panels allows to estimate fixed-effect models that principally seek to correct for both time-invariant unobserved heterogeneity and measurement error. This estimation strategy is

[3]"Nixtamalization" refers to the process where maize is soaked and cooked in limewater, and then washed two or three times. This procedure adds nutritional value to maize and has been used since pre-Hispanic times (Paredes Lopez, Guevara Lara, and Bello Perez, 2009).

similar to that of Bellemare, Fajardo-Gonzalez, and Gitter (2016), a very recent paper that analyzes the effect of quinoa prices—a non-staple product—on household per capita consumption.

Our findings suggest that rising tortilla prices increase food insecurity rates in Mexico, particularly among households in the lowest quintiles, as well as for urban households, which is consistent with the findings from previous works for other developing countries that address the effects of rising staple prices on household food insecurity. The results also indicate that the prices of lower-quality tortillas have a greater impact on food insecurity, which may be an indication of a coping strategy adopted by households when facing rising prices.

The remainder of this paper is organized as follows: Section 3.2 provides background about the Mexican tortilla. Section 3.3 describes the data used for this paper and the description of the recent trends regarding food insecurity in Mexico. Section 3.4 explains the econometric estimation and provides the identification strategy for estimating causal effects. Section 3.5 presents and discusses the estimates, while section 3.6 provides some robustness checks. Finally, Section 3.7 concludes.

3.2 Background

According to the official household-level data from the Mexican Institute of Statistics (INEGI) for our period of study (2008–2014), about 80 percent of Mexican households bought maize tortillas. Dissagregating by per capita household income, those belonging to the middle-income quintiles (3 and 4) are among those who consume the most (more than 85 percent of these households), whereas the poorest and richest quintiles (1 and 5) are among those who consume the least (shares of less than 75 and 80 percent, respectively), as displayed by Figure 3.1. Maize tortilla represents an average of 9.4 percent of total food-at-home expenditure and corresponds to more than 42 percent of household expenditure on cereal-based products, as displayed in Figure 3.2.

Vazquez Carrillo et al. (2011) state that households prefer buying tortillas in tortillerías rather than in grocery stores because consumers are capable of noticing sensory differences between traditional and packaged tortillas. As explained by these authors, traditional tortillas are distinguished by the smell of nixtamalized maize, easy rolling, and astringency, without lumpiness or dryness, whereas the packaged tortillas are characterized by the lack of the smell of nixtamalized maize. Instead, they smell like acetic acid, and they are lumpier, non-astringent, and drier than their locally-produced counterparts. Households' tendency to purchase from tortillerías, however, has changed in recent times, probably driven by the relative rise of tortilla prices at tortillerías with respect to grocery stores. According to the official household-level data from the INEGI, 56.5 percent of consuming households bought tortillas at tortillerías in 2008, yet this dropped to 49.1 percent in 2014, meaning that tortillas sold in grocery stores have gained market share during recent years, as displayed by Figure 3.3. Analyzing by income quintiles (Figures 3.4 and 3.5), we observed that poorest and richest households are more prone to buy tortillas at grocery stores, whereas middle-income households are more likely to buy them at tortillerías. These data display that households from quintile 1 purchase tortillas at the cheapest place available, while those from quintile 5 might not consider tortillas as an essential good that deserves to be purchased freshly, unlike households from the second to fourth income quintiles.

Anecdotal evidence suggests that, in general, the production of tortilla is a labor-intensive process.[4] Indeed, the procedure followed by tortillerías involves more labor than the process implemented by factories. Moreover, tortillerías produce on a smaller scale so that they can sell tortillas the same day that they are produced. In contrast, factories sell a higher volume of tortillas, so the product they offer is designed to have a longer lifespan between production and its use by the final consumer. Consequently, tortillerías may offer a more expensive product compared to grocery stores. Official data from the

[4]We interviewed the manager of a tortillería located in the Minneapolis-Saint Paul area. Full transcript of the interview is available in the Appendix.

Mexican Department of Economic Affairs indicate that tortillas available at grocery stores are more affordable than those from tortillterías. For 2008, the average real price of packaged tortillas was 6.5 MEX$ per kilogram, while the average real price of traditional tortillas was 10.2 MEX$ per kilogram.[5] Both tortilla prices have increased over time: the average real prices at tortillerías and grocery stores rose by 8.7 and 35.8 percent between 2008 and 2014, respectively, as displayed by Figure 3.6.

Last, but not least, it is important to remark that recent crime trends can also have some impact on the shift of the aforementioned market shares. Newspapers have reported that owners and employees of tortillerías have been extorted or even killed by groups related to drug trafficking, and this situation has caused the closure of several tortillerías (Balderas, 2016). Although the reports state that overall sales at supermarkets or grocery stores have been affected by the recent insecurity episodes, there is no evidence that it has also had an impact on tortilla sales (Consejo Coordinador Empresarial, 2012; Ruel et al., 2010).

3.3 Data

We use the Mexican National Survey of Household Income and Expenditure (ENIGH), which is conducted biannually by the National Institute of Statistics and Geography (INEGI). The ENIGH collects detailed information on household income, tracking its sources, amounts, and expenses. It also includes data on dwelling characteristics, household composition, economic activity, labor, and education. The ENIGH is representative at the national level, as well as for urban and rural areas. The ENIGH does not track households across years. Thus, this study uses the repeated cross sections from 2008 to 2014, which together contain $85,604$ household-year observations. Section 3.4 provides details on the construction of the different pseudo-panels based on repeated cross-sectional data.

An useful feature of the ENIGH is the way the INEGI tracks households to collect

[5] Between 2008 and 2014,the average exchange was 12.7 MEX$ per USD.

data. Each household is interviewed over seven consecutive days to obtain information about daily expenses. This follow-up does not occur simultaneously for all participating households. The INEGI collects data from households using ten different schedules. After collecting the 7-day data from each household, the INEGI extrapolates this information to compute 3-month expenditures. In the public database, researchers observe the 3-month period to which the corresponding expenditure data belong. As explained below, that arrangement allows exploiting more time-series variation in tortilla prices.

The INEGI introduced the food security supplement (FSS-ENIGH) to the ENIGH in 2008, and since that year it has been part of the survey. The FSS-ENIGH addresses daily life episodes where households might have faced trouble having enough and varied food consumption due to the lack of monetary resources during the last 90 days. The FSS-ENIGH follows the guidelines of the Latin American and Caribbean Food Security Scale (ELCSA for its acronym in Spanish), with some minor changes. The ELCSA defines food insecurity as the household-level condition of limited or uncertain access to sufficient and adequate food products, based on the Food Security Supplement to the U.S. Current Population Survey (FSS-CPS).[6] The original ELCSA includes a battery of 15 questions to identify food insecurity (eight for households without children).[7] The 2008 FSS-ENIGH questionnaire includes 12 questions (six for households without children), and for 2010 onwards, the questionnaire includes 16 questions (nine for households without children). The FSS-ENIGH is collected during the first day of each of the ten interview schedules.

In this paper, the outcome of interest is an indicator variable that is equal to one if the household is food insecure and zero otherwise. To construct this variable, we count the number of affirmative answers, since every question from the FSS-ENIGH is constructed in such a way that households can only answer either "yes" or "no". In this paper, we categorize households as food insecure if they answer "yes" to three or more

[6] https://www.ers.usda.gov/topics/food-nutrition-assistance/food-security-in-the-us/measurement/

[7] Comité Científico de la ELCSA (2012) describes in more detail the construction of the ELCSA.

questions, which is the same threshold established by the United States Department of Agriculture when using the Current Population Survey (FSS-CPS) as the data source. The ELCSA establishes the threshold that determines food insecurity after one affirmative answer. However, several previous works that have addressed food insecurity in Mexico use different thresholds, and only when we use the same rule from the USDA are we able to replicate the official national food insecurity rates reported by the Mexican Secretariat of Social Development (SEDESOL).

Between 2008 and 2014, an average of 24.4 percent of Mexican households were categorized as food insecure. As displayed by Figure 3.7, food insecurity rates increased over time. Households from the poorest income quintile are more likely to be food insecure, averaging an incidence rate of above 30 percent, experiencing a small decrease during 2014. As expected, households from the fifth quintile exhibit the lowest food insecurity rates. However, we find the incidence of food insecurity for this group not only increased in 2014, but also went closer to 10 percent. We presume this might be the result of measurement error from the income variable. Figure 3.8 displays a significant variation in food insecurity rates across states. For example, in 2012 the incidence of food insecurity across all Mexican states ranged between 4 percent and 48 percent.

As in González Dávila (2010), the data on tortilla prices used in this paper come from the National System of Market Information (SNIIM).[8] The SNIIM collects these data every Monday, Wednesday, and Friday from selected tortillerías and grocery stores in cities across all Mexican states. These data are representative at the national and state levels. The sample includes 384 tortillerías and 120 grocery stores in 53 cities. To exploit the time variation from the ENIGH that we explained at the beginning of this section, we calculate state-level average tortilla prices in tortillerías and grocery stores for the previous 90 days with respect to the first day of each of the ten interview schedules. That is, for any given year, in any state, there are ten different measures of average prices, for

[8] http://www.economia-sniim.gob.mx/Tortilla.asp

both tortillerías and grocery stores. Then, we assign to each household the corresponding state average prices, according to the date they were interviewed. Although this data structure reduce variation in prices, the prices data are more accurate and less subject to measurement error than the self-reported prices by households in the ENIGH.

3.4 Empirical Framework

3.4.1 Econometric Estimation

Consider the following linear regression model that accounts for household-level food insecurity status as a function of a price measure:

$$FI_i = \alpha_0 + \alpha_1 P_i + u_i \tag{3.1}$$

where FI_i corresponds to household i's food insecurity condition (one if food insecure, zero otherwise), P_i refers to the measure of tortilla prices (prices at tortillerías, prices at grocery stores, and the price ratio, expressed as the ratio of the price at grocery stores to the price at tortillerías), and u_i is a zero-mean error. The estimation of Equation 3.1 through ordinary least squares (OLS) could lead to biased estimators of our parameter of interest (α_1), mostly due to omitted variables (e.g., persistence of past shocks, macroeconomic conditions, or changes in some relevant household characteristics that are correlated with the price measure). Even with the inclusion of a comprehensive battery of household-level characteristics (X_i) and geographic-level indicators (i.e., fixed effects), this regression model is not able to fully correct for unobserved heterogeneity, and to capture time-variant factors that should affect households' food insecurity status. As explained in Section 3.3, the ENIGH does not track households across years. Therefore, it is not possible to conduct any fixed-effect model estimation when using households as the unit of observation.

To overcome this data limitation, we follow Deaton (1985) by constructing pseudo-panels that use groups of observations (e.g., districts, municipalities, states) as the units of analysis. For example, previous works regarding the welfare effects of rising food prices in Peru (Bellemare, Fajardo-Gonzalez, and Gitter, 2016) or the state-level determinants of the incidence of food insecurity in the United States (Gundersen, Kreider, and Pepper, 2011), used this methodology. This econometric approach brings an important trade-off: grouping observations into larger units of analysis leads to fewer observations in the final data set, decreasing statistical power.

To analyze this trade-off, we aggregate the data by using two different units of analysis, based on geographical and household income criteria. First, we construct a pseudo-panel at the sate level, comprising 128 state-year observations, since states are the smallest geographical unit represented consistently in every wave of the ENIGH. The Mexican territory is divided in 32 states—including the federal district of Mexico City, the nation's capital—and comprises $2,457$ municipalities.[9] The INEGI uses census information to divide the country into geographically-based sampling units, composed by households that share certain socioeconomic characteristics. At each sampling unit, the INEGI randomly selects a sub-sample of households that conforms to a nationally representative sample. As a result, the ENIGH does not include households from every Mexican municipality. Only state capitals are represented in all samples.

Additionally, since we expect that households can react differently to tortilla price shocks according to their income level, we estimate per capita income for each of them in order to construct a distribution that allows us to categorize households into five different income quintiles.[10] Then, we group households based on their geographic location (i.e., state) and the per capita income quintile they belong, allowing us to conform a 640 state-

[9] http://cuentame.inegi.org.mx/territorio/division/default.aspx?tema=T

[10] To ensure comparability across observations over time, we use the same income thresholds from 2008 for every subsequent year. We convert all household per-capita income values as well as the income thresholds from nominal to real terms by using the nationwide yearly-average Mexican Consumer Price Index (CPI) as deflator. Data is taken from the INEGI (http://www.inegi.org.mx/est/contenidos/proyectos/inp/inpc.aspx.)

income quintile-year observation pseudo-panel. For every year, we have at least one observation that belongs to each income quintile at every state, conforming a balanced pseudo-panel data set.

Based on this data structure, the outcome of interest represents the average food insecurity rate at the corresponding unit of analysis (e.g., state or state-quintile observation), at a given point of time:

$$\overline{FI}_{jt} = \frac{1}{H_{jt}} \sum_{i=1}^{H_{jt}} I[FI_{ijt} = 1] \tag{3.2}$$

where H_{jt} indicates the total number of households in unit j at year t, and $I[FI_{ijt} = 1]$ denotes the indicator function that is equal to one if household i is food insecure, zero otherwise.

Our set of price measures corresponds to the average of real tortilla prices at tortillerías and grocery stores (measured in logarithms), and the price ratio, at a given year:

$$\overline{PT}_{jt} = \frac{1}{H_{jt}} \sum_{i=1}^{H_{jt}} log(PT_{ijt}) \tag{3.3}$$

$$\overline{PG}_{jt} = \frac{1}{H_{jt}} \sum_{i=1}^{H_{jt}} log(PG_{ijt}) \tag{3.4}$$

$$\overline{PR}_{jt} = \frac{1}{H_{jt}} \sum_{i=1}^{H_{jt}} \left(\frac{PG_{ijt}}{PT_{ijt}} \times 100 \right) \tag{3.5}$$

Figure 3.6 displays considerable collinearity between tortilla prices at tortillerías and grocery stores. More precisely, the coefficient of correlation is about 0.57 and is statistically significant at the one-percent level or less. Therefore, including both price variables simultaneously in our regression model would lead to larger standard errors of the parameters of interest. For that reason, we start estimating our regression model by including one price measure at a time. Consequently, the regression model that uses the price ratio intends to address the relative prices that households face when choosing the purchasing place to maximize their utility subject to their budget constraint.

Our regression model also includes a variable that captures whether households received in-kind transfers of tortilla. This is a relevant coping strategy used by the poorest households when facing positive price shocks. At the same time, the inclusion of this variable would also help to explain the lower share of households from the poorest income quintile that purchase tortilla. Our aggregated measure of in-kind transfers is the following:

$$\overline{K}_{jt} = \frac{1}{H_{jt}} \sum_{i=1}^{H_{jt}} I[K_{ijt} = 1] \tag{3.6}$$

where $I[K_{ijt} = 1]$ corresponds to the indicator variable that is equal to one if household i in unit j receives in-kind transfers of tortilla at time t, zero otherwise.

Additionally, we include a variable that accounts for the violence across Mexican states. As explained in Section 3.2, the increasing violence in Mexico has caused the closure of an important number of tortillerías. Using administrative data from the ENIGH, we construct a variable that measures the proportion of violent deaths among all deceases at each Mexican state at a given point of time:[11]

$$\overline{V}_{jt} = \frac{W_{jt}}{D_{jt}} \times 100 \tag{3.7}$$

where W_{jt} indicates the total number of violent deaths in state j at year t, and D_{jt} denotes

[11] `http://www.beta.inegi.org.mx/proyectos/registros/vitales/mortalidad/`

the total number of deaths in state j at year t.

Therefore, our regression model is:

$$\overline{FI}_{jt} = \beta_0 + \beta_1 \overline{P}_{jt} + \beta_2 \overline{K}_{jt} + \beta_3 \overline{V}_{jt} + \gamma_j + \epsilon_{jt} \tag{3.8}$$

where $\overline{FI}_{jt}$ corresponds to the average food insecurity rate for unit j in year t, $\overline{P}_{jt}$ represents our price measure; $\overline{K}_{jt}$ corresponds to the average share of households that receive in-kind transfers of tortilla; $\overline{V}_{jt}$ represents the proportion of violent deaths over the total number of deaths for unit j in year t; γ_j represents the set of unit-level fixed effects, and ϵ_{jt} is the zero-mean error term. The regression estimates of the parameters associated with the logarithm of tortillerías and grocery stores represent the percentage-point change on food insecurity rates after a one-percent change of prices, while the parameter associated with the price ratio can be interpreted as the percentage-point change on food insecurity rates after a one-percentage-point change on the price ratio.

3.4.2 Identification Strategy

We can claim a causal effect from our parameters of interest in Equation 3.8 if the regression model controls for the three potential sources of statistical endogeneity: (i) unobserved heterogeneity, (ii) measurement error, and (iii) reverse causality.

With respect to unobserved heterogeneity, recall from Section 3.4.1 that the INEGI randomly selects households from different sampling units to conform a nationally representative sample. Thus, households in our aggregated units of observation of interest (e.g., states or states by income quintiles) are comparable across years, on both observable and unobservable characteristics. Therefore, the implementation of the pseudo-panel techniques allows to construct units of analysis that can be tracked over time, permitting the estimation of fixed-effect models that account for time-invariant unobserved characteristics at the unit of analysis. Also, since changes in tortilla prices might be affected by changes in consumption (that could be affected by changes in household income, for example) we first control by converting tortilla prices and per-capita household income from nominal to real values. Additionally, in our state-level regressions we include a set of variables that account for the share of households that belong to the different income quintiles. At the same time, to address the effect of time that might help to explain the variation in food prices that our controls cannot account for, we include a linear time trend.

Measurement error would come from both the dependent variable (food insecurity rates) and the price measures. On one side, categorization of households as food (in)secure comes from self-reported answers from questionnaires. Therefore, the estimation of the incidence of food insecurity is likely to come with some noise. For example, households could have provided wrong answers by misunderstanding the questions. If the error that comes from the dependent variable is uncorrelated with the independent variables—which we assume since household-level data from the ENIGH and official data on tortilla prices are independent—we expect the standard errors from the regression estimates to be larger, but the estimated parameters to remain unbiased. On the other hand, any measurement error that comes from the data on tortilla prices will cause attenuation bias on the estimation of β_1. However, we expect this bias to be smaller compared with using self-reported data on prices from households.

Last, but not least, we do not consider reverse causality (i.e., changes in food insecurity rates cause changes in tortilla prices) to be an issue. As described in Section 3.1, the increase in local prices has been mostly due to the rise of international maize prices rather than changes in local demand.

3.5 Results

Table 3.1 reports the regression estimates when using the state-level pseudo-panel. Each cell of this table—and the remaining tables in this paper—contains the estimated parameter (and its standard error in parentheses) from the regression model that includes the corresponding price measure and the additional controls that are listed at the bottom. As explained in Section 3.4.1, tortillería and grocery store prices are considerably correlated. Thus, we estimate the regression models including only one price variable at a time. Consequently, our measure of relative prices aim to capture the trade-off between tortillas in tortillerías and grocery stores.

From Table 3.1 we observe that tortilla prices have a positive impact on average food insecurity rates for most of the regression models. When we include linear time trends, the significance of the parameters of interest vanishes in most of the cases. More precisely, a one-percent increase of prices at tortillerías has an effect on food insecurity rates that ranges between 0.14 and 0.23 percentage points. If we take into account the average increase in tortillería prices during the period 2008–2014 (8.7 percent), the corresponding estimated impact lies between 1.2 and 2.0 percentage points. With respect to grocery store prices, the estimated average impact is between 0.09 and 0.13 percentage points. Although these estimates are smaller in comparison with the parameters from the regression models that include prices at tortillerías, if we extrapolate the results with the average surge in grocery store prices (35.8 percent), we find an impact on food insecurity rates that ranges between 3.2 and 4.7 percentage points. Regarding the price ratio that accounts for the fraction of prices in grocery stores over tortillería prices, we find that a one-percentage-point change in relative prices affects food insecurity rates between 0.1 and 0.2 percentage points. Between 2008 and 2014, the price ratio increased in 14.5 percentage points. Therefore, the average effect on food insecurity ranges between 1.45 and 2.9 percentage points.

Table 3.2 reports the regression results for the state-income quintile-level pseudo-panel, that aims to capture differences in the impact of prices across different income levels. Unlike Table 3.1, prices at tortillerías have a positive and statistically significant effect on all regression models, even after including the linear time trend. The average effect is between 0.14 and 0.33 percentage points—or 1.2 and 2.9 percentage points when taking into account the average increase in tortillería prices during the period of study. With respect to prices at grocery stores, the average impact is between 0.15 and 0.16 percentage points, or 5.4 and 5.7 percentage points after the price surge between 2008 and 2014. The estimated parameters of interest are not longer statistically significant for the regression models that include the linear time trend. Regarding the price ratio, the effect on food insecurity rates lies between 0.2 and 0.3 percentage points (or 2.9 and 4.4 percentage points, respectively, in the context of the price surge).

In summary, we find a positive effect of tortilla prices in tortillerías and grocery stores on food insecurity in Mexico for the period 2008–2014. The average impact of grocery store prices is higher than the average effect of tortillería prices, and the positive coefficients of the regressions for the relative prices confirm this finding. Additionally, we find that the regression estimates of the state-level pseudo-panel are similar to those from the state-income quintile-level pseudo-panel, which means that our findings are consistent across the different units of observations. In the next section we present a series of regression estimates that seek to test the hypothesis whether households react differently to price surges according to their income level.

3.6 Robustness Checks

Following our findings from Section 3.5, we first build a series of state-level pseudo-panels for each income quintile. The results from Tables 3.3 to 3.7 display some interesting findings. Regarding the price at tortillerías, we observe that households from the lowest income quintile are the most affected (the average impact is between 0.36 and 0.4

percentage points, or 3.1 and 3.5 percentage point if we take into account the observed average price surge between 2008 and 2014). With respect to the price at grocery stores, is possible to observe the greatest impact corresponds to households that belong to the second income quintile. More precisely, that effect is on average 0.21 percentage points—7.5 percentage points in the context of the price surge. On the other hand, the effect of the relative prices is homogeneous among quintiles one to four. The estimated impact is about 0.3 percentage points, or 4.4 percentage points after the observed increase in this ratio. These results do not only confirm the differentiated impact of rising tortilla prices on food insecurity rates among different levels of household income, but also suggest that households may apply different coping strategies to alleviate the increase of food prices, as stated by Hadley et al. (2012). Surprisingly, we observe that tortilla prices still have an impact on food insecurity for the highest quintile. More precisely, the parameter estimates for the regression models that include prices at grocery stores is positive and significant. The same happens with the price ratio. This finding holds for the models that do not include the linear time trend.

Additionally, we split our state-level pseudo-panel between urban and rural areas to evaluate if there is evidence that rural households have more coping strategies to mitigate the effects of surging food prices, as explained by Headey and Fan (2008), Ruel et al. (2010), and Brinkman et al. (2010). The results from Table 3.8 do not display a consistent relationship between tortilla prices and food insecurity in rural households. The only exceptions come when we control separately by income or violence in our regression models. In these cases, prices at torillerías or prices at grocery stores have separately an effect on food insecurity, but the price ratio does not have any impact. This result could be providing evidence that the recent violence trends in Mexico might have an impact on the closure of some tortillerías in the countryside, with the corresponding consequences in prices. Additionally, since rural households have less places to choose where to buy tortillas, they might be bound to either produce them at home, or just stop their consumption.

On the other hand, the regression estimates displayed in Table 3.9 confirm that households from urban areas are more sensitive to the increase in prices. This finding is consistent with the FAO-provided fact—cited by Ruel et al. (2010)—that 97 percent of urban residents are net food buyers, compared with 75 percent of rural inhabitants. These authors argue that even though about 50 percent of urban households in Latin America practice urban agriculture, usually this activity is not considered the primary source for food consumption. Moreover, food producing households in urban areas depend on their plot production for only a few months yearly. The results from Table 3.9 indicate that the impact from tortillería prices lies between 0.15 and 0.31 percentage points—1.3 and 2.7 percentage points, if we consider the observed increase in prices for the period of interest—. With respect to grocery store prices, the impact ranges between 0.09 and 0.16 percentage points, or 3.2 and 5.7 percentage points after taking into account the price surge. Regarding the price ratio, the average estimated effect is 0.1 percentage point (1.4 percentage points after the observed increase in prices). For all price measures, the greatest estimated coefficients always come from the regression models that only include the share of households by income quintiles as a control. These results help to provide evidence on the hypothesis that households apply different coping strategies to mitigate food insecurity.

As a robustness check to our measure of relative prices, we conduct a principal components analysis (PCA) to construct a series of scores that represent a linear combination between our prices of interest, while capturing the highest variance possible. In this particular case, the first component score accounts for more than 90 percent of the total variation on both prices. Moreover, the value of the loading factors (i.e., eigenvectors) for the first component is the same for prices in tortillerías and grocery stores, allowing us to interpret the corresponding predicted score as a normalized representation of the simple average between prices. On the other hand, the second component score has the same loading factors as the first component score, but the sign of the score from the price at grocery stores is negative. Therefore, we interpret this score as a normalized variable that captures individual characteristics that help to explain the observed variation on each price, but not simultaneously for both. The results from Table 3.10 report a positive relation between the first component score and food insecurity rates. Overall, a one-standard-deviation change of this score has an impact on food insecurity that ranges between 1.6 and 2.6 percentage points. Is important to highlight that the estimated parameters for the first component score are always greater for the state-income quintile-level data. With respect to the second component score, the estimated parameters are always negative, but only statistically significant for the state-income quintile-level pseudo-panel.

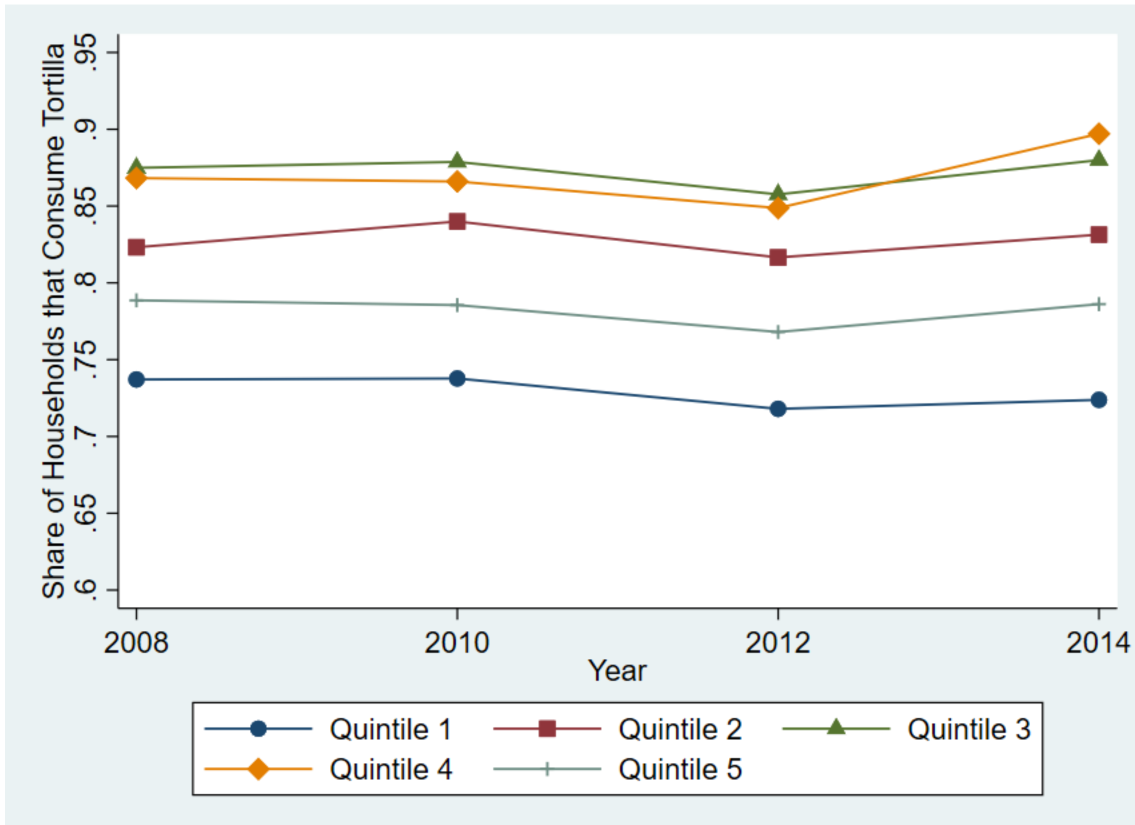
Finally, as explained in Section 3.3, we are able to replicate the official food insecurity rates in Mexico only when we use the USDA-based threshold that determines food insecurity, instead of following the guidelines from the ELCSA. In order to test the sensitivity of the results from Section 3.5, we replicate Tables 3.1 and 3.2 by using the ELSA threshold that ranks a household as food insecure when it affirmatively answers to one or more questions from the FSS-ENIGH. The regression estimates from Tables 3.11 and 3.12 indicate that tortilla prices have an impact on food insecurity rates only when we use the state-income quintile-level pseudo-panel. Overall, the results from Table 3.12 are generally consistent from the estimates displayed in Table 3.2.

3.7 Conclusions

In this paper, we estimate the effects of the rising maize tortilla prices on household food insecurity in Mexico. These prices experienced a significant surge during the period 2008–2014, coinciding with the global food price crisis. As noted by the literature, rising food prices have adverse effects on poverty, food consumption, nutrition, food insecurity, and even on health and wellbeing (Hadley et al., 2012). Using repeated cross-section data from the ENIGH, we construct a series of pseudo-panels—as proposed by Deaton (1985)—to estimate fixed-effect regression models that allow us to control by time-invariant unobserved heterogeneity and error measurement. Additionally, we use official tortilla price data, disaggregated by the place of purchase—tortillerías and grocery stores—that enables us to evaluate whether households prefer buying lower-quality tortillas to maintain their consumption level.

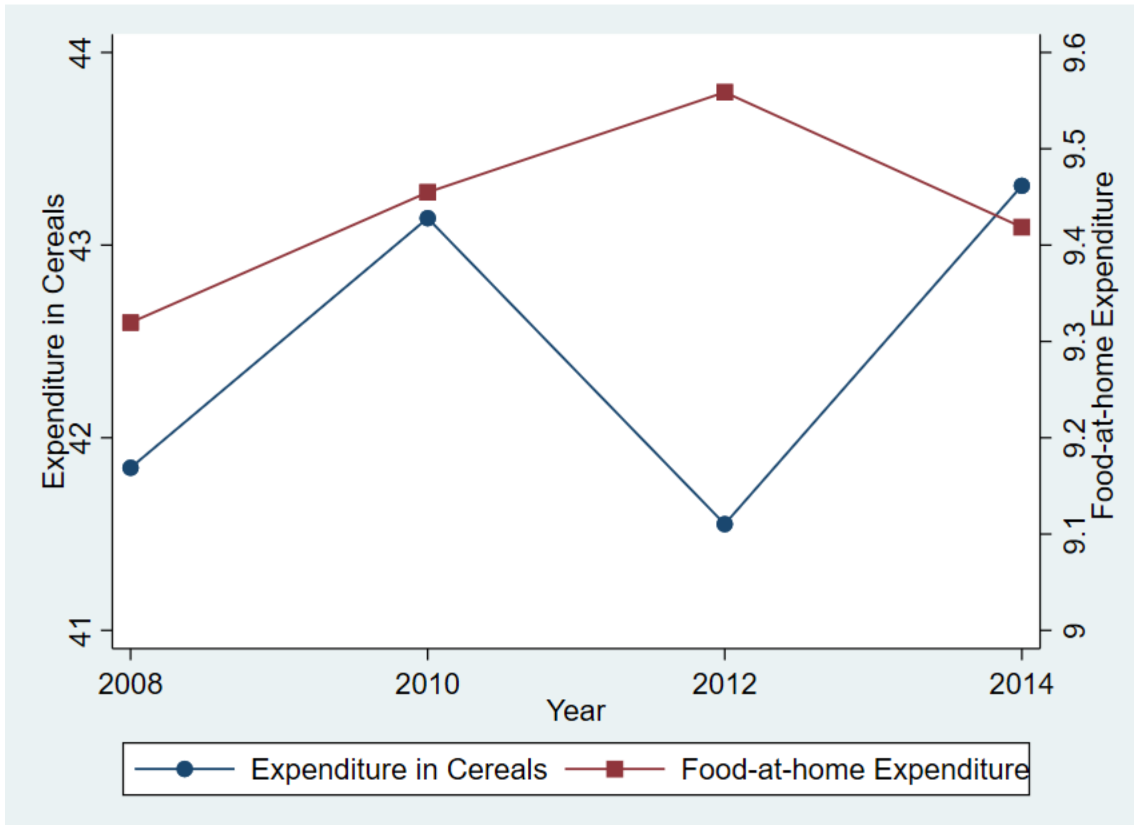
The findings of this paper suggest that increasing tortilla prices boost food insecurity rates in Mexico, and the effects are heterogeneous according to the income level. As has been documented by the literature, households from lower income quintiles are the most affected by the price surges. According to our regression estimates, the effect of the relative prices and the higher impact of prices at grocery stores indicate that one of the coping strategies applied by the families is to replace high-quality tortillas from tortillerías by those from grocery stores, that are of lower quality, but more affordable. Even though food insecurity rates are higher in rural areas, urban households are more vulnerable to changes in tortilla prices since those families are net buyers of food, so they have fewer coping strategies to maintain their food consumption. Further work aims to analyze whether the consumption of complementary goods—such as meat, cheese, rice, or beans—has diminished because of the surge of tortilla prices. Those goods are more expensive than the maize tortilla but are also part of the Mexican diet. Thus, changes in their consumption might affect food insecurity rates too.

Figure 3.1: **Tortilla Consumption in Mexico by Income Quintiles (share of households)**



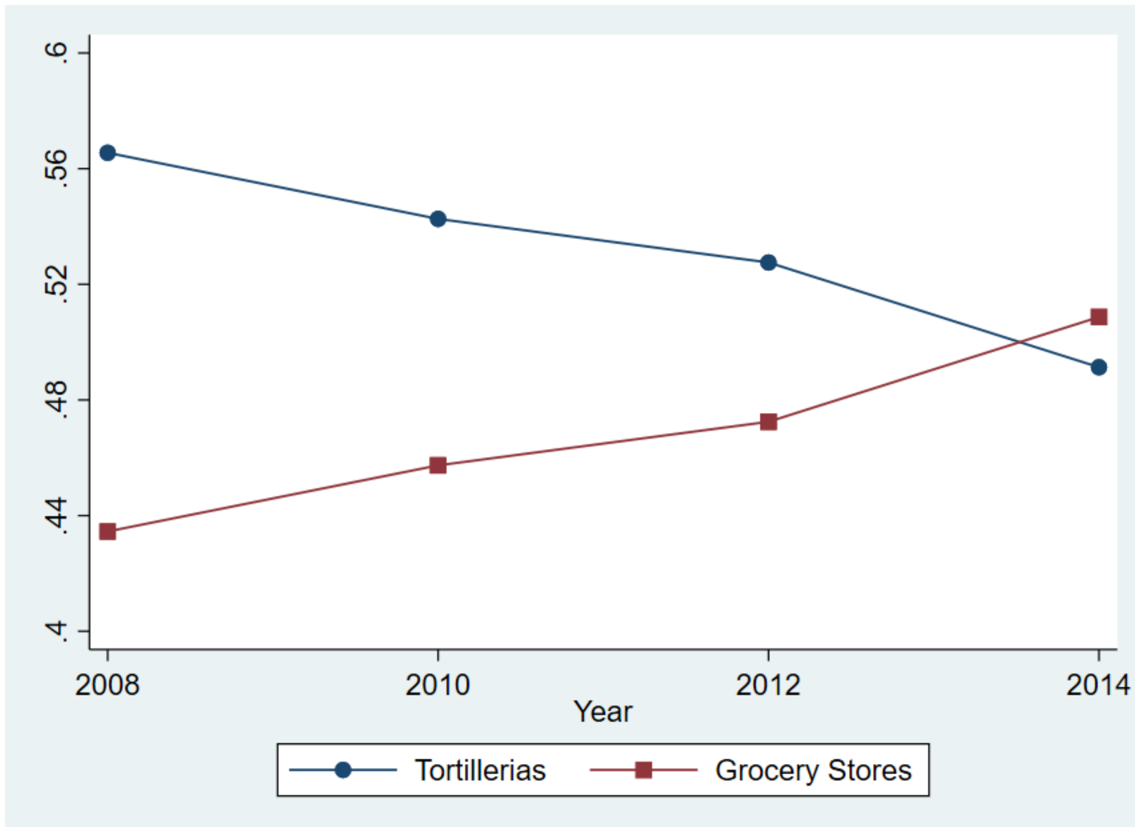
Source: 2008, 2010, 2012, and 2014 Mexican National Survey of Household Income and Expenditure (ENIGH).

Figure 3.2: **Tortilla Expenditure in Mexico as a Share of Total Household Expenditure**



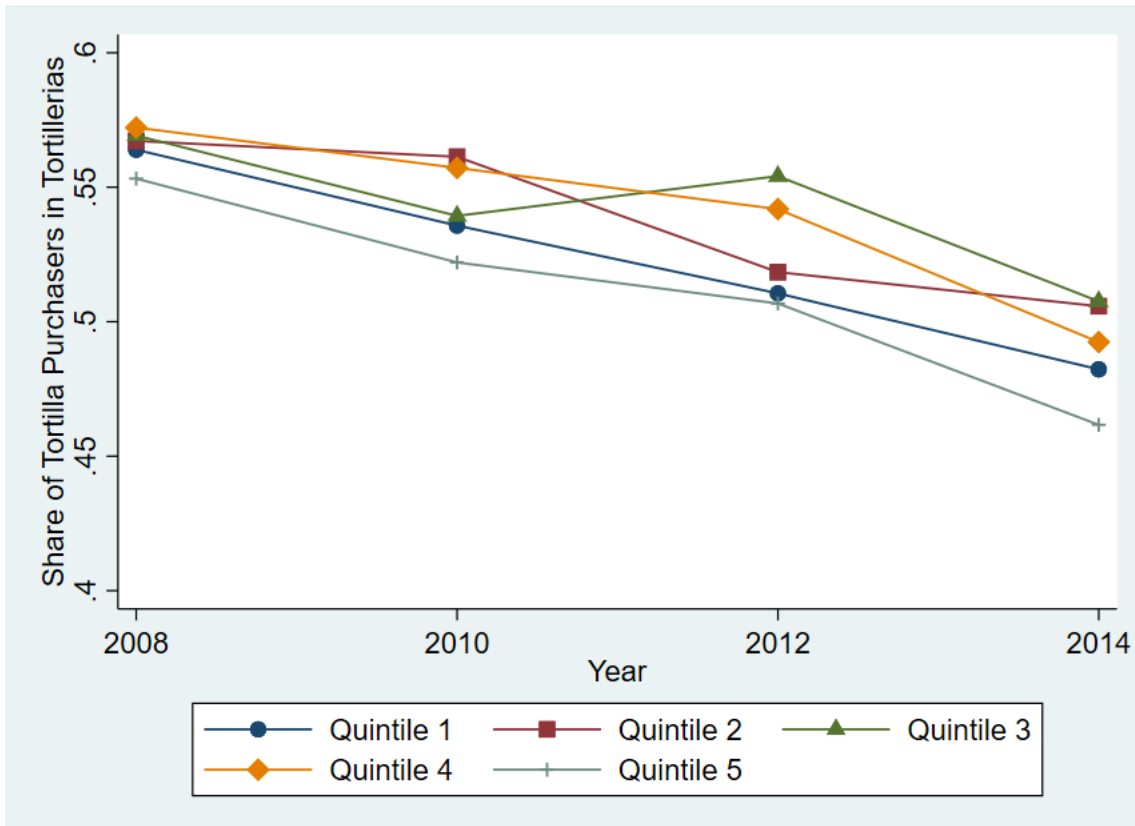
Source: 2008, 2010, 2012, and 2014 Mexican National Survey of Household Income and Expenditure (ENIGH).

Figure 3.3: **Tortilla Consumption by Purchasing Place (share of households that purchase tortilla)**



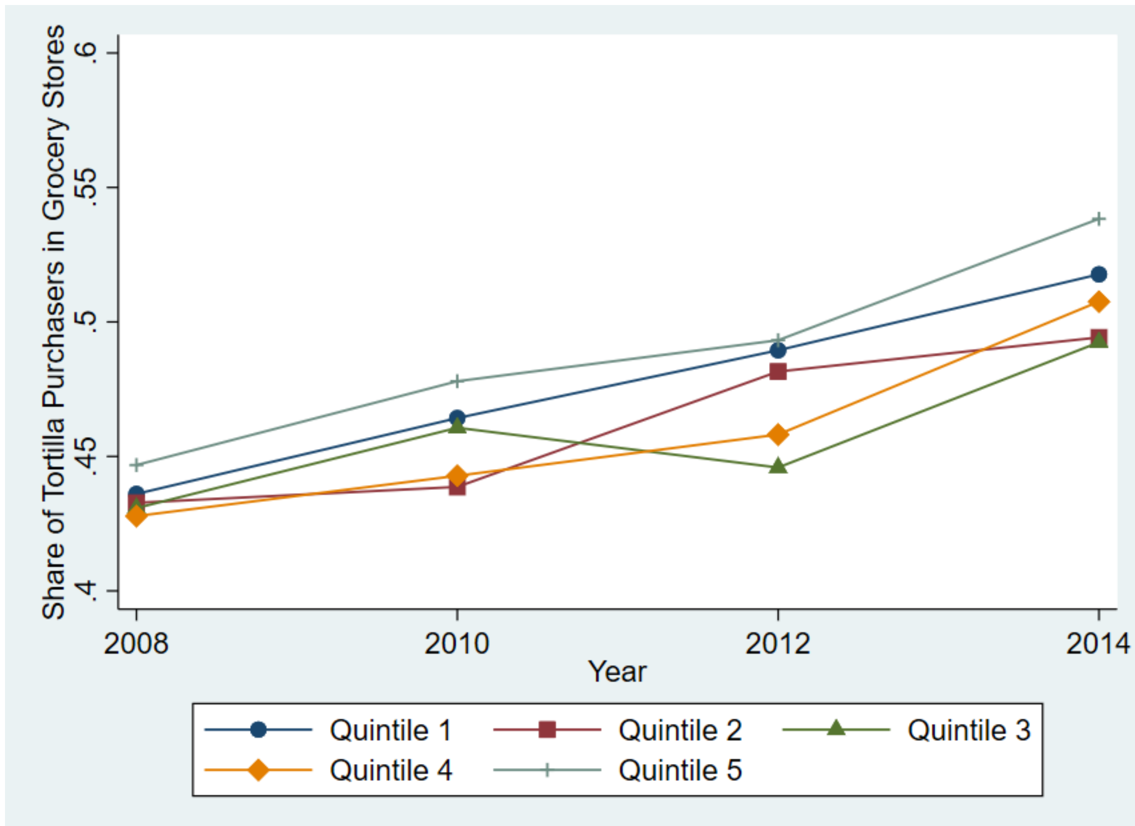
Source: 2008, 2010, 2012, and 2014 Mexican ENIGH.

Figure 3.4: **Tortilla Purchasers at Tortillerías by Income Quintiles (share of households that purchase tortilla)**



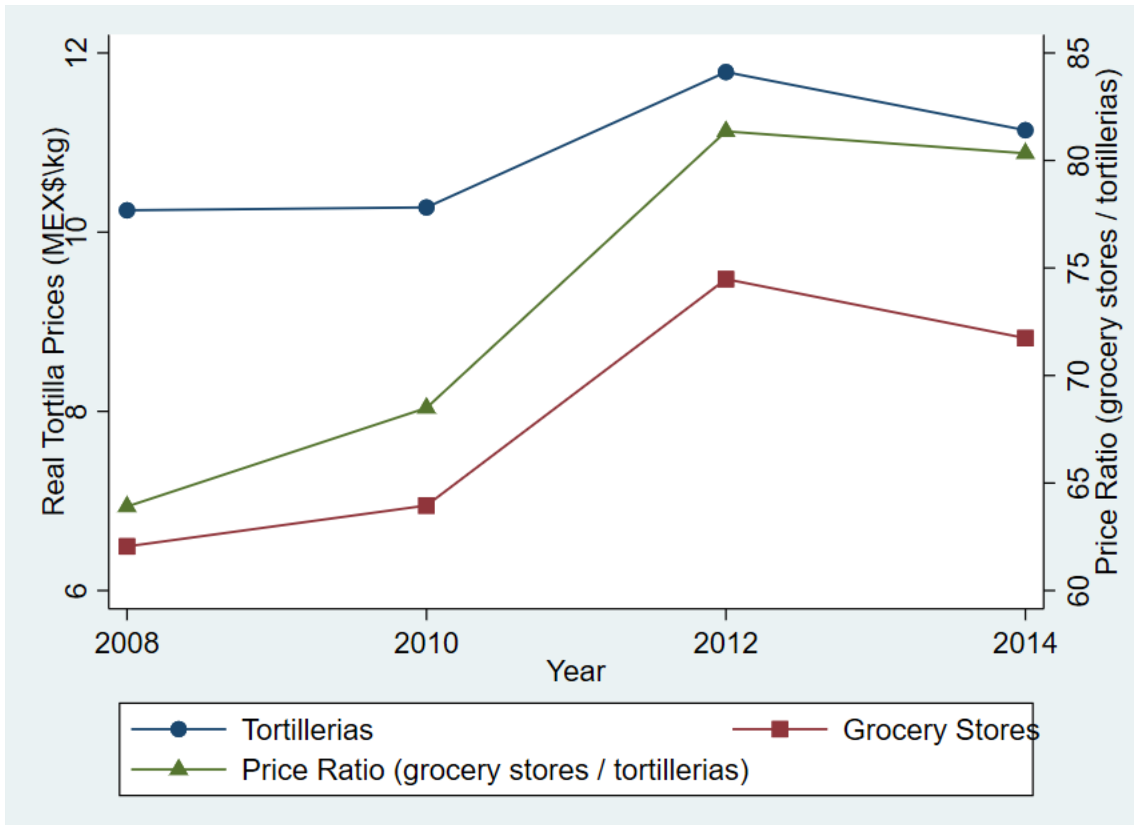
Source: 2008, 2010, 2012, and 2014 Mexican ENIGH.

Figure 3.5: **Tortilla Purchasers at Grocery Stores by Income Quintiles (share of households that purchase tortilla)**



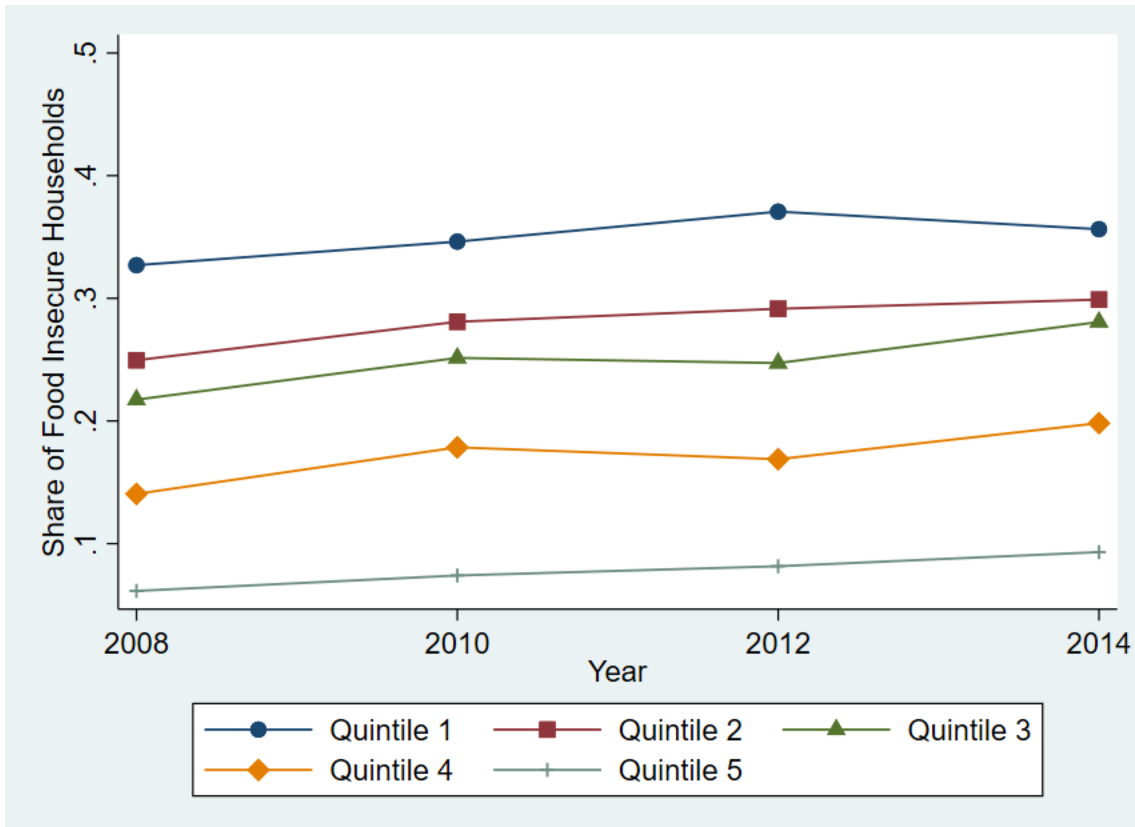
Source: 2008, 2010, 2012, and 2014 Mexican ENIGH.

Figure 3.6: **Real Tortilla Prices, National Averages (in 2008 Mexican Pesos)**



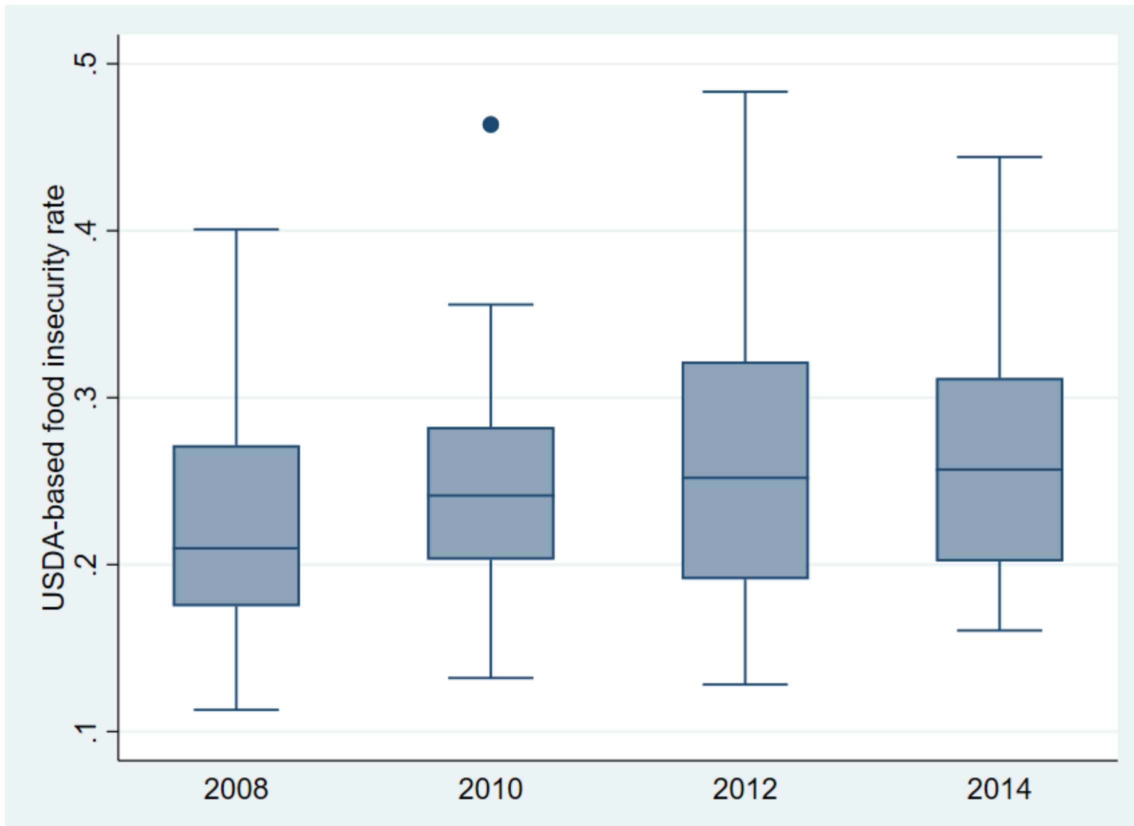
Source: Mexican Department of Economic Affairs.

Figure 3.7: **Food Insecurity Rates by Income Quintiles (share of households)**



Source: 2008, 2010, 2012, and 2014 Mexican ENIGH.

Figure 3.8: **Food Insecurity Rates, State-level Averages (share of households)**



Source: 2008, 2010, 2012, and 2014 Mexican ENIGH.

Table 3.1: **State Pseudo-Panel Estimates**

Price Variable	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
log(Real avg. price at tortillerias)	0.200***	0.237***	0.199***	0.197***	0.102	0.137**
	(0.050)	(0.054)	(0.050)	(0.051)	(0.064)	(0.064)
log(Real avg. price at grocery stores)	0.088***	0.126***	0.088***	0.087***	0.017	0.056
	(0.026)	(0.032)	(0.027)	(0.027)	(0.043)	(0.047)
Price Ratio (Grocery Stores / Tortillerias)	0.001**	0.002**	0.001**	0.001**	−0.001	−0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Observations	128	128	128	128	128	128
Income Quintile Vars.		Yes				Yes
Transfers/Donations Var.			Yes			Yes
Violence Var.				Yes		Yes
Linear Time Trend					Yes	Yes

Note: Each cell contains the parameter estimate and standard error for the corresponding price measure from the regression model that also includes the controls that are listed at the bottom of this table.

Standard errors clustered at the state level in parentheses.

Significant at *** p<0.01, ** p<0.05, * p<0.1

Own calculations. Source: 2008, 2010, 2012, and 2014 Mexican ENIGH.

Table 3.2: **State-Income Quintile Pseudo-Panel**

Price Variable	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**
log(Real avg. price at tortillerias)	0.328***	0.318***	0.330***	0.145***	0.140***
	(0.042)	(0.041)	(0.043)	(0.049)	(0.049)
log(Real avg. price at grocery stores)	0.155***	0.152***	0.159***	0.041	0.041
	(0.019)	(0.018)	(0.019)	(0.033)	(0.033)
Price Ratio (Grocery Stores / Tortillerias)	0.002***	0.002***	0.003***	−0.001	−0.001
	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)
Observations	640	640	640	640	640
Transfers/Donations Var.		Yes			Yes
Violence Var.			Yes		Yes
Linear Time Trend				Yes	Yes

Note: Each cell contains the parameter estimate and standard error for the corresponding price measure from the regression model that also includes the controls that are listed at the bottom of this table.

Standard errors clustered at the state-income quintile level in parentheses.

Significant at *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Own calculations. Source: 2008, 2010, 2012, and 2014 Mexican ENIGH.

Table 3.3: **State Pseudo-Panel Estimates, Quintile 1 Only**

Price Variable	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**
log(Real avg. price at tortillerias)	0.401***	0.361***	0.400***	0.203	0.183
	(0.109)	(0.106)	(0.114)	(0.126)	(0.130)
log(Real avg. price at grocery stores)	0.184***	0.166***	0.185***	0.056	0.049
	(0.053)	(0.052)	(0.055)	(0.101)	(0.100)
Price Ratio (Grocery Stores / Tortillerias)	0.003***	0.002**	0.003**	−0.001	−0.001
	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)
Observations	128	128	128	128	128
Transfers/Donations Var.		Yes			Yes
Violence Var.			Yes		Yes
Linear Time Trend				Yes	Yes

Note: Each cell contains the parameter estimate and standard error for the corresponding price measure from the regression model that also includes the controls that are listed at the bottom of this table.

Standard errors clustered at the state level in parentheses.

Significant at *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Own calculations. Source: 2008, 2010, 2012, and 2014 Mexican ENIGH.

Table 3.4: **State Pseudo-Panel Estimates, Quintile 2 Only**

Price Variable	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**
log(Real avg. price at tortillerias)	0.433***	0.433***	0.433***	0.144	0.144
	(0.108)	(0.109)	(0.106)	(0.128)	(0.127)
log(Real avg. price at grocery stores)	0.211***	0.211***	0.214***	0.017	0.013
	(0.045)	(0.046)	(0.043)	(0.083)	(0.080)
Price Ratio (Grocery Stores / Tortillerias)	0.003***	0.003***	0.003***	−0.001	−0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Observations	128	128	128	128	128
Transfers/Donations Var.		Yes			Yes
Violence Var.			Yes		Yes
Linear Time Trend				Yes	Yes

Note: Each cell contains the parameter estimate and standard error for the corresponding price measure from the regression model that also includes the controls that are listed at the bottom of this table.

Standard errors clustered at the state level in parentheses.

Significant at *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Own calculations. Source: 2008, 2010, 2012, and 2014 Mexican ENIGH.

Table 3.5: **State Pseudo-Panel Estimates, Quintile 3 Only**

Price Variable	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**
log(Real avg. price at tortillerias)	0.360***	0.376***	0.369***	0.179	0.207**
	(0.086)	(0.078)	(0.088)	(0.108)	(0.101)
log(Real avg. price at grocery stores)	0.164***	0.166***	0.171***	0.045	0.056
	(0.042)	(0.040)	(0.044)	(0.078)	(0.079)
Price Ratio (Grocery Stores / Tortillerias)	0.003***	0.003***	0.003***	−0.000	−0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Observations	128	128	128	128	128
Transfers/Donations Var.		Yes			Yes
Violence Var.			Yes		Yes
Linear Time Trend				Yes	Yes

Note: Each cell contains the parameter estimate and standard error for the corresponding price measure from the regression model that also includes the controls that are listed at the bottom of this table.

Standard errors clustered at the state level in parentheses.

Significant at *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Own calculations. Source: 2008, 2010, 2012, and 2014 Mexican ENIGH.

Table 3.6: **State Pseudo-Panel Estimates, Quintile 4 Only**

Price Variable	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**
log(Real avg. price at tortillerias)	0.405***	0.385***	0.403***	0.236**	0.211**
	(0.081)	(0.085)	(0.083)	(0.090)	(0.096)
log(Real avg. price at grocery stores)	0.182***	0.173***	0.183***	0.084	0.068
	(0.037)	(0.038)	(0.039)	(0.061)	(0.064)
Price Ratio (Grocery Stores / Tortillerias)	0.003***	0.003***	0.003***	−0.000	−0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Observations	128	128	128	128	128
Transfers/Donations Var.		Yes			Yes
Violence Var.			Yes		Yes
Linear Time Trend				Yes	Yes

Note: Each cell contains the parameter estimate and standard error for the corresponding price measure from the regression model that also includes the controls that are listed at the bottom of this table.

Standard errors clustered at the state level in parentheses.

Significant at *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Own calculations. Source: 2008, 2010, 2012, and 2014 Mexican ENIGH.

Table 3.7: **State Pseudo-Panel Estimates, Quintile 5 Only**

Price Variable	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**
log(Real avg. price at tortillerias)	0.037	0.041	0.043	−0.040	−0.028
	(0.045)	(0.043)	(0.046)	(0.053)	(0.053)
log(Real avg. price at grocery stores)	0.037*	0.037*	0.041*	0.002	0.010
	(0.021)	(0.020)	(0.021)	(0.036)	(0.035)
Price Ratio (Grocery Stores / Tortillerias)	0.001**	0.001*	0.001**	0.000	0.001
	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)
Observations	128	128	128	128	128
Transfers/Donations Var.		Yes			Yes
Violence Var.			Yes		Yes
Linear Time Trend				Yes	Yes

Note: Each cell contains the parameter estimate and standard error for the corresponding price measure from the regression model that also includes the controls that are listed at the bottom of this table.

Standard errors clustered at the state level in parentheses.

Significant at *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Own calculations. Source: 2008, 2010, 2012, and 2014 Mexican ENIGH.

Table 3.8: **State Pseudo-Panel in rural Areas**

Price Variable	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
log(Real avg. price at tortillerias)	0.130	0.195**	0.125	0.139*	0.077	0.095
	(0.086)	(0.096)	(0.086)	(0.081)	(0.118)	(0.113)
log(Real avg. price at grocery stores)	0.059	0.098**	0.055	0.065*	0.032	0.033
	(0.041)	(0.047)	(0.040)	(0.039)	(0.092)	(0.082)
Price Ratio (Grocery Stores / Tortillerias)	0.001	0.002	0.001	0.001	−0.000	−0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)
Observations	127	127	127	127	127	127
Income Quintile Vars.		Yes				Yes
Transfers/Donations Var.			Yes			Yes
Violence Var.				Yes		Yes
Linear Time Trend					Yes	Yes

Note: Each cell contains the parameter estimate and standard error for the corresponding price measure from the regression model that also includes the controls that are listed at the bottom of this table.

Standard errors clustered at the state level in parentheses.

Significant at *** p<0.01, ** p<0.05, * p<0.1

Own calculations. Source: 2008, 2010, 2012, and 2014 Mexican ENIGH.

Table 3.9: **State Pseudo-Panel in urban Areas**

Price Variable	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
log(Real avg. price at tortillerias)	0.245***	0.310***	0.242***	0.241***	0.148**	0.182***
	(0.054)	(0.053)	(0.053)	(0.055)	(0.064)	(0.061)
log(Real avg. price at grocery stores)	0.103***	0.161***	0.102***	0.101***	0.032	0.086*
	(0.031)	(0.032)	(0.031)	(0.032)	(0.047)	(0.050)
Price Ratio (Grocery Stores / Tortillerias)	0.001**	0.002***	0.001**	0.001**	−0.001	−0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Observations	128	128	128	128	128	128
Income Quintile Vars.		Yes				Yes
Transfers/Donations Var.			Yes			Yes
Violence Var.				Yes		Yes
Linear Time Trend					Yes	Yes

Note: Each cell contains the parameter estimate and standard error for the corresponding price measure from the regression model that also includes the controls that are listed at the bottom of this table.

Standard errors clustered at the state level in parentheses.

Significant at *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Own calculations. Source: 2008, 2010, 2012, and 2014 Mexican ENIGH.

Table 3.10: **Pseudo-Panel Estimates, Using Principal Component Scores for Prices**

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: State-level Pseudo-panel						
First Component Score	0.016***	0.022***	0.016***	0.016***	0.012	0.019**
	(0.003)	(0.004)	(0.003)	(0.003)	(0.009)	(0.010)
Second Component Score	−0.024	−0.019	−0.023	−0.025	−0.024	−0.017
	(0.019)	(0.017)	(0.019)	(0.020)	(0.020)	(0.018)
Observations	128	128	128	128	128	128
Panel B: State-Income quintile-level Pseudo-panel						
First Component Score	0.026***		0.025***	0.026***	0.018***	0.018***
	(0.003)		(0.003)	(0.003)	(0.007)	(0.007)
Second Component Score	−0.027**		−0.026**	−0.027**	−0.027**	−0.026**
	(0.013)		(0.013)	(0.013)	(0.013)	(0.013)
Observations	640		640	640	640	640
Income Quintile Vars.		Yes				Yes
Transfers/Donations Var.			Yes			Yes
Violence Var.				Yes		Yes
Linear Time Trend					Yes	Yes

Note: Standard errors clustered at the state (Panel A) and state-income quintile (Panel B) in parentheses.

Significant at *** p<0.01, ** p<0.05, * p<0.1

Own calculations. Source: 2008, 2010, 2012, and 2014 Mexican ENIGH.

Table 3.11: **State Pseudo-Panel Estimates, Using the ELCSA Threshold for Determining Food Insecurity**

Price Variable	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
log(Real avg. price at tortillerias)	0.083	0.126	0.080	0.098	0.143*	0.183**
	(0.063)	(0.079)	(0.062)	(0.064)	(0.073)	(0.078)
log(Real avg. price at grocery stores)	0.014	0.035	0.014	0.022	0.050	0.102
	(0.037)	(0.053)	(0.037)	(0.038)	(0.064)	(0.068)
Price Ratio (Grocery Stores / Tortillerias)	−0.000	−0.000	−0.000	−0.000	−0.000	0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Observations	128	128	128	128	128	128
Income Quintile Vars.		Yes				Yes
Transfers/Donations Var.			Yes			Yes
Violence Var.				Yes		Yes
Linear Time Trend					Yes	Yes

Note: Each cell contains the parameter estimate and standard error for the corresponding price measure from the regression model that also includes the controls that are listed at the bottom of this table.

Standard errors clustered at the state level in parentheses.

ELCSA Threshold for Food Insecurity = 1 if one affirmative answer or more, zero otherwise.

Significant at *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Own calculations. Source: 2008, 2010, 2012, and 2014 Mexican ENIGH.

Table 3.12: **State-Income Quintile Pseudo-Panel, Using the ELCSA Threshold for Determining Food Insecurity**

Price Variable	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**
log(Real avg. price at tortillerias)	0.204***	0.191***	0.227***	0.171***	0.186***
	(0.046)	(0.045)	(0.047)	(0.054)	(0.052)
log(Real avg. price at grocery stores)	0.082***	0.077***	0.097***	0.072*	0.101***
	(0.023)	(0.022)	(0.023)	(0.039)	(0.038)
Price Ratio (Grocery Stores / Tortillerias)	0.001**	0.001**	0.001***	−0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)
Observations	640	640	640	640	640
Transfers/Donations Var.		Yes			Yes
Violence Var.			Yes		Yes
Linear Time Trend				Yes	Yes

Note: Each cell contains the parameter estimate and standard error for the corresponding price measure from the regression model that also includes the controls that are listed at the bottom of this table.

Standard errors clustered at the state-income quintile level in parentheses.

ELCSA Threshold for Food Insecurity = 1 if one affirmative answer or more, zero otherwise.

Significant at *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Own calculations. Source: 2008, 2010, 2012, and 2014 Mexican ENIGH.

Chapter 4

Food Price Fluctuations and Household Food Insecurity in the United States, 2005–2010

4.1 Introduction

Food insecurity is a problem that affects the most vulnerable population in the United States. Between 1995 and 2007, just after the Department of Agriculture (USDA) started measuring the magnitude of this problem, and before the Great Recession took place, the incidence of food insecurity on US households was stable. In 2008, in the midst of the Great Recession, that incidence jumps to historic peaks. Nowadays, even after the economic recovery, the prevalence of food insecurity remains high and has not yet returned to its pre-Recession levels.

As noted by Gundersen, Kreider, and Pepper (2011), food insecurity has drawn the attention of the academic community and policymakers in the United States during the last decades. Most of these articles refer to the determinants or consequences of food insecurity on a wide range of household-related outcomes (e.g., health conditions, school attendance, or nutrient intakes), and the effects of welfare participation on that condition. These authors observe that little attention has been devoted to the study of the effects of food prices on food insecurity in developed nations, including the United States. Most works focus on developing countries, as described by Ivanic and Martin (2008). Despite the fact that food shares in total household expenditure remain larger in most developing countries, and, consequently, prices should have a more significant impact on household decisions, there is evidence for developed nations that food prices also influence the wellbeing of low-income households (Beatty, 2010; Broda, Leibtag, and Weinstein, 2009; Gregory and Coleman-Jensen, 2011). Moreover, in the case of the United States, Feeding America (2016) reports an interesting relationship between food prices and food insecurity at the county level: 44 counties are in the top 10 percent on both food prices and food insecurity rates.

In this paper, I match data on food prices from the USDA with the Current Population Survey (CPS)—the official source for measuring food insecurity in the United

States—to analyze the association between food prices and household food insecurity between 2005 and 2010. This period covers the years before, during, and after the Great Recession, where average food security rates rose from about 11 percent of American households to almost 15 percent, an unprecedented jump since this condition has been officially measured. The combination of these two databases allows using the variation of food prices and food insecurity rates in both temporal and spatial dimensions. The constructed database consists of a panel of metropolitan areas in the United States between 2005 and 2010, with the corresponding data on food prices for the market (as defined by the USDA) each area belongs to.

To my knowledge, Gregory and Coleman-Jensen (2011) is the only published article that uses these data combination, analyzing the effect of food prices on food insecurity only for participating households in the Supplemental Nutrition Assistance Program (SNAP).[1] This paper analyzes that same situation, but for the American population as a whole. Additionally, I analyze whether unexpected changes in prices (i.e., price shocks) are associated with changes in food insecurity rates. For that purpose, I follow the methodology proposed by Tuttle (2013) for estimating the effects of food price shocks. Results suggest that increases, as well as positive shocks (i.e., unexpected rises) in the price of grain and dairy products are positively correlated with higher food insecurity rates across metropolitan areas in the United States. Additionally, unexpected rises in the price of meats and eggs, as well as fats and prepared goods, are associated with higher food insecurity rates in the last month.

The remainder of this paper is organized as follows: Section 4.2 discusses the recent trends on food insecurity and food prices in the United States. Section 4.3 describes the data. Section 4.4 explains the empirical approach and the identification strategy. Section 4.5 presents the estimation results. Section 4.6 provides some robustness checks to the regression estimates by using alternate definitions of prices. Section 4.7 concludes and

[1] Gregory and Coleman-Jensen (2011) follow Lokshin and Sajaia (2011) by implementing an endogenous switching model to address the endogeneity of SNAP participation.

lists the further work to conduct.

4.2 Background

Between December 2007 and June 2009, the United States experienced the largest economic downturn since the Great Depression of 1929 (Farber, 2011). During the *Great Recession*, the gross domestic product (GDP) contracted by 4.3 percent, more than 8.7 million jobs were lost (Barello, 2014), and unemployment rates jumped from 5 percent in December 2007 to 9.5 percent by the end of recession, reaching a peak of 10 percent of the economically-active population in October of 2009. The United States had not experienced such those high unemployment rates since the period between September 1982 and June 1983 (U.S. Bureau of Labor Statistics, 2012). It took almost four years to the country to recover its economy to the pre-Recession levels. As stated by Hoynes, Miller, and Schaller (2012), the effects of the Great Recession in terms of employment were not uniform across the different demographic groups in the country: male workers, as well as African-Americans, Hispanics, and the youth population were among the most affected.

Official data on the incidence of food insecurity among American households is available since 1995. For that year, 11.9 percent of households were categorized as food insecure. As displayed by Figure 4.1, between 1995 and 2007, the average proportion of food insecure households in the United Stated was about 11 percent. During the Great Recession, the incidence of households under food insecurity jumped to an average of 14.6 percent, reaching a historic peak in 2011 (14.9 percent). Since then, food insecurity rates have slowly declined, without having returned to the pre-Recession levels.

With respect to the evolution of food prices, Figure 4.2 displays a sharp rise of the consumer price index (CPI) for all food products between 2007 and 2008 (first panel), mostly driven by the increase of food-at-home prices (second panel). Between 2008 and 2009, just after the end of the recession, food-at-home prices remained stable, but the average price of food products away from home experienced greater increases (third panel).

Henceforth, the overall change in food prices was mostly influenced by the evolution of food-away-from-home prices. This behavior is not surprising when analyzing the evolution of food shares as a proportion of total household income over the period of interest, as displayed by Figure 4.3. Before 2008, the share of food at home experienced a constant decline, whereas the share of food away from home slightly increased. During the Great Recession, the aforementioned trends shifted, and continued for the remaining years.

Even with a sustained increase in SNAP participation during and after the Great Recession, despite some recent cuts in benefits (jumping from 11.8 million households in 2007 to 15.2 million in 2009, to more than 22 million in 2014), American households have also relied on other informal mechanisms to access to more food.[2] As described by Heflin and Price (2018) the use of food pantries—small, community-based locals that distribute unprepared food products to households with needs—during the Great Recession became as an alternative when SNAP benefits were not enough. More precisely, these authors find that socio-demographic characteristics from food pantry users were very similar from SNAP recipients during the Recession. However, that composition has been slightly changing during the last decade, since older and more educated people have become more frequent food pantry users.

4.3 Data

4.3.1 Current Population Survey (CPS)

In 1995, the Bureau of Labor Statistics (BLS) and the Census Bureau started collecting information on food security conditions as a supplement to the nationally representative Current Population Survey (CPS). Between 1995 and 2000, the Food Security Supplement (FSS) was administered on a yearly basis, although in different months. Since 2001, it has been conducted every December. This supplement provides the official measures on food insecurity for the United States, already described in section 4.2. For this paper, I use the

[2] https://www.fns.usda.gov/pd/supplemental-nutrition-assistance-program-snap

publicly-available data version from the IPUMS-CPS project, that includes integrated and harmonized information on household characteristics, such as demographic composition, education, employment, geographical location, and poverty.[3]

The FSS contains a series of 15 "yes-no" questions designed to capture the degree of food insecurity of American households. The first eight questions are asked for all the eligible households, whereas the remaining seven are answered only by households with children. Any household interviewed in the basic CPS during the month of December is potentially eligible to answer the FSS. However, households with family income above the 185 percent of the poverty line first have to go through two screening questions regarding food stress before answering the FSS. Food stress indicates whether households have run short of money for food, and either they had not enough to eat or sufficient of the kinds of food the households wanted to have. If a household reported not having any food stress issues, they are screened out from the FSS and, automatically, considered as food secure. In addition to the questionnaire, the FSS includes questions regarding household participation in food-related welfare programs like SNAP and Women, Infants, and Children (WIC).[4] According to the guidelines given by the USDA, households (with or without children) are considered food insecure if they affirmatively answer three or more questions from the questionnaire. The FSS identifies food security conditions during the last 12 months as well as for the last 30 days. For both time windows, the questionnaire is the same. In this paper, I use both measures for robustness purposes in the estimates.

4.3.2 Quarterly Food-at-Home Price Database (QFAHPD)

Using information from Nielsen's Homescan Panel, the USDA constructed the Quarterly Food-at-home Price Databse (QFAHPD), a data set that includes quarterly market-level food prices in the United States, for the period 1999–2010.[5,6] For each quarter, the

[3] Flood et al. (2015)
[4] Appendix B.1 presents the list of questions from the FSS.
[5] `http://www.ers.usda.gov/data-products/quarterly-food-at-home-price-database.aspx`
[6] `http://www.ncppanel.com/content/ncp/ncphome.html`

QFAHPD aggregates information for 35 market groups (30 between 1999 and 2001), including prices for 54 food products. These prices come from Nielsen's data on household-level purchases of both universal product coded (UPC) and random-weighted food products. The QFHD contains more products and a more detailed level of disaggregation than other food price time series for the United States (e.g., Average Price Data from the BLS).

Appendix B.2 displays the markets defined by the USDA for the QFAHPD and Appendix B.3 lists the market correspondences between the QFAHPD and Nielsen's Homescan Data. The markets can be categorized between metropolitan and non-metropolitan areas. As explained by Todd, Mancino, and Leibtag (2010), issues with sample sizes in some markets forced the USDA to group several metropolitan areas into more aggregated markets, compared to those already defined by Nielsen (e.g., Metro Midwest 2 groups the Nielsen-defined markets of Kansas City, Minneapolis, St. Louis, Des Moines, and Omaha). The remaining nine non-metro markets were defined based on Census divisions.

As described before, The QFAHPD contains information on prices for 54 different food products, classified into four groups, following the Dietary Guidelines from the United States Departments of Agriculture and Health: fruits and vegetables, grains and dairy, meats and eggs, and fats and prepared foods.[7] Appendix B.4 lists the products for each group. Table 4.1 displays official information on food-at-home shares—as a percentage of total household expenditure—from the Consumer and Expenditure Survey (CEX) for the period 2005–2010. From this table is possible to observe the category that groups fats and processed foods (labeled as *other food at home*) has the greatest share, with an average of 2.6 percent of total household expenditure, followed by grains and dairy (1.8 percent combined), meats and eggs (1.6 percent), and fruits and vegetables (1.3 percent).

For any market, the QFAHPD reports quarterly data on prices per 100 grams for each product, after calculating the corresponding conversions for liquid items. Also, the database contains information on standard errors, number of households taken from each

[7] http://health.gov/dietaryguidelines/2015/

market for price estimates, Census division, the aggregate sum of household weights, and the total weighted value of the expenditures for each item at any market.

For this paper, I calculate average prices for each one of the four main food groups on each market for every quarter between 2005 and 2010. Following Todd, Mancino, and Leibtag (2010), the formula for estimating these prices is:

$$P_{gjt} = \frac{\sum_{i=1}^{k}(P_{ijt} \times TOTEXP_{ijt})}{TOTEXP_{gjt}} \tag{4.1}$$

where g represents each food group, $i = 1, ..., k$ denotes the number of products in group g; j is the corresponding market and t is the quarter of interest. $TOTEXP_{ijt}$ is the total expenditure for product i on market j for quarter t, and the sum over all products for group g corresponds to $TOTEXP_{gjt}$.[8] In summary, P_{gjt} is the expenditure-weighted sum of all prices for all products on group g. Finally, these prices are converted to real terms by using the Consumer Price Index for Urban Wage Earners and Clerical Workers (CPI-W) from the BLS as deflator. This is the same series the Social Security Administration uses to adjust SNAP benefits.

As mentioned in Section 4.3.1, the CPS provides two measures of food insecurity (12-month and 30-day). Therefore, for the 30-day food insecurity measure, I just assign the observed food price for each group at each market during the fourth quarter of the corresponding year. With respect to the 12-month food insecurity measure, I calculate the yearly average price for each food group at each market.

[8] The QFAHPD only reports total expenditure for each prodcut at each market for every quarter. Information about quantities purchased is not available.

4.3.3 Descriptive Statistics

Using FIPS codes for metropolitan areas and counties, it is possible to merge the CPS and the QFAHPD. For the period between 2005 and 2010, the final sample includes 225,197 household observations, an average of 37,533 per year. From the CPS, it is only possible to track households up to two years, on a rolling basis. In this paper, I construct a metropolitan area-level panel data set for the econometric estimations.[9]

Table 4.2 displays the descriptive statistics for the outcomes of interest (12-month and 30-day food insecurity measures) and the socio-economic controls at the metropolitan-area level from the CPS. Regarding food insecurity, as explained in Section 4.2, both measures experienced a relevant jump in 2008, when the Great Recession took place. These facts are supported by Figures 4.4 and 4.5, that display the distribution of food insecurity rates among all metropolitan areas for the years of interest. With respect to participation in SNAP, the most important food assistance program in the United States, participation rates are lower (an average of eight percent of households during the period of study) when compared with the official rates from the USDA's Food and Nutrition Service (about 15 percent).[10] These differences are not surprising. As stated by Gregory and Coleman-Jensen (2011) and Kreider et al. (2012), participation in welfare programs in the United States is usually—if not always—underreported in household surveys. With respect to the metropolitan area-level rates of the characteristics of the household head or householder, the statistics reported by Table 4.2 reveal they do not drastically change over time.

Regarding real food prices, Figures 4.6 and 4.7 display the box graphs for the yearly average and fourth quarter prices for all food groups, respectively. According to these figures, average prices of grains and dairy products experienced a significant jump after 2008, whereas the other average prices of fats and prepared goods, as well as of fruits

[9]The construction and econometric implications of these data are explained in section 4.4.
[10]`https://www.fns.usda.gov/pd/supplemental-nutrition-assistance-program-snap`

and vegetables had no significant changes around that year. With respect to the average price of meats and eggs, it is possible to observe a downward trajectory until the year 2008, followed by a slight recovery in 2009 and 2010. Likewise, the longitudinal graphs (Figures 4.8 and 4.8) display that the majority of the QFAHPD-defined markets follow a similar trajectory in prices. Therefore, the difference across markets is based on their levels.

4.4 Empirical Framework and Identification Strategy

As stated in Section 4.3.3, households from the CPS can be followed only for two years, on a rolling basis. Therefore, I follow Deaton (1985) by constructing a pseudo-panel that use groups of observations. More precisely, using original sampling weights, I aggregate data from the CPS to the metropolitan area level, resulting in a $1,440$ MSA-year observation database. For the United States, Gundersen, Kreider, and Pepper (2011) follow the same methodology to estimate the determinants of food insecurity across states. The use of these pseudo-panels comes with a cost: as the unit of observation becomes larger (e.g., passing from households to municipalities or metropolitan areas), measurement error decreases, but statistical power may also go down.

Based on this data structure, the outcome of interest corresponds to the food insecurity rate—during the last 12 months or last 30 days—for metropolitan area j at year t:

$$\overline{FI}_{jt} = \frac{1}{H_{jt}} \sum_{i=1}^{H_{jt}} I[FI_{ijt} = 1] \tag{4.2}$$

where H_{jt} represents the total number of households in metropolitan area j at year t, and $I[FI_{ijt} = 1]$ corresponds to the indicator function that is equal to one if household i lives in metropolitan area j is food insecure at year t, zero otherwise.

The treatment variable in the paper corresponds to the average real food prices for metropolitan area j at year t. This data comes from the QFAHPD, and, as explained in section 4.3.2, corresponds to four different measures for the respective food groups the USDA constructs: fruits and vegetables, grains and dairy, meats and eggs, fats and prepared goods, all transformed into logarithms. For the 12-month food insecurity rate, I use the yearly average food price measure, whereas for the 30-day food insecurity rate, the respective treatment variable is the fourth quarter price measure.

To claim a casual effect from the regression estimates of food insecurity on food prices, the price measures should be exogenous. However, there are three aspects that could undermine such that exogeneity: (i) unobserved heterogeneity, (ii) measurement error, and (iii) reverse causality. First, Unobserved heterogeneity would be the result of omitting variables that are correlated with the different price measures, like, for example, macroeconomic conditions (periods of growth or recession), market characteristics (road infrastructure, ease of access to grocery stores, intermediation chains between producers and sellers), or weather shocks (floods, droughts). To address the potential bias from unobserved heterogeneity, I include metropolitan area-level fixed effects. This set of indicators seek to account for time-invariant unobserved characteristics at the unit of analysis. Additionally, I introduce a battery of metropolitan area-level socio-demographic controls—listed in Table 4.2—to control for time-variant characteristics that might affect food prices. Some of these factors might also help to explain the observed variation in food insecurity rates. Last, but not least, to address for the passage of time in the estimations, I include a linear time trend.

Second, measurement error could come from both the dependent and the independent variables. Regarding the outcome of interest—food insecurity rates in metropolitan areas—it is likely to expect that households might have misunderstood some of the questions from the FSS. Therefore, any estimation of the incidence of food insecurity in metropolitan areas should some with some noise. As long as that error term is not correlated with the independent variables, the regression estimates of the coefficients associated with food prices remain unbiased, but their corresponding standard errors could be greater. On the other hand, any measurement error that comes from food prices might cause attenuation bias on the regression estimates. Todd, Mancino, and Leibtag (2010) recognizes that the gram weight of liquid products can vary depending on the density of each liquid. However, they use a conversion factor (29.57 grams/ounce) for all liquids. Ignoring these differences in density should bring some noise to the estimation of prices. Therefore, the regression estimates should be interpreted as a representation of the association between food insecurity rates and food prices.

Third, I do not consider reverse causality (i.e., changes in food insecurity rates cause changes in food prices) a main source of endogeneity. As described in Sections 4.2 and 4.3.3, food prices experienced a significant jump in the United States 2008, the same year when the incidence of household food insecurity also peaked to historic levels. However, that observed raise in prices was principally caused by the global food price crisis.

Given the above, the regression model of interest is the following:

$$\overline{FI}_{jt} = \alpha^{'}\overline{X}_{jt} + \sum_{g=1}^{G} \beta_g P_{gjt} + \gamma T + v_j + e_{jt} \tag{4.3}$$

where $\overline{FI}_{jt}$ denotes the food insecurity rate for metropolitan area j at year t, $\overline{X}_{jt}$ groups the set of socio-demographic variables; P_{Gjt} are the price measures; T corresponds to the linear time trend; v_j represents the metropolitan area-level fixed effect, and e_{ij} is a zero-mean error term. In this equation, the parameters of interest are β_g, which capture the association between prices and average food insecurity rates in metropolitan areas.

Since households' decision on food expenditure is affected by the simultaneous behavior of food prices, all price measures should be included at the same time in the regression model. However, the presence of high collinearity among prices could have some consequences on the estimated parameters (i.e., a switch in their signs and greater variances). The price measures used this paper exhibit high collinearity. For example, the smallest pairwise correlation is above 0.67 and is statistically significant at one percent or less. In Section 4.5, I begin reporting the estimates from the regression models that only include one price measure at a time.

4.5 Results

Tables 4.3 and 4.4 report the regression estimates for the 12-month and 30-day food insecurity rates, respectively, when only one price variable is included. Each cell from these tables report the parameter estimate (and standard error) from the regression model that only includes the corresponding price measure and the additional controls listed at the bottom.

The results from Table 4.3 display a positive correlation between 12-month food insecurity rates and most of the price measures, but only for the regression models that do not account for the linear time trend (columns 1 and 3). When the time trend is included (columns 2 and 4), the sign of the estimated parameters is usually negative, and the coefficients are statistically significant for fruits and vegetables (column 2), and meats and eggs (columns 2 and 4). The only case when the estimated coefficients are always positive and statistically significant—regardless the specification—is for the price of grains and dairy. Moreover, the estimated parameter is always the greatest (in absolute terms) among all price measures.[11]

Table 4.4 displays similar results for the coefficient associated with the price of grains and dairy: the parameters are positive and statistically significant. With respect to the price of fruits and vegetables, as well as the price of meats and eggs, their corresponding estimates display a positive correlation with 30-day food insecurity rates for the regression models that do not include the linear time trend (columns 1 and 3). Regarding the price of fats and prepared good, the estimated coefficients are positive and statistically significant

[11] The same results take place when using a set of year fixed effects instead of the time trend.

for the regression models displayed in columns 2 (ignoring socio-demographic controls only) and 3 (ignoring the linear time trend only).

In summary, the regression models that account for one price measure at a time indicate that the price of grains and dairy have a strong and positive correlation with both 12-month and 30-day food insecurity rates. With respect to the rest of prices, the results are mixed, and do not lead to make some initial conclusions about their relationship with food insecurity rates.

What happens when all price measures are included at the same time in the regression model? Tables 4.5 and 4.6 report the estimates. Each column from these tables correspond to the regression model that simultaneously includes all four price measures, in addition to the set of controls listed at the bottom. From Table 4.5 is possible to observe that only the parameter associated with the price of grains and dairy is statistically significant across all four specifications. More specifically, a one-percent change in this price is associated with higher 12-month food insecurity rates, ranging from 0.20 to 0.25 percentage points. With respect to the other measures of interest, the parameter associated with the price of fruits and vegetables is negative and statistically significant for the regression model that only excludes the set of socio-demographic controls (column 2). For the remaining price variables, their estimated parameters are not significant.

In order to test whether all prices are jointly significant to explain the variation in food insecurity rates ($H_0 : \beta_1 = 0, ..., \beta_4 = 0$), I run the F-test for multiple restrictions. The null hypothesis is rejected at one percent of less for all the regression models. These tests provide evidence that the joint variation of all price measures help to explain the observed variation in 12-month food insecurity rates. However, based on the results presented by Tables 4.3 and 4.4, there is a preliminary evidence that the price of grains and dairy is the only price variable that has a strong correlation with the 12-month food insecurity rates. Therefore, I estimate the test whether all the parameters associated with the price measures but grains and dairy are equal to zero. Only when the linear time trend is not included (columns 2 and 4), is possible to reject the null hypothesis at five percent or less. In consequence, the results presented in 4.5 provides evidence that, regarding grocery products, the price of grains and dairy is the most relevant driver that helps to explain the observed variation in 12-month food insecurity rates.

Likewise, the results from Table 4.6 are similar. More precisely, the parameter associated with the price of grains and dairy is the only one with individual statistical significance. A one-percent change in this price is positively associated with more 30-day food insecurity rates, ranging between 0.15 and 0.17 percentage points. At the same time, I reject the null hypothesis from the F-test for joint significance of all price measures at one percent or less, for all the regression models. However, I cannot reject the null hypothesis that all but the price of grains and dairy are equal to zero. The results of these tests provide evidence that the price of grains and dairy is the most relevant to explain the observed variation in 12-month food insecurity rates.

Overall, the price of grains and dairy display the strongest correlation with food insecurity rates in metropolitan areas in the United States. To some extent, this finding is not surprising, since grain-based products like bread, pasta, or cereal are among the cheapest grocery items, and, thus, they are a significant part from the average American diet. On the other hand, dairy-based products, such as milk, yogurt, or cheese, are relatively more expensive. Thus, the observed correlation between the price of grains and dairy and food insecurity might be driven principally by grain-based products. As reported by Table 4.1, grains and dairy account for 1.8 percent of total household expenditure for the period 2005–2010, only surpassed by fats and prepared goods (2.6 percent).

4.6 Robustness Checks

One way to overcome the high collinearity among all price measures is to conduct a principal components analysis (PCA), by creating a set of uncorrelated scores that represent a linear combination between the variables of interest, while capturing the highest variance possible. For the yearly average and the fourth quarter prices, their first component score absorb more than 88 and 85 percent of total variance, respectively. Moreover, the value of the loading factors (i.e., eigenvectors) for each first component is very similar across the four price measures. Therefore, the first component scores could be interpreted as a normalized representation of the simple average between the four prices.

On the other hand, the interpretation of the rest of scores is more complicated, since their corresponding loading factors vary in magnitude among prices and, additionally, their signs are also different. For both yearly average and fourth quarter food prices, the values of the eigenvectors for the second component score are all negative excepting for the price of meats and eggs, whereas for the third component score the loading factor from the price of fruits and vegetables is the only one with a positive sign. For the fourth component score, all eigenvectors are positive, with the exception of the corresponding one from the price of fats and goods. Therefore, the remaining scores would be representing idiosyncratic characteristics from those price measures whose loading factors are different in sign with respect to the other prices.

Tables 4.7 and 4.8 summarize the regression estimates when using these scores from the PCA for yearly average and fourth quarter food prices, respectively. From both tables is possible to observe that the coefficient associated with the first component score is positive and statistically significant, but only for the regression models that exclude the linear time trend and the set of socio-demographic controls (column 1 of Tables 4.7 and 4.8). Henceforth, this coefficient is no longer significant for the remaining regression models, with the exception of the regression model in Table 4.8 that includes all controls but the linear time trend (column 3). Consequently, the results displayed in Tables 4.7 and 4.8 are providing some (weak) evidence regarding the relevance of average grocery prices on the observed variation in food insecurity rates.

With respect to the rest of scores, the results displayed by Tables 4.7 and 4.8 indicate the second component score is negatively associated with both food insecurity rates, whereas the third component score is negatively correlated with 12-month food insecurity rates (Table 4.7), but usually exhibits a positive association with 30-day food insecurity rates (4.8). In summary, is not possible to find a clear pattern from the parameters associated with the principal component scores that would be capturing idiosyncratic features of some of the price measures.

In addition to the food price measures described in section 4.3.2, I use an alternate measure that captures price shocks for any market. The purpose behind this specification is to test whether unexpected changes in prices are associated with changes on food insecurity rates. To identify these price shocks, I follow Tuttle (2013) by first estimating the following regression model:

$$P_{gjt} = \delta Trend_t + \omega Trend_t^2 + v_j + u_{jt} \tag{4.4}$$

where P_{gjt} is the corresponding price measure (yearly average price or fourth quarter price) for food group g on market j in period t, *Trend* denotes the time difference between the current year and 2005 (i.e., linear trend); v_j is the market-level fixed effect, and u_{jt} represents a zero-mean error term.

After estimating equation 4.4, I obtain the standardized residuals. A price shock is defined as an indicator variable that is equal to one if the residual is one standard deviation away (in absolute terms) from the mean, zero otherwise. Since the correlation between positive (unexpected rises) or negative (unexpected falls) price shocks with food insecurity can be different, I create separate binary indicators for positive and negative shocks, respectively. As noted by Tuttle (2013), this criterion is arbitrary, but helps to analyze the effect of unexpected price changes under a simple framework.

Therefore, the regression model of food insecurity on price shocks is the following:

$$\overline{FI}_{jt} = \alpha^{'}\overline{X}_{jt} + \beta_1 I[POS_{Gjt} = 1] + \beta_2 I[NEG_{Gjt} = 1] + \gamma T + v_j + e_{jt} \tag{4.5}$$

where $I[POS_{Gjt} = 1]$ and $I[NEG_{Gjt} = 1]$ correspond to the dummy variables that account for the existence of either positive or negative price shocks for food group G on metropolitan area j at time t. For the regression models that use the 12-month food security measure, I will use the set of dummy variables that account for unexpected changes on the yearly average prices. On the other hand, when the 30-day food insecurity measure is the dependent variable, price shocks will be represented by the dummy variables that come from fourth quarter prices.

Tables 4.9 and 4.10 display the regression estimates when using the price shock indicators for the 12-month and the 30-day food insecurity measures, respectively. From Table 4.9 is not possible to identify a consistent pattern across the different estimates. Moreover, the sign of some of the estimated coefficients is contrary to expected. For example, unexpected increases (i.e., positive shocks) on the price of meats and eggs are associated with less food insecurity rates, as displayed by columns 1 and 3. Likewise, negative shocks in the price of grains and dairy are positively correlated higher with food insecurity rates. The only exception would come from unexpected falls in the price of fats and prepared goods. The sign of the associated coefficient is negative and statistically significant, but only for the regression models that do not account for socio-demographic controls (columns 1 and 2).

Unlike the results from Table 4.9, the regression estimates from Table 4.10 display clearer associations for some price measures. More precisely, unexpected rises in the price of grains and dairy, meats and eggs, as well as fats and prepared goods, are positively associated with higher food insecurity rates. In particular, the association of the price of grains and dairy with food insecurity ranges between 1.8 and 1.9 percentage points. With respect to the price of meats and eggs, that correlation lies between 0.9 and 1.0 percentage points. Regarding the price of fats and prepared goods, the correlation between positive shocks and 30-day food insecurity rates ranges between 1.3 and 1.7 percentage points.

4.7 Conclusions

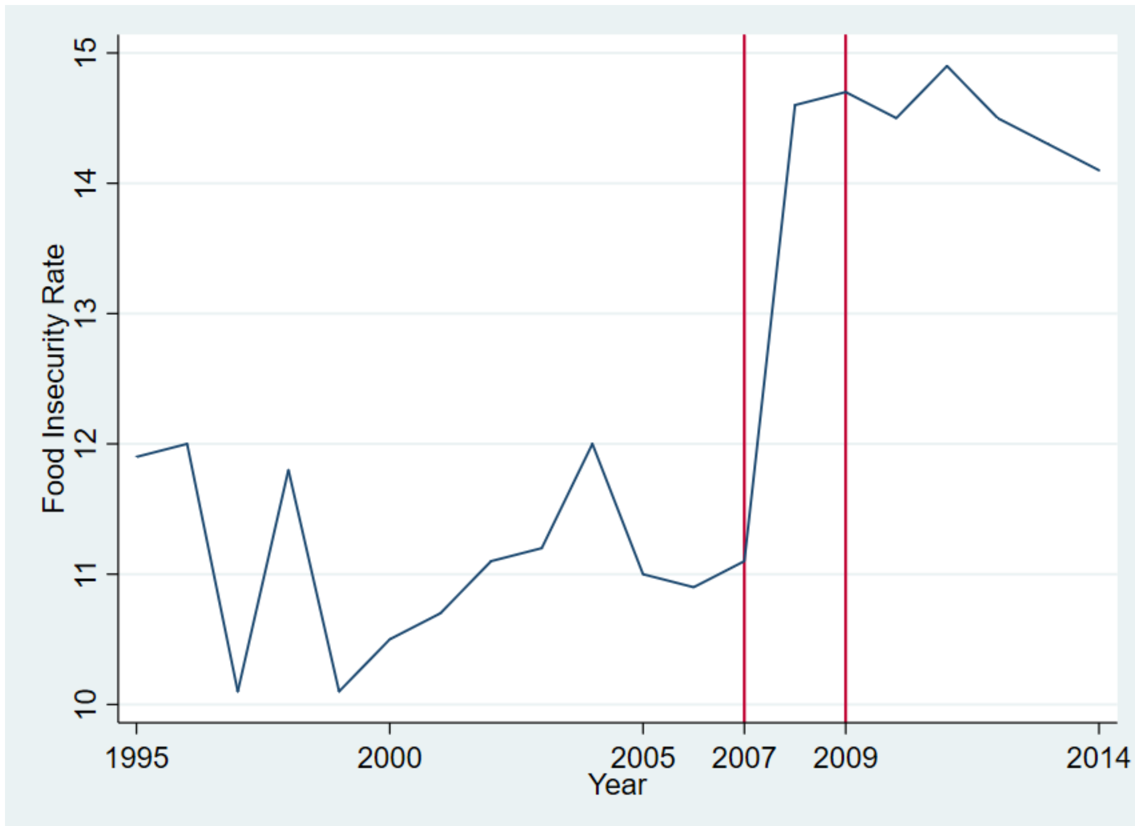
Using an unique combination of household-level data (CPS) and prices (QFAHPD), this paper addresses the relationship between food prices and the probability of being food insecure in the United States, between 2005 and 2010. The results suggest a positive correlation between the price of grains and dairy products and food insecurity rates across metropolitan areas. Moreover, unexpected increases in these prices (i.e., positive price shocks) are also associated with higher 30-day food insecurity rates. Additionally, positive price shocks of the prices of fruits and vegetables, as well as fats and prepared goods are also correlated with food insecurity during the last month.

Despite the small magnitude of the estimates presented in this paper, the results leave some relevant conclusions and aspects to consider for further work. First, the sign of those estimates are as expected, since poorer households tend to have greater shares of food expenditure on grain-based products. Therefore, (expected and unexpected) raises in these prices should have consequences with food insecurity. In other words, the regression estimates would be providing evidence that these products can be considered as staples for the United States. Nevertheless, the results should be taken with care. The construction of the food groups from the QFAHPD by Todd, Mancino, and Leibtag (2010) pools together products that have different price behavior (like, for example, grains an dairy). Therefore, it would be important to disaggregate such those groups and revise the regression estimates in order to find whether the results change due to the recomposition of the food groups.

Second, the regression estimates do not incorporate the potential *substitution bias* (Hausman, 2002) that usually carries this type of work that uses price indexes. The data used in this paper do not incorporate potential changes in consumption patterns in the short run (i.e., changes in market basket) due to changes on prices that lead consumers to purchase cheaper products. Additionally, as explained by Hausman (2002), that shift in shopping patterns leads to an *outlet bias*, in which consumers move to grocery stores that sells those cheaper products. Further work should make a significant effort to understand how the results obtained from the regression estimates are incorporating these biases.

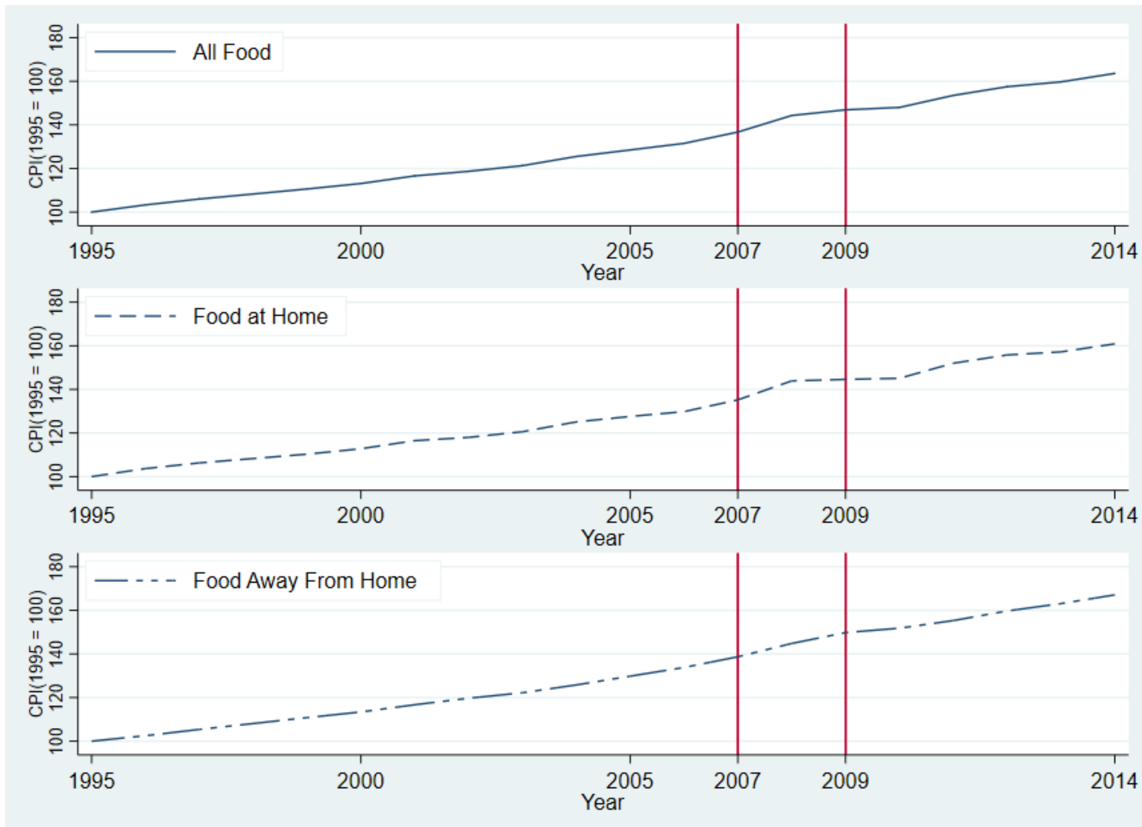
Third, as noted in section 4.2, the number of participating households in formal (SNAP) and informal (food pantries) mechanisms of food assistance not only significantly increased during the Greatest Recession, but remained high after the economic downturn. Although the regression estimates account for the share of households under SNAP and WIC, they do not incorporate any selection bias from participation in these programs. Households' decision of participation in food assistance programs is also driven by changes in food prices.

Figure 4.1: **Food Insecurity Trends, 1995-2014**



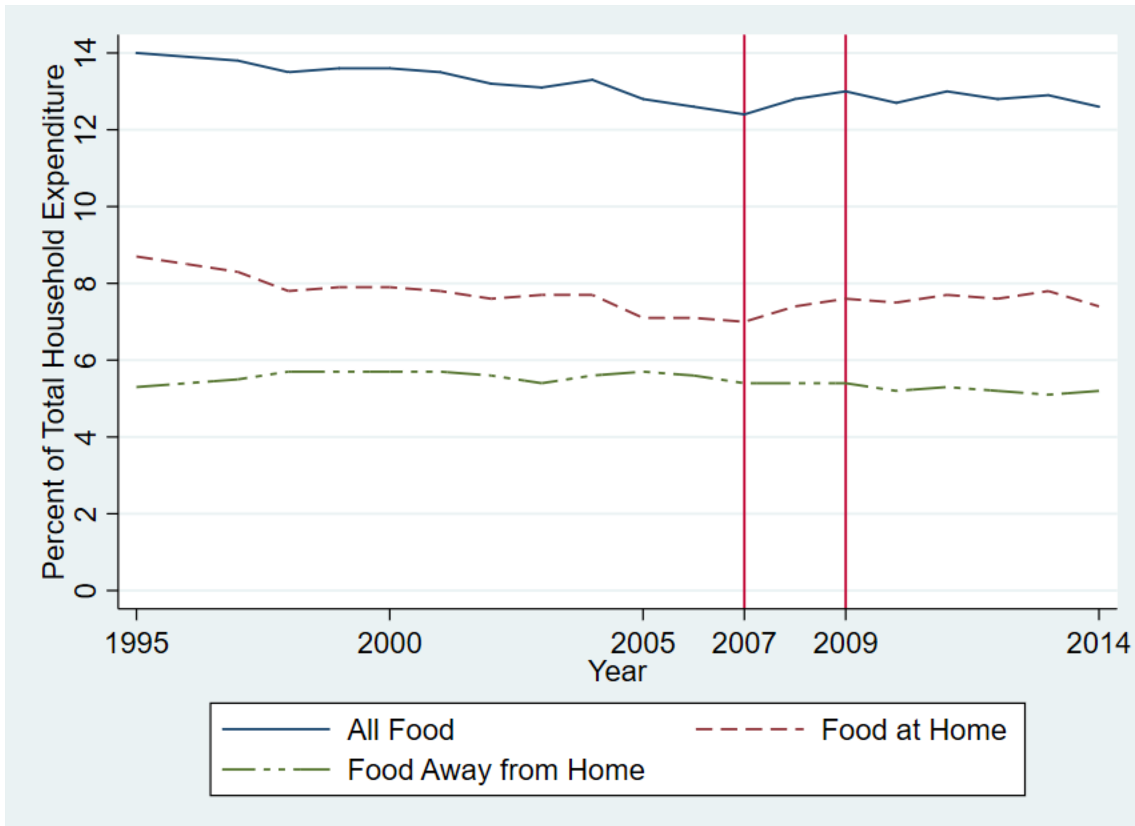
Source: United States Department of Agriculture (USDA)

Figure 4.2: **Food Price Trends, 1995-2014**



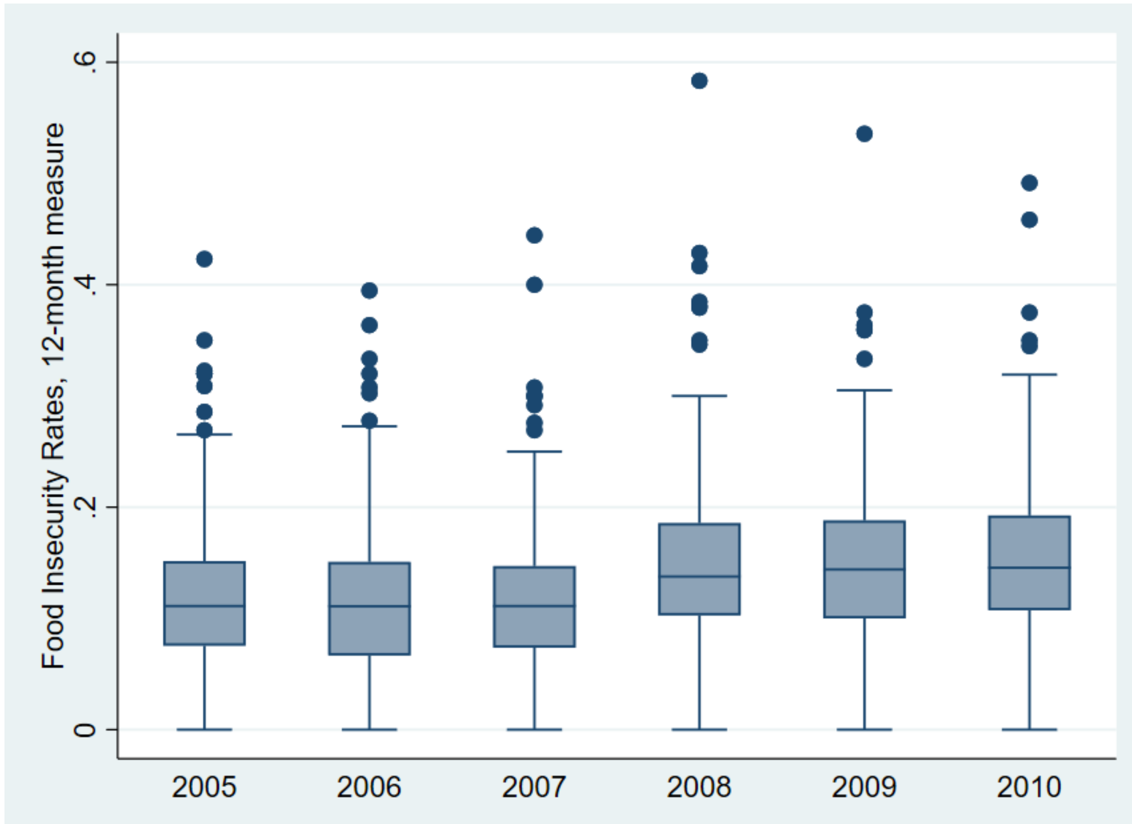
Source: Bureau of Labor Statistics (BLS)

Figure 4.3: **Food Shares as a Proportion of Household Expenditure, 1995-2014**



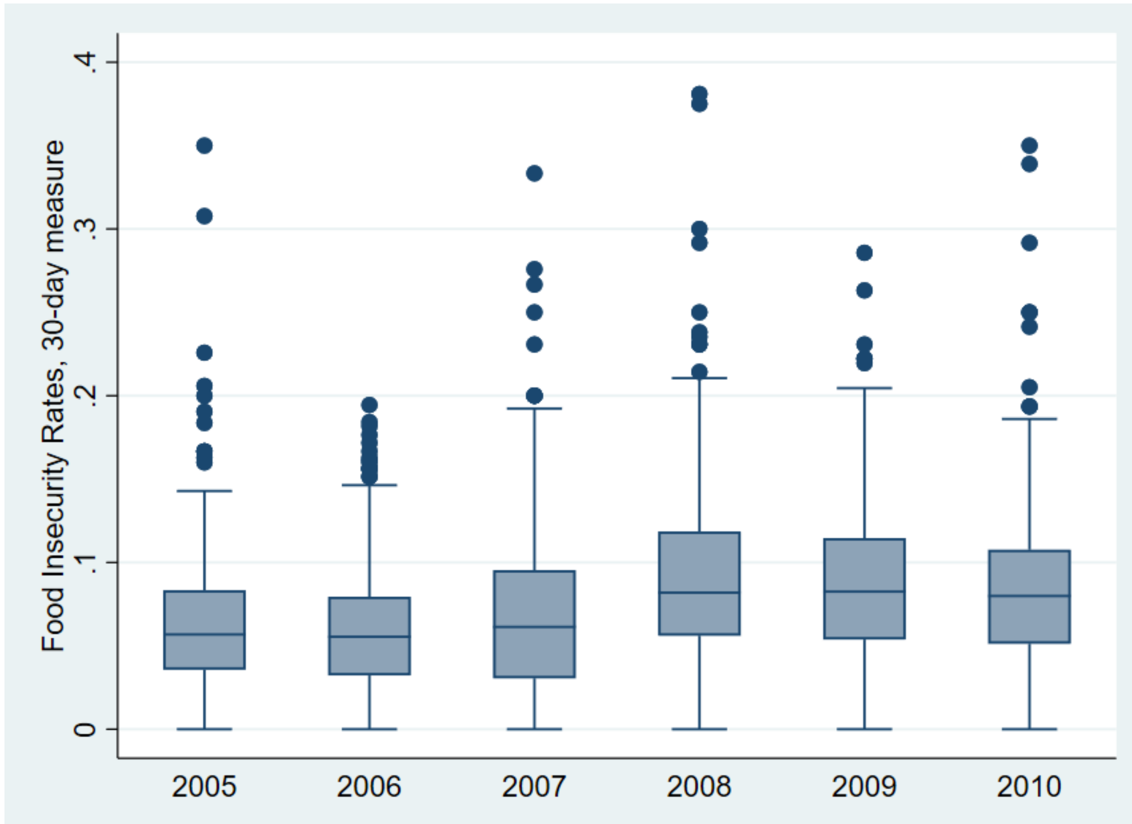
Source: Consumer Expenditure Survey (CEX)

Figure 4.4: **Food Insecurity Rates, 12-month Measure**



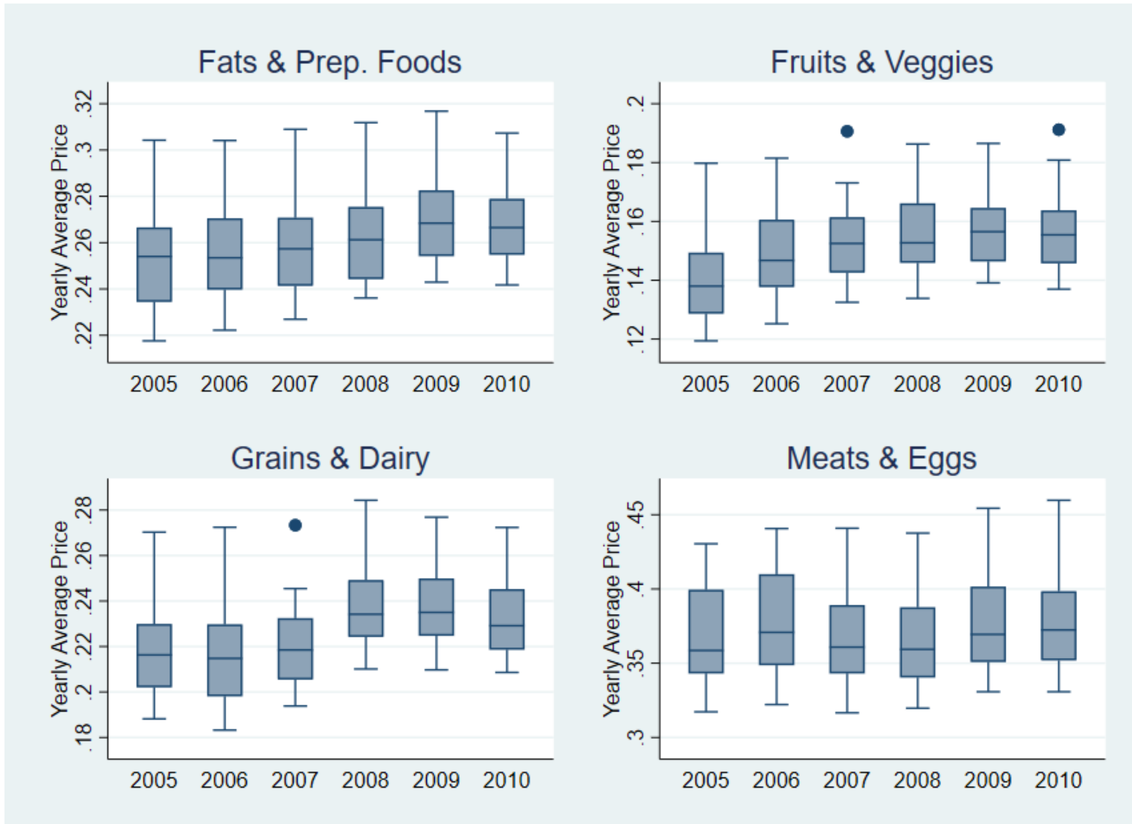
Own Calculations. Source: 2005-2010 Current Population Survey

Figure 4.5: **Food Insecurity Rates, 30-day Measure**



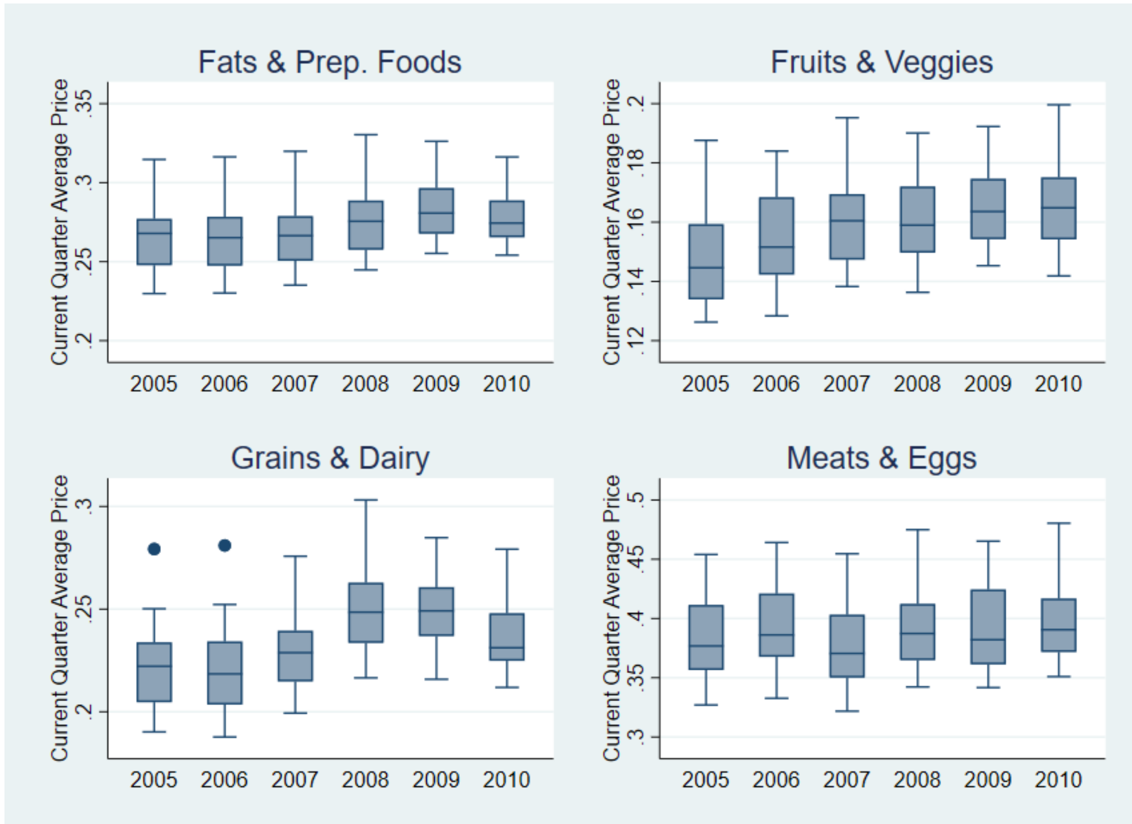
Own Calculations. Source: 2005-2010 Current Population Survey

Figure 4.6: **Yearly Real Average Food Prices, 2005-2010 (Box Graphs)**



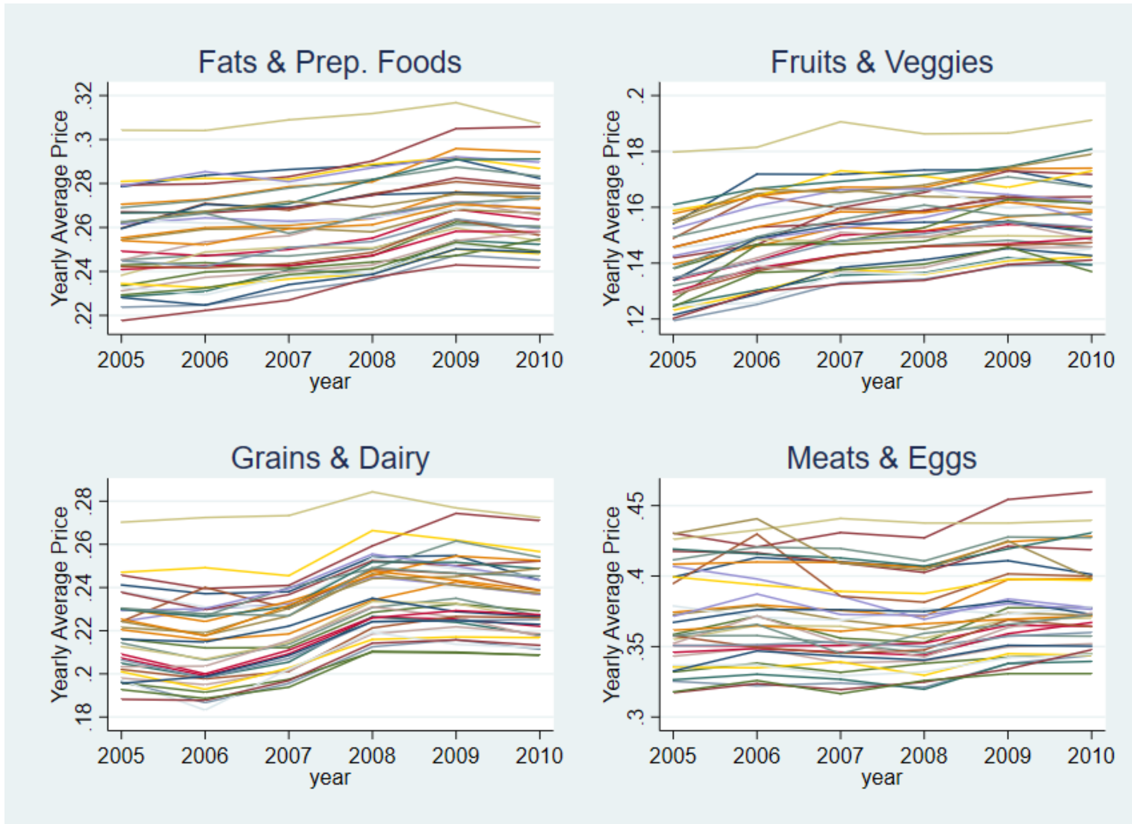
Own Calculations. Source: Quarterly Food-at-home Price Data, 2005-2010

Figure 4.7: **Current Quarter Real Food Prices, 2005-2010 (Box Graphs)**



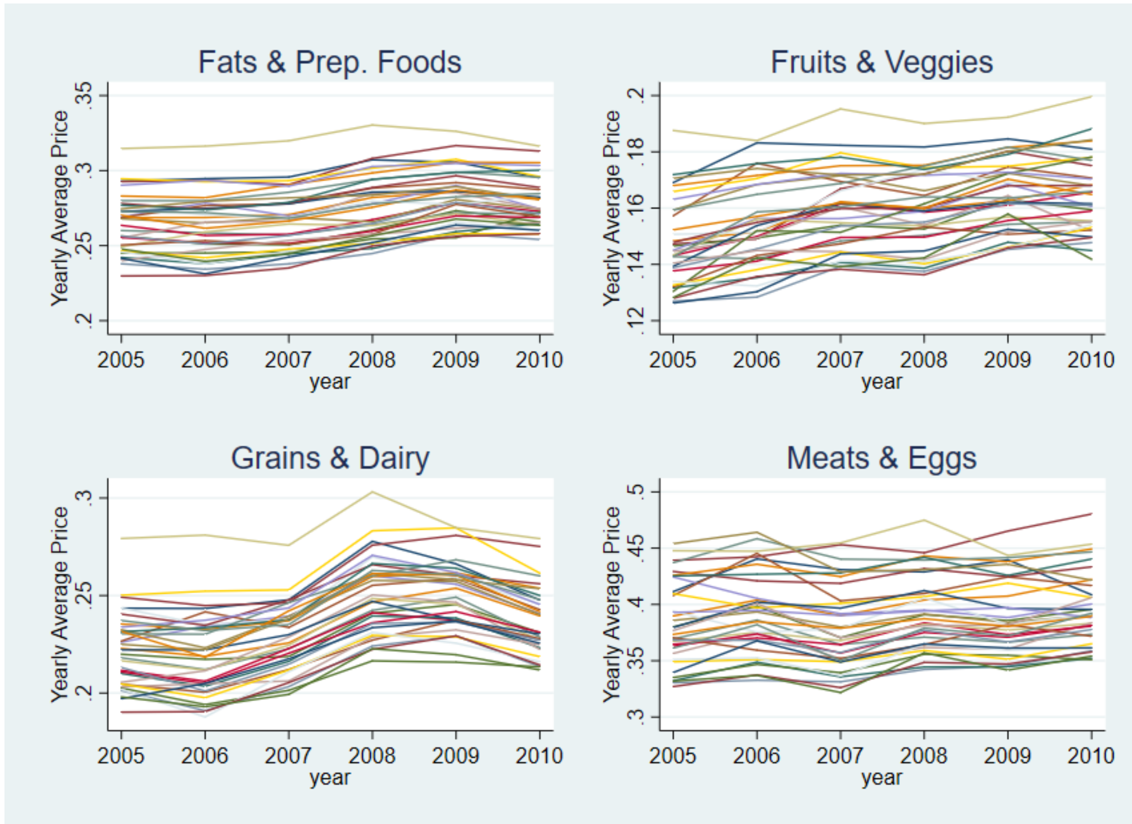
Own Calculations. Source: Quarterly Food-at-home Price Data, 2005-2010

Figure 4.8: **Yearly Real Average Food Prices, 2005-2010 (Longitudinal Graphs)**



Own Calculations. Source: Quarterly Food-at-home Price Data, 2005-2010

Figure 4.9: **Current Quarter Real Food Prices, 2005-2010 (Longitudinal Graphs)**



Own Calculations. Source: Quarterly Food-at-home Price Data, 2005-2010

Table 4.1: **Food-at-home Expenditure as a Share of Total Household Expenditure, 2005–2010**

	2005	2006	2007	2008	2009	2010	Average
Food at home	**7.1**	**7.1**	**7.0**	**7.4**	**7.6**	**7.5**	**7.3**
Cereals and bakery products	**1.0**	**0.9**	**0.9**	**1.0**	**1.0**	**1.0**	**1.0**
Cereals and cereal products	0.3	0.3	0.3	0.3	0.4	0.3	0.3
Bakery products	0.7	0.6	0.6	0.7	0.7	0.7	0.7
Meats, poultry, fish, and eggs	**1.6**	**1.6**	**1.6**	**1.7**	**1.7**	**1.6**	**1.6**
Beef	0.5	0.5	0.4	0.5	0.5	0.5	0.5
Pork	0.3	0.3	0.3	0.3	0.3	0.3	0.3
Other meats	0.2	0.2	0.2	0.2	0.2	0.2	0.2
Poultry	0.3	0.3	0.3	0.3	0.3	0.3	0.3
Fish and seafood	0.2	0.3	0.2	0.3	0.3	0.2	0.3
Eggs	0.1	0.1	0.1	0.1	0.1	0.1	0.1
Dairy products	**0.8**	**0.8**	**0.8**	**0.9**	**0.8**	**0.8**	**0.8**
Fresh milk and cream	0.3	0.3	0.3	0.3	0.3	0.3	0.3
Other dairy products	0.5	0.5	0.5	0.5	0.5	0.5	0.5
Fruits and vegetables	**1.2**	**1.2**	**1.2**	**1.3**	**1.3**	**1.4**	**1.3**
Fresh fruits	0.4	0.4	0.4	0.4	0.4	0.5	0.4
Fresh vegetables	0.4	0.4	0.4	0.4	0.4	0.4	0.4
Processed fruits	0.2	0.2	0.2	0.2	0.2	0.2	0.2
Processed vegetables	0.2	0.2	0.2	0.2	0.2	0.3	0.2
Other food at home	**2.5**	**2.5**	**2.5**	**2.6**	**2.7**	**2.7**	**2.6**
Sugar and other sweets	0.3	0.3	0.3	0.3	0.3	0.3	0.3
Fats and oils	0.2	0.2	0.2	0.2	0.2	0.2	0.2
Miscellaneous foods	1.3	1.3	1.3	1.3	1.5	1.4	1.4
Nonalcoholic beverages	0.7	0.7	0.7	0.7	0.7	0.7	0.7

Source: Consumer Expenditure Survey (CEX), 2005–2010

Table 4.2: **Descriptive Statistics**

	2005		2006		2007		2008		2009		2010	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Food Insecurity Rate, 12-month	0.120	0.068	0.114	0.067	0.117	0.068	0.149	0.079	0.147	0.074	0.151	0.076
Food Insecurity Rate, 30-day	0.064	0.049	0.061	0.042	0.068	0.055	0.093	0.060	0.087	0.050	0.085	0.054
Snap Participation Rate	0.076	0.066	0.069	0.060	0.069	0.061	0.080	0.067	0.090	0.066	0.108	0.073
Share households below 180-percent poverty line	0.290	0.103	0.297	0.118	0.303	0.127	0.322	0.131	0.337	0.113	0.334	0.111
Average household size	2.497	0.311	2.472	0.307	2.467	0.352	2.487	0.377	2.495	0.349	2.509	0.321
Average number of children in household	0.720	0.285	0.832	0.315	0.853	0.403	0.838	0.385	0.888	0.360	0.716	0.290
Share household head/householders age 15-24 YO	0.058	0.040	0.062	0.048	0.055	0.042	0.053	0.042	0.054	0.039	0.053	0.041
Share household head/householders age 25-39 YO	0.252	0.076	0.246	0.072	0.242	0.083	0.248	0.074	0.245	0.077	0.236	0.078
Share household head/householders age 40-59 YO	0.404	0.077	0.402	0.081	0.403	0.089	0.390	0.081	0.390	0.077	0.390	0.081
Share household head/householders age 60+ YO	0.286	0.089	0.290	0.096	0.300	0.102	0.310	0.099	0.312	0.094	0.320	0.104
Share white household head/householders	0.860	0.111	0.855	0.113	0.858	0.114	0.862	0.109	0.851	0.117	0.852	0.114
Share African-American household head/householders	0.099	0.108	0.102	0.108	0.101	0.108	0.096	0.102	0.107	0.112	0.104	0.110
Share household head/householders from other race	0.041	0.049	0.043	0.049	0.041	0.051	0.042	0.049	0.042	0.052	0.045	0.052
Share married household head/householders	0.538	0.089	0.527	0.089	0.524	0.097	0.530	0.093	0.526	0.085	0.520	0.083
Share divorced household head/householders	0.185	0.065	0.185	0.065	0.188	0.078	0.184	0.062	0.185	0.055	0.194	0.063
Share widowed household head/householders	0.102	0.056	0.101	0.056	0.101	0.061	0.106	0.061	0.103	0.053	0.101	0.052
Share single household head/householders	0.175	0.075	0.187	0.079	0.186	0.081	0.181	0.076	0.187	0.075	0.184	0.070
Share Latino household head/householders	0.087	0.147	0.094	0.151	0.096	0.156	0.099	0.160	0.101	0.157	0.102	0.161
Share household head/householders with no degree	0.122	0.077	0.113	0.079	0.112	0.080	0.113	0.077	0.112	0.073	0.107	0.070
Share household head/householders with high school	0.504	0.101	0.504	0.113	0.504	0.115	0.502	0.104	0.498	0.102	0.492	0.104
Share household head/householders with associate degree	0.093	0.049	0.099	0.051	0.097	0.060	0.100	0.052	0.096	0.059	0.103	0.055
Share household head/householders with bachelors degree or more	0.270	0.107	0.272	0.112	0.276	0.116	0.275	0.118	0.283	0.109	0.287	0.105
Share employed household head/householders	0.641	0.097	0.638	0.103	0.633	0.119	0.615	0.098	0.593	0.096	0.591	0.091
Share unemployed household head/householders	0.027	0.027	0.026	0.026	0.032	0.036	0.042	0.033	0.059	0.039	0.054	0.037
Share out-of-the-labor-market household head/householders	0.332	0.094	0.336	0.101	0.335	0.112	0.344	0.095	0.348	0.092	0.355	0.090

Own estimates. Source: 2005-2010 Current Population Survey (CPS)

Table 4.3: **Addressing the Association Between Yearly Average Food Prices and 12-month Food Insecurity Rates**

Price Variable	(1)	(2)	(3)	(4)
Log(Fruits and Vegetables)	0.211^{***}	-0.124^{*}	0.087^{**}	-0.057
	(0.035)	(0.070)	(0.037)	(0.064)
Log(Grains and Dairy)	0.295^{***}	0.166^{***}	0.165^{***}	0.145^{***}
	(0.035)	(0.060)	(0.038)	(0.052)
Log(Meats and Eggs)	0.197^{**}	-0.164^{**}	-0.079	-0.228^{***}
	(0.077)	(0.078)	(0.073)	(0.075)
Log (Fats & Prep. Goods)	0.397	-0.016	0.140^{**}	-0.115
	(0.054)	(0.102)	(0.059)	(0.095)
Observations	1,440	1,440	1,440	1,440
MSA Fixed Effects	YES	YES	YES	YES
Linear Time Trend		YES		YES
Socio-demographic Controls			YES	YES

Note: Each cell contains the parameter estimate and standard error for the corresponding price measure from the regression model that also includes the controls that are listed at the bottom of this table. For the list of socio-demographic controls, see Table 4.2.

Note: Standard errors clustered at the metro area level in parentheses.

Significant at *** p<0.01, ** p<0.05, * p<0.1

Own calculations. Source: 2005-2010 Current Population Survey (CPS) and Quarterly Food-at-Home Price Database (QFAHPD.

Table 4.4: **Addressing the Association Between Fourth Quarter Food Prices and 30-day Food Insecurity Rates**

Price Variable	(1)	(2)	(3)	(4)
Log(Fruits and Vegetables)	0.161^{***}	-0.045	0.076^{**}	-0.038
	(0.026)	(0.047)	(0.030)	(0.046)
Log(Grains and Dairy)	0.198^{***}	0.140^{***}	0.141^{***}	0.135^{***}
	(0.021)	(0.032)	(0.025)	(0.030)
Log(Meats and Eggs)	0.208^{***}	0.026	0.102^{**}	0.023
	(0.048)	(0.049)	(0.045)	(0.045)
Log (Fats & Prep. Goods)	0.308	0.135^{**}	0.168^{***}	0.078
	(0.039)	(0.061)	(0.047)	(0.056)
Observations	1,440	1,440	1,440	1,440
MSA Fixed Effects	YES	YES	YES	YES
Linear Time Trend		YES		YES
Socio-demographic Controls			YES	YES

Note: Each cell contains the parameter estimate and standard error for the corresponding price measure from the regression model that also includes the controls that are listed at the bottom of this table. For the list of socio-demographic controls, see Table 4.2.

Note: Standard errors clustered at the metro area level in parentheses.

Significant at *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Own calculations. Source: 2005-2010 Current Population Survey (CPS) and Quarterly Food-at-Home Price Database (QFAHPD.

Table 4.5: **Addressing the Association Between Yearly Average Food Prices and 12-month Food Insecurity Rates (Regression Models Including all Four Price Measures at the Same Time)**

Price Variable	(1)	(2)	(3)	(4)
Log(Fruits and Vegetables)	-0.033	-0.151^{**}	-0.007	-0.067
	(0.059)	(0.071)	(0.056)	(0.066)
Log(Grains and Dairy)	0.245^{***}	0.189^{***}	0.202^{***}	0.175^{***}
	(0.063)	(0.066)	(0.056)	(0.058)
Log(Meats and Eggs)	-0.107	-0.103	-0.133	-0.129
	(0.105)	(0.104)	(0.096)	(0.096)
Log (Fats & Prep. Goods)	0.169	-0.045	-0.043	-0.146
	(0.119)	(0.128)	(0.119)	(0.126)
Observations	1,440	1,440	1,440	1,440
Joint F-test Prices = 0	18.2	4.7	6.6	5.2
P-value	0.000	0.001	0.000	0.000
F-test all but Grains & Dairy = 0	0.7	2.7	1.8	3.6
P-value	0.564	0.044	0.149	0.014
MSA Fixed Effects	YES	YES	YES	YES
Linear Time Trend		YES		YES
Socio-demographic Controls			YES	YES

Note: Standard errors clustered at the metro area level in parentheses. For the list of socio-demographic controls, see Table 4.2.

Significant at *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Own calculations. Source: 2005-2010 Current Population Survey (CPS) and Quarterly Food-at-Home Price Database (QFAHPD).

Table 4.6: **Addressing the Association Between Fourth Quarter Food Prices and 30-day Food Insecurity Rates (Regression Models Including all four price measures at the same time)**

Price Variable	(1)	(2)	(3)	(4)
Log(Fruits and Vegetables)	-0.005	-0.080	-0.028	-0.066
	(0.043)	(0.050)	(0.040)	(0.049)
Log(Grains and Dairy)	0.163^{***}	0.149^{***}	0.167^{***}	0.160^{***}
	(0.034)	(0.035)	(0.034)	(0.034)
Log(Meats and Eggs)	0.040	0.004	0.021	0.003
	(0.048)	(0.048)	(0.045)	(0.045)
Log (Fats & Prep. Goods)	0.070	-0.000	-0.037	-0.070
	(0.062)	(0.066)	(0.064)	(0.064)
Observations	1,440	1,440	1,440	1,440
Joint F-test Prices = 0	23.1	5.2	8.9	5.8
P-value	0.000	0.001	0.000	0.000
F-test all but Grains & Dairy = 0	0.7	0.9	0.5	1.2
P-value	0.536	0.457	0.702	0.309
MSA Fixed Effects	YES	YES	YES	YES
Linear Time Trend		YES		YES
Socio-demographic Controls			YES	YES

Note: Standard errors clustered at the metro area level in parentheses. For the list of socio-demographic controls, see Table 4.2.

Significant at *** p<0.01, ** p<0.05, * p<0.1

Own calculations. Source: 2005-2010 Current Population Survey (CPS) and Quarterly Food-at-Home Price Database (QFAHPD)

Table 4.7: **Addressing the Association Between Principal Component Indexes of Yearly Average Food Prices and 12-month Food Insecurity Rates**

Variable	(1)	(2)	(3)	(4)
First Component Score	0.012^{***}	-0.004	0.002	-0.005
	(0.003)	(0.006)	(0.003)	(0.005)
Second Component Score	-0.004	-0.011	-0.017^{**}	-0.014^{*}
	(0.006)	(0.008)	(0.007)	(0.008)
Third Component Score	0.002	-0.017^{**}	-0.011^{*}	-0.013^{**}
	(0.003)	(0.007)	(0.006)	(0.006)
Fourth Component Score	-0.005	-0.014^{*}	-0.013	0.014
	(0.005)	(0.008)	(0.006)	(0.011)
Observations	1,440	1,440	1,440	1,440
Joint F-test Scores = 0	19.5	4.7	6.9	5.1
P-value F-test	0.000	0.001	0.000	0.001
MSA Fixed Effects	YES	YES	YES	YES
Linear Time Trend		YES		YES
Socio-demographic Controls			YES	YES

Note: Standard errors clustered at the metro area level in parentheses. For the list of socio-demographic controls, see Table 4.2.

Significant at *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Own calculations. Source: 2005-2010 Current Population Survey (CPS) and Quarterly Food-at-Home Price Database (QFAHPD).

Table 4.8: **Addressing the Association Between Principal Component Indexes of Current Quarter Food Prices and 30-day Food Insecurity Rates**

Variable	(1)	(2)	(3)	(4)
First Component Score	0.013***	0.004	0.006**	0.002
	(0.002)	(0.004)	(0.003)	(0.004)
Second Component Score	0.004	−0.008*	−0.008*	−0.008**
	(0.004)	(0.004)	(0.004)	(0.004)
Third Component Score	0.006**	−0.008*	0.009**	0.012**
	(0.003)	(0.004)	(0.004)	(0.005)
Fourth Component Score	0.002	−0.008**	0.012*	0.010*
	(0.004)	(0.004)	(0.005)	(0.005)
Observations	1,440	1,440	1,440	1,440
Joint F-test Scores = 0	24.0	5.3	9.0	5.8
P-value F-test	0.000	0.000	0.000	0.000
MSA Fixed Effects	YES	YES	YES	YES
Linear Time Trend		YES		YES
Socio-demographic Controls			YES	YES

Note: Standard errors clustered at the metro area level in parentheses. For the list of socio-demographic controls, see Table 4.2.

Significant at *** p<0.01, ** p<0.05, * p<0.1

Own calculations. Source: 2005-2010 Current Population Survey (CPS) and Quarterly Food-at-Home Price Database (QFAHPD).

Table 4.9: **Addressing the Association Between Yearly Average Food Price Shocks and 12-month Food Insecurity Rates**

Price Variable	(1)	(2)	(3)	(4)
Fruits and Vegetables				
Positive Shocks	0.003	0.002*	0.001	0.001
	(0.005)	(0.005)	(0.005)	(0.005)
Negative Shocks	0.009*	0.010*	0.010	0.009*
	(0.005)	(0.005)	(0.005)	(0.005)
Grains and Dairy				
Positive Shocks	0.003	0.007***	0.006	0.007*
	(0.004)	(0.004)	(0.004)	(0.004)
Negative Shocks	−0.014***	−0.005	−0.006	−0.003
	(0.004)	(0.004)	(0.004)	(0.004)
Meats and Eggs				
Positive Shocks	−0.011*	−0.012	−0.011**	−0.011**
	(0.006)	(0.006)	(0.005)	(0.005)
Negative Shocks	−0.006	−0.002	0.000	0.001
	(0.005)	(0.005)	(0.005)	(0.005)
Fats & Prep. Goods				
Positive Shocks	0.001	−0.004*	−0.004	−0.006
	(0.004)	(0.004)	(0.004)	(0.004)
Negative Shocks	−0.009*	−0.009**	−0.006	−0.006
	(0.005)	(0.004)	(0.004)	(0.004)
Observations	1,440	1,440	1,440	1,440
MSA Fixed Effects	YES	YES	YES	YES
Linear Time Trend		YES		YES
Socio-demographic Controls			YES	YES

Note: Standard errors clustered at the metro area level in parenthesis. For the list of socio-demographic controls, see Table 4.2.

Significant at *** p<0.01, ** p<0.05, * p<0.1

Own calculations. Source: 2005-2010 Current Population Survey (CPS) and Quarterly Food-at-Home Price Database (QFAHPD

Table 4.10: **Addressing the Association Between Fourth Quarter Food Price Shocks and 30-day Food Insecurity Rates**

Price Variable	(1)	(2)	(3)	(4)
Fruits and Vegetables				
Positive Shocks	-0.003	-0.001	0.000	0.000
	(0.005)	(0.005)	(0.005)	(0.005)
Negative Shocks	0.006	-0.000	0.002	-0.001
	(0.004)	(0.004)	(0.004)	(0.004)
Grains and Dairy				
Positive Shocks	0.018^{***}	0.016	0.019^{***}	0.018^{***}
	(0.003)	(0.003)	(0.003)	(0.003)
Negative Shocks	-0.004	-0.001	-0.002	-0.000
	(0.003)	(0.003)	(0.003)	(0.003)
Meats and Eggs				
Positive Shocks	0.010^{***}	0.007	0.009^{**}	0.007^{**}
	(0.004)	(0.004)	(0.004)	(0.004)
Negative Shocks	0.005	-0.000	0.000	-0.001
	(0.004)	(0.004)	(0.003)	(0.003)
Fats & Prep. Goods				
Positive Shocks	0.013^{***}	0.017^{**}	0.015^{***}	0.017^{***}
	(0.004)	(0.004)	(0.004)	(0.004)
Negative Shocks	-0.009^{**}	-0.003	-0.004	-0.002
	(0.004)	(0.004)	(0.004)	(0.004)
Observations	1,440	1,440	1,440	1,440
MSA Fixed Effects	YES	YES	YES	YES
Linear Time Trend		YES		YES
Socio-demographic Controls			YES	YES

Note: Standard errors clustered at the metro area level in parenthesis. For the list of socio-demographic controls, see Table 4.2.

Significant at *** p<0.01, ** p<0.05, * p<0.1

Own calculations. Source: 2005-2010 Current Population Survey (CPS) and Quarterly Food-at-Home Price Database (QFAHPD

Bibliography

Agudelo, C.A., J. Cardona, J. Ortega, and R. Robledo. 2011. "Sistema de salud en Colombia: 20 años de logros y problemas." *Ciênc. Saúde coletiva* 16:2817–2828.

Angrist, J.D., and J.S. Pischke. 2009. *Mostly Harmless Econometrics: An Empiricist's Companion*. Princeton University Press.

Attanasio, O., and A. Mesnard. 2006. "The Impact of a Conditional Cash Transfer Programme on Consumption in Colombia." *Fiscal Studies* 27:421–442.

Balderas, O. 2016. "Tortillas y crteles: cómo el narco se metió hasta las tortillerías en México." `https://goo.gl/BQdYPK`, Online; accessed 20 December 2017.

Barello, S. 2014. "Consumer spending and U.S. employment from the 2007-2009 recession through 2022." Working paper, U.S. Bureau of Labor Statistics, October.

Barrett, C.B. 2010. "Measuring Food Insecurity." *Science* 327:825–828.

BDO International, and CCRP. 2000. "Evaluation of SISBEN: Efficiency and Institutional Efficacy of the Identification, Classification, and Beneficiary Selection Processes. Final Report." Working paper, Ministry of Health.

Beatty, T.K. 2010. "Do the Poor Pay More for Food? Evidence from the United Kingdom." *American Journal of Agricultural Economics* 92:608–621.

Bellemare, M.F., J. Fajardo-Gonzalez, and S.R. Gitter. 2016. "Foods and Fads: The Welfare Impacts of Rising Quinoa Prices in Peru." Working Paper No. 2016-06, Towson University, March.

Bitrán, R., U. Giedion, and R. Muñoz. 2004. "Fondos de Riesgo, ahorro y prevención: estudio regional de políticas para la protección de los más pobres de los efectos de los shocks de salud: estudio de caso de Colombia." Working paper, The World Bank.

Brinkman, H.J., S. de Pee, I. Sanogo, L. Subran, and M.W. Bloem. 2010. "High Food Prices and the Global Financial Crisis Have Reduced Access to Nutritious Food and Worsened Nutritional Status and Health." *The Journal of Nutrition* 140:153S–161S.

Broda, C., E. Leibtag, and D.E. Weinstein. 2009. "The Role of Prices in Measuring the Poor's Living Standards." *The Journal of Economic Perspectives* 23:77–97.

Camacho, A., and E. Conover. 2013. "Effects of Subsidized Health Insurance on Newborn Health in a Developing Country." *Economic Development and Cultural Change* 61:633–658.

—. 2011. "Manipulation of Social Program Eligibility." *American Economic Journal: Economic Policy* 3:41–65.

Castañeda, T. 2005. "Targeting Social Spending to the Poor with Proxy Means Testing: Colombias SISBEN System." World Bank Social Protection Unit Discussion Paper 0526.

Comité Científico de la ELCSA. 2012. "Escala Latinoamericana de Seguridad Alimentaria (ELCSA): manual de uso y aplicaciones." Working paper.

Consejo Coordinador Empresarial. 2012. "Tiendas de autoservicio firman convenio en materia de seguridad." `http://www.cce.org.mx/tiendas-de-autoservicio-firman-convenio-en-materia-de-seguridad/`, Online; accessed 20 December 2017.

Corona, S. 2016. "Esas medias hermanas mexicanas llamadas tortillas." `https://www.historiacocina.com/paises/articulos/mexico/tortillas.htm`, Online; accessed 20 December 2017.

Cuesta, J., and M. Olivera. 2014. "The impact of social security reform on the labor market: The case of Colombia." *Journal of Policy Modeling* 36:1118–1134.

Deaton, A. 1985. "Panel Data from Time Series of Cross-Sections." *Journal of Econometrics* 30:109–126.

DiNardo, J., and D.S. Lee. 2011. "Chapter 5 - Program Evaluation and Research Designs." Elsevier, vol. 4, Part A of *Handbook of Labor Economics*, pp. 463–536.

EcuRed. 2008. "Tortilla Mexicana." `https://www.ecured.cu/Tortilla_mexicana`, Online; accessed 20 December 2017.

Enthoven, A.C. 1978a. "Consumer Choice Health Plan (first of two parts). Inflation and Inequity in Health Care Today: Alternatives for Cost Control and an Analysis of Proposals for National Health Insurance." *New England Journal of Medicine* 298:650–658.

—. 1978b. "Consumer Choice Health Plan (second of two parts). Inflation and Inequity in Health Care Today: Alternatives for Cost Control and an Analysis of Proposals for National Health Insurance." *New England Journal of Medicine* 298:709–720.

FAO. 2017. "FAO Food Price Index Database." `http://www.fao.org/worldfoodsituation/foodpricesindex/en/`, Online; accessed 20 December 2017.

Farber, H.S. 2011. "Job Loss in the Great Recession: Historical Perspective from the Displaced Workers Survey, 1984-2010." Working Paper No. 17040, National Bureau of Economic Research, May.

Feeding America. 2016. "Map the Meal Gap 2016: Highlights of Findings for Overall anf Child Food Insecurity. A Report on County and Congressional District Food Insecurity and County Food Cost in the United States in 2014." Executive summary, Feeding America.

Flood, S., M. King, S. Ruggles, and J.R. Warren. 2015. "Integrated Public Use Microdata Series, Current Population Survey: Version 4.0. [Machine-readable database]." University of Minnesota.

Foster, J., J. Greer, and E. Thorbecke. 1984. "A Class of Decomposable Poverty Measures." *Econometrica* 52:761–766.

Gaviria, A., C. Medina, and C. Mejía. 2006. "Assessing Health Reform in Colombia: From Theory to Practice." *Economía* 7:29–72.

González Dávila, O. 2010. "Food security and poverty in Mexico: the impact of higher global food prices." *Food Security* 2:383–393.

Green, R., L. Cornelsen, A.D. Dangour, R. Turner, B. Shankar, M. Mazzocchi, and R.D. Smith. 2013. "The effect of rising food prices on food consumption: systematic review with meta-regression." *BMJ* 346.

Gregory, C., and A. Coleman-Jensen. 2011. "Do Food Prices Affect Food Security for SNAP Households? Evidence from the Quarterly Food At Home Price Database Matched to CPS 2002-2006." Working paper.

Grosh, M.E., and J. Baker. 1995. "Proxy Means Tests for Targeting Social Programs." World Bank Living Standards Measurement Study Working Paper 118.

Gundersen, C. 2008. "Measuring the extent, depth, and severity of food insecurity: an application to American Indians in the USA." *Journal of Population Economics* 21:191–215.

Gundersen, C., B. Kreider, and J. Pepper. 2011. "The Economics of Food Insecurity in the United States." *Applied Economic Perspectives and Policy* 33:281–303.

Hadley, C., E.G.J. Stevenson, Y. Tadesse, and T. Belachew. 2012. "Rapidly rising food prices and the experience of food insecurity in urban Ethiopia: Impacts on health and well-being." *Social Science & Medicine* 75:2412 – 2419, Part Special Issue: Place, migration & health.

Hahn, J., P. Todd, and W. Van der Klaauw. 2001. "Identification and Estimation of Treatment Effects with a Regression-Discontinuity Design." *Econometrica* 69:201–209.

Hansen, L.P. 1982. "Large Sample Properties of Generalized Method of Moments Estimators." *Econometrica* 50:1029–1054.

Haughton, J.H., and S.R. Khandker. 2009. *Handbook on poverty and inequality*. The World Bank.

Hausman, J. 2002. "Sources of Bias and Solutions to Bias in the CPI." Working Paper No. 9298, National Bureau of Economic Research, October.

Headey, D., and O. Ecker. 2013. "Rethinking the measurement of food security: from first principles to best practice." *Food Security* 5:327–343.

Headey, D., and S. Fan. 2008. "Anatomy of a crisis: the causes and consequences of surging food prices." *Agricultural Economics* 39:375–391.

Heflin, C., and A. Price. 2018. "Food pantry assistance and the great recession." *Journal of Hunger & Environmental Nutrition*, March, pp. 1–15.

Hoynes, H., D.L. Miller, and J. Schaller. 2012. "Who Suffers During Recessions." *Journal of Economic Perspectives* 26(3):27–48.

Ivanic, M., and W. Martin. 2008. "Implications of higher global food prices for poverty in low-income countries." *Agricultural Economics* 39:405–416.

Jaramillo, I. 2001. "Evaluaciòn de la descentralizaciòn en salud en Colombia." Archivos de Economìa 170, Departamento Nacional de Planeaciòn.

Kreider, B., J.V. Pepper, C. Gundersen, and D. Jolliffe. 2012. "Identifying the Effects of SNAP (Food Stamps) on Child Health Outcomes When Participation Is Endogenous and Misreported." *Journal of the American Statistical Association* 107:958–975.

Lee, D.S., and T. Lemieux. 2010. "Regression Discontinuity Designs in Economics." *Journal of Economic Literature* 48:281–355.

Lokshin, M., and Z. Sajaia. 2011. "Impact of interventions on discrete outcomes: Maximum likelihood estimation of the binary choice models with binary endogenous regressors." *Stata Journal* 11:368–385(18).

Lopez-Arana, S., M. Avendano, F.J. van Lenthe, and A. Burdorf. 2016. "The impact of a conditional cash transfer programme on determinants of child health: evidence from Colombia." *Public Health Nutrition* 19:2629–2642.

Maxwell, D., B. Vaitla, and J. Coates. 2014. "How do indicators of household food insecurity measure up? An empirical comparison from Ethiopia." *Food Policy* 47:107 – 116.

McGee, R. 1999. "Technical, Objective, Equitable and Uniform? A Critique of the Colombian System for the Selection of the Beneficiaries of Social Programs SISBEN." IDPM Discussion Papers, Working Paper 57.

Melgar-Quinonez, H.R., A.C. Zubieta, B. MkNelly, A. Nteziyaremye, M.F.D. Gerardo, and C. Dunford. 2006. "Household food insecurity and food expenditure in Bolivia, Burkina Faso, and the Philippines." *The Journal of Nutrition* 136:1431S–1437S.

Miller, G., D. Pinto, and M. Vera-Hernández. 2013. "Risk Protection, Service Use, and Health Outcomes under Colombia's Health Insurance Program for the Poor." *American Economic Journal: Applied Economics* 5:61–91.

Montiel-Olea, J.L., and C. Pflueger. 2013. "A Robust Test for Weak Instruments." *Journal of Business & Economic Statistics* 31:358–369.

Panopoulus, G., and C.E. Vélez. 2001. "Subsidized Health Insurance, Proxy Means Testing, and the Demand for Health Care among the Poor in Colombia." In *Colombia Poverty Report, vol. 2*. The World Bank.

Paredes Lopez, O., F. Guevara Lara, and L. Bello Perez. 2009. "La nixtamalización y el valor nutritivo del maíz." *Ciencias* 92:60–70.

Pflueger, C., and S. Wang. 2014. "A Robust Test for Weak Instruments in Stata." Mimeo.

Ruel, M.T., J.L. Garrett, C. Hawkes, and M.J. Cohen. 2010. "The Food, Fuel, and Financial Crises Affect the Urban and Rural Poor Disproportionately: A Review of the Evidence." *The Journal of Nutrition* 140:170S–176S.

Ruiz, F., S. Reyes, N. Acosta, J.I. Eslava, C.A. Puente, Z. Ardila, and E. Peñaloza. 1999. *Entorno, aeguramiento y acceso en el régimen subsidiado en Colombia: Seis estudios de caso*. Fundación Corona, Ford Foundation, and Pontificia Universidad Javeriana - Centro de Proyectos para el Desarrollo (CENDEX).

Sargan, J.D. 1958. "The Estimation of Economic Relationships using Instrumental Variables." *Econometrica* 26:393–415.

Stock, J.H., and M. Yogo. 2002. "Testing for Weak Instruments in Linear IV Regression." Working Paper No. 284, National Bureau of Economic Research, November.

The World Bank. 2016. "Rural population (% of total population)." Data retrieved from World Development Indicators, `http://data.worldbank.org/indicator/SP.RUR.TOTL.ZS?locations=CO`.

Todd, J.E., L. Mancino, and E. Leibtag. 2010. "Methodology Behind the Quarterly Food-at-Home Price Database." Working paper No. 1926, United States Department of Agriculture - Economic Research Service.

Trujillo, A.J., J.E. Portillo, and J.A. Vernon. 2005. "The Impact of Subsidized Health Insurance for the Poor: Evaluating the Colombian Experience using Propensity Score Matching." *International Journal of Health Care Finance and Economics* 5:211–239.

Tuttle, C. 2013. "Household Decisions Related to Food Access and Expenditure: Essays on Food Insecurity and SNAP Participation in the United States." PhD dissertation, University of Minnesota.

U.S. Bureau of Labor Statistics. 2012. "BLS Spotlight on Statistics: The Recession of 2007–2009." Working paper, U.S. Bureau of Labor Statistics, February.

Vazquez Carrillo, M., G. Avila Uribe, A. Hernandez Montes, J. Castillo Merino, and O. Angulo Guerrero. 2011. "Sensory evaluation of freshly made and packed maize tortillas." *Revista Mexicana de Ciencias Agrícolas* 2:161–167.

Verardi, V., C. Dehon, et al. 2010. "Multivariate outlier detection in Stata." *The Stata Journal* 10:259–266.

White, H. 1980. "A Heteroskedasticity-Consistent Covariance Matrix Estimator and a Direct Test for Heteroskedasticity." *Econometrica* 48:817–838.

Zezza, A., B. Davis, C. Azzarri, K. Covarrubias, L. Tasciotti, and G. Anriquez. 2008. "The Impact of Rising Food Prices on the Poor." Working Papers No. 08-07, Agricultural and Development Economics Division of the Food and Agriculture Organization of the United Nations (FAO - ESA).

Appendix A
The Effects of Rising Staple Prices on Food Insecurity: The Case of Tortilla in Mexico

A.1 Interview to the manager of a tortillería located in Minneapolis-Saint Paul area

The following interview was made on December 11 2017 via email to the manager of a tortillería to understand the tortilla manufacturing process and the differences between tortillas from tortillerías and grocery stores.

Question 1. Which ingredients do you use to produce a tortilla? Is it more labor intensive than machine based?
Answer: We use a combination of corn flours to produce a tortilla that can be used in both retail and restaurant settings. Making tortillas is usually a labor intensive process, because we use heavy duty machinery we would not consider our product fully hand-made. However, we're not fully automated, and hands-on interaction is involved throughout the entire process.

Question 2. Based on your knowledge, how do they differ from tortillas sold in grocery stores and supermarkets?
Answer: Normally you'll find two types of tortillas, Retail tortillas and commercial kitchen tortillas. Retail tortillas are usually made with higher quality ingredients. At our tortillería we make one tortilla that is used in both retail and commercial kitchens. Our tortilla out performs the competition.

Question 3. We understand that tortillas made in tortillerías are more expensive than those sold in grocery stores. Is that right? What is our opinion about the situation?
Answer: Yes, Tortillas made in tortillerías are more expensive because of the volume. Supermarkets and grocery stores buy products in bulk, high volume. Tortillerías are usually on a much smaller scale and therefore have a better price based on volume and consistency. When you buy tortillas directly form the tortillería, you get the freshest tortillas made on that same day. Our distributors work closely with us in creating a program that allows companies to resupply every other day, with this method we're able to stock only the freshest tortillas at local stores.

Question 4. Do you think that tortillas sold at grocery stores and supermarkets represent a threat for tortillas sold at tortillerías? Why?
Answer: There is a definite threat from larger corporations with much higher resources than smaller companies. Large corporations cloud and clog the market wile pushing smaller companies out of the competition. This is why customers tend to find shelves upon shelves stocked with only one brand.

Question 5. Do you think customers are able to tell the difference between hand-made and commercially produced?
Answer: Yes, of course. Hand-made tortillas are usually made to order, and brought directly to the table. It is impossible to produce hand-made quality tortillas in a factory setting. The product volume would not be enough to supply tortillas in bulk. Here at our tortillería we use a hybrid system where we can be hands-on, but with the help of machinery.

Question 6. Based on your understanding, are tortillas an affordable product for all Mexican households? Is it possible that some households are not able to buy them?
Answer: Tortillas are a staple in the Mexican diet. Tortillas have been apart of Mexican culture and Native American history for centuries, and in Mexico, it is seen as one of the most widely available and easily accessible foods around.

Appendix B

Food Price Fluctuations and Household Food Insecurity in the United States, 2005–2010

B.1 Questionnaire Used by the United States Department of Agriculture to Assess Household Food Security in the Current Population Survey

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?
    (a) Did this ever happen in the last 30 days?
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?
    (a) Did this ever happen in the last 30 days?
3. "We couldn't afford to eat balanced meals." Was that often, sometimes, or never true for you in the last 12 months?
    (a) Did this ever happen in the last 30 days?
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?
    (a) How often did this happen–almost every month, some months but not every month, or in only 1 or 2 months?
    (b) Now think about the last 30 days. During that time did (you/ you or other adults in your household) ever cut the size of your meals or skip meals because there wasn't enough money for food?
        i. How many days did this happen in the last 30 days?
5. In the last 12 months, did you ever eat less than you felt you should because there wasn't enough money for food?
    (a) How often did this happen-almost every month, some months but not every month, or in only 1 or 2 months?
    (b) Did this happen in the last 30 days?
        i. In the last 30 days, how many days did you eat less than you felt you should because there wasn't enough money for food?
6. In the last 12 months, were you ever hungry, but didn't eat, because there wasn't enough money for food?
    (a) How often did this happen–almost every month, some months but not every month, or in only 1 or 2 months?
    (b) Did this happen in the last 30 days?
        i. In the last 30 days, how many days were you hungry but didn't eat because there wasn't enough money for food?

7. In the last 12 months, did you lose weight because there wasn't enough money for food?
    (a) Did this ever happen in the last 30 days?
8. 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?
    (a) How often did this happen–almost every month, some months but not every month, or in only 1 or 2 months?
    (b) Now think about the last 30 days. During that time did (you/ you or other adults in your household) ever not eat for a whole day because there wasn't enough money for food?
        i. How many times did this happen in the last 30 days?

(Questions 9–15 were asked only if the household included children age 0-17)

9. "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?
    (a) Did this ever happen in the last 30 days?
10. "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?
    (a) Did this ever happen in the last 30 days?
11. "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?
    (a) Did this ever happen in the last 30 days?
12. 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?
    (a) How often did this happen–almost every month, some months but not every month, or in only 1 or 2 months?
    (b) Did this ever happen in the last 30 days?
        i. In the last 30 days, how many days did you cut the size of (the child's/any of the children's) meals because there wasn't enough money for food?
13. In the last 12 months, were the children ever hungry but you just couldn't afford more food?
    (a) How often did this happen–almost every month, some months but not every month, or in only 1 or 2 months?

(b) Did this ever happen in the last 30 days?

    i. In the last 30 days, how many days did you cut the size of (the child's/any of the children's) meals because there wasn't enough money for food?

14. In the last 12 months, did any of the children ever skip a meal because there wasn't enough money for food?

    (a) How often did this happen–almost every month, some months but not every month, or in only 1 or 2 months?

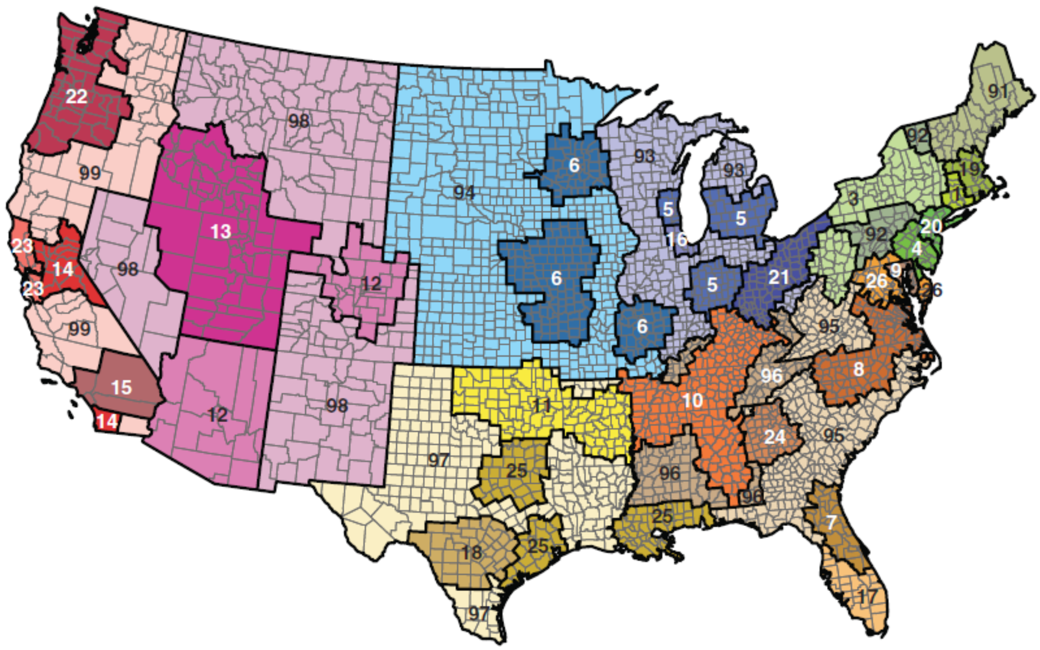
    (b) Now think about the last 30 days. Did (the child/any of the children) ever skip a meal during that time because there wasn't enough money for food?

        i. How many days did this happen in the last 30 days?

15. 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?

    (a) Did this ever happen in the last 30 days?

B.2 Markets Defined by the United States Department of Agriculture for the Quarterly Food-at-home Price Database



Notes: For 1999-2001, markets 91 and 92 are combined as market 81; markets 93 and 94 are combined as market 82; markets 95, 96, and 97 are combined as market 83; and markets 98 and 99 are combined as market 84.

1	Hartford	19	Boston
2	Urban NY	20	Other NY
3	Western NY/PA	21	Metro Ohio
4	Philadelphia	22	North Pacific
5	Metro Midwest 1	23	San Francisco
6	Metro Midwest 2	24	Atlanta
7	North Florida	25	Metro South 4
8	Metro South 1	26	Washington, DC
9	Baltimore	91	Nonmetro New England
10	Metro South 2	92	Nonmetro Middle Atlantic
11	Metro South 3	93	Nonmetro East North Central
12	Metro Mountain	94	Nonmetro West North Central
13	Salt Lake City	95	Nonmetro South Atlantic
14	Metro California	96	Nonmetro East South Central
15	Los Angeles	97	Nonmetro West South Central
16	Chicago	98	Nonmetro Mountain
17	South Florida	99	Nonmetro Pacific
18	San Antonio		

Source: Todd, Mancino, and Leibtag (2010)

B.3 Market Correspondence Between the Quarterly Food-at-home Price Database and Nielsen's Homescan Database

Census region	Census division	QFAHPD market group	Nielsen-identified markets included in the QFAHPD market group
East	New England	Hartford	Hartford
		Boston	Boston
		Nonmetro New England	n/a
	Middle Atlantic	Urban NY	Urban NY
		Western NY/PA	Pittsburg, Buffalo, Albany, Syracuse
		Philadelphia	Philadelphia
		Other NY	Suburban NY, Exurban NY
		Nonmetro Middle Atlantic	n/a
Central	East North Central	Metro Midwest 1	Indianapolis, Detroit, Milwaukee, Grand Rapids
		Chicago	Chicago
		Metro Ohio	Cincinnati, Cleveland, Columbus
		Nonmetro East North Central	n/a
	West North Central	Metro Midwest 2	Kansas City, Minneapolis, St. Louis, Des Moines, Omaha
		Nonmetro West North Central	n/a
South	South Atlantic	North Florida	Jacksonville, Orlando
		Metro South 1	Raleigh-Durham, Charlotte, Richmond
		Baltimore	Baltimore
		South Florida	Miami, Tampa
		Atlanta	Atlanta
		Washington, DC	Washington, DC
		Nonmetro South Atlantic	n/a
	East South Central	Metro South 2	Nashville, Birmingham, Memphis, Louisville
		Nonmetro East South Central	n/a
	West South Central	Metro South 3	Little Rock, Oklahoma City-Tulsa
		San Antonio	San Antonio
		Metro South 4	Houston, Dallas, New Orleans
		Nonmetro West South Central	n/a
West	Mountain	Metro Mountain	Denver, Phoenix
		Salt Lake City	Salt Lake City
		Nonmetro Mountain	n/a
	Pacific	Metro California	San Diego, Sacramento
		Los Angeles	Los Angeles
		Metro Northwest	Seattle, Portland
		San Francisco	San Francisco
		Nonmetro Pacific	n/a

Source: Todd, Mancino, and Leibtag (2010)

B.4 Classification of Food Products at the Quarterly Food-at-home Price Database

Fruits and Vegetables		Grains and Dairy	
1	Fresh/Frozen fruit	16	Whole grain bread, rolls, rice, pasta, cereal
2	Canned fruit	17	Whole grain flour and mixes
3	Fruit juice	18	Whole grain frozen/ready to cook
4	Fresh/Frozen dark green vegetables	19	Other bread, rolls, rice, pasta, cereal
5	Canned dark green vegetables	20	Other flour and mixes
6	Fresh/Frozen orange vegetables	21	Other frozen/ready to cook grains
7	Canned orange vegetables	22	Low fat milk
8	Fresh/Frozen starchy vegetables	23	Low-fat cheese
9	Canned starchy vegetables	24	Low-fat yogurt & other dairy
10	Fresh/Frozen select nutrient vegetables	25	Regular fat milk
11	Canned select nutrients	26	Regular fat cheese
12	Fresh/Frozen other vegetables	27	Regular fat yogurt & other dairy
13	Canned other vegetables		
14	Frozen/Dried legumes		
15	Canned legumes		
Meats and Eggs		**Fats and Prepared Foods**	
28	Fresh/frozen low fat meat	38	Oils
29	Fresh/frozen regular fat meat	39	Solid fats
30	Canned meat	40	Raw sugars
31	Fresh/frozen poultry	41	Non-alcoholic non-diet carbonated beverages
32	Canned poultry	42	Non-carbonated caloric beverages
33	Fresh/frozen fish	43	Water
34	Canned fish	44	Ice cream and frozen desserts
35	Raw nuts and seeds	45	Baked good mixes
36	Processed nuts, seeds and nut butter	46	Packaged sweets/baked goods
37	Eggs	47	Bakery items, ready to eat
		48	Frozen entrees and sides
		49	Canned soups, sauces, prepared foods
		50	Packaged snacks
		51	Ready to cook meals and sides
		52	Ready to eat deli items (hot and cold)
		53	Non-alcoholic diet carbonated beverages
		54	Unsweetened coffee and tea

Source: Todd, Mancino, and Leibtag (2010)