UKCPR
University of Kentucky Center for Poverty Research

Discussion Paper Series
DP 2013-05

ISSN: 1936-9379

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Preferred citation

Jensen, H. & Zhylyevskyy, O. The Effect of Household Financial, Time and Environmental Constraints on Very Low Food Security among Children. *University of Kentucky Center for Poverty Research Discussion Paper Series, DP2013-05*. Retrieved [Date] from http://www.ukcpr.org/Publications/DP2013-05.pdf.

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Final Report

The Effect of Household Financial, Time and Environmental Constraints on Very Low Food Security among Children

Report on a small grant project conducted under the terms of the *Research Program on Childhood Hunger* of the University of Kentucky Center for Poverty Research (UKCPR)[*]

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August 12, 2013

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[*] This project was supported with a grant from the University of Kentucky Center for Poverty Research through funding by the U.S. Department of Agriculture, Food and Nutrition Service, contract number AG-3198-B-10-0028. The opinions and conclusions expressed herein are solely those of the author(s) and should not be construed as representing the opinions or policies of the UKCPR or any agency of the Federal Government.

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Abstract

Food insecurity is detrimental to children's well-being. A better understanding of factors contributing to low and very low food security among children in the United States can guide the design of food assistance programs. We analyze the effects of household characteristics and local food environment attributes, including food prices and availability of food stores and eating places, on children's food insecurity. We also investigate the effects of these characteristics and attributes on food preparation time. Using Becker's household production approach, we propose an economic model that formalizes the use of constrained financial and time resources in the household. The model motivates empirical specifications of food insecurity and food preparation time equations, which are estimated jointly by maximum likelihood. We assemble a large dataset of households with children by pooling across years and matching the Food Security Supplement of the Current Population Survey, 2002–2010, and the American Time Use Survey, 2003–2011. These data are supplemented with location-specific variables from several large national sources. The estimates suggest intuitively plausible effects of demographic and socioeconomic characteristics on food insecurity and food preparation time. They also indicate that residing in a location with higher fast food prices and with fewer convenience stores and specialty food stores tends to exacerbate food insecurity. Public policies supporting parents' financial, transportation, and childcare needs, enhancing parents' resource management skills, supporting the food needs of school-age children, and encouraging businesses to open specialty food stores in poorer neighborhoods can help alleviate very low food security among children.

Executive Summary

Very low food security is detrimental to the well-being of children. Previous studies indicate that food insecurity negatively affects children's current health and also link food insecurity to negative outcomes in children's physical, intellectual, and social development. Given a non-negligible incidence of food insecurity in low-income households with children in the United States and the adverse consequences of food insecurity, a better understanding of household and other factors that may contribute to low and very low food security among children has substantial public policy interest and can guide the design of federal food assistance programs.

This report focuses on the impact of household financial, time, and environmental constraints on low and very low food security among children. In particular, we analyze the effects of demographic and socioeconomic characteristics of the household and the effects of local food environment attributes such as food prices and food outlet availability measures on food insecurity among children and additionally investigate effects of these characteristics and attributes on food preparation time. Previous research indicates that income levels near or below the poverty threshold are consistently associated with higher levels of food insecurity. However, because household income is an imperfect predictor of food security, research attention has recently shifted toward the role of a broad range of other factors. These other, potentially important contributors to low and very low food security among children include household type, size, and composition; minority status of household members; and educational attainment of the householder. In addition, food insecurity may be influenced by attributes of the local food environment that determine accessibility and affordability of food. In particular, local food prices and availability of food stores and restaurants in the neighborhood can impact the ease of access to food and the time costs of food shopping and related travel.

Besides the constraints related to financial resources and food environment, all households face time constraints. Some households, especially single-headed households with children, are believed to be relatively more time-constrained than others, which can negatively affect the ability to meet children's food needs and effectively utilize federal food assistance. In addition to the time needed to prepare meals at home, the use of time resources in the household production related to food can involve the time spent food shopping and in related travel. Previous research indicates that lower-income households are more likely than others to utilize a range of food shopping and food preparation strategies that involve using relatively more time as a means to reduce monetary expenditures on food. Because work and childcare impose significant time demands on parents, single-headed households with children, especially those with less income, are relatively more likely to experience low and very low food security.

We propose a relatively simple economic model, based on Becker's household production framework, that formalizes the use of constrained financial and time resources in the household and accounts for potential impacts of demographic, socioeconomic, and other factors including local food environment attributes, on food insecurity among children. This theoretical model is employed to motivate empirical specifications of children's food insecurity and household food preparation time equations, which are estimated jointly using a maximum likelihood approach.

To implement the estimation, we assemble a large dataset of households with children using several data sources. The main sources of data are the Food Security Supplement of the Current Population Survey, 2002–2010, and the American Time Use Survey, 2003–2011. These two datasets are pooled across the years and cross-linked to construct a matched analytical sample (N = 13,474). These matched data are supplemented with location-specific variables obtained using data from other sources, including the Quarterly Food-at-Home Price Database, a price database of the American Chamber of Commerce Researchers Association, and the County Business Patterns database. Our measure of food security among children is referenced to the last twelve months and is based on eight child-specific questions in the Food Security Supplement. An advantage to pooling the data across the years is that we are able to compile a sufficiently large sample in order to investigate the relatively rare phenomenon of very low food security among children (66 households in total in the sample).

The estimation results reveal the importance of demographic, socioeconomic, and environmental factors contributing to food insecurity among children. Households with a single head (i.e., no spouse present) and households with more children are more likely to experience low and very low food security among children than married-couple households and households with fewer children, respectively. Lower household income and lower educational attainment of the householder are associated with more food insecurity. Also, being identified as a minority household significantly increases the incidence of low and very low food security among children. Beyond these characteristics, the estimates indicate that residing in a location with higher fast food prices tends to contribute to more food insecurity among children. In comparison, residing in a location with relatively more convenience stores and specialty food stores tends to mitigate food insecurity. Individual and household characteristics also have statistically significant effects on the amount of time devoted to food preparation by the householder or the householder's spouse or unmarried partner. Men spend substantially less time in food preparation than women. Children are associated with more time in food preparation. More time is spent in food preparation when the householder is older or is Hispanic or foreign-born. In addition, the daily duration of food preparation tends to be longer among lower-income households. Furthermore, the estimates reveal that the amount of time in food preparation systematically varies across days of the week and suggest that the daily duration of food preparation is lower in the summer.

The results inform the design of public policies and programs aimed at reducing the incidence of low and very low food security among children in the United States. In particular, our findings can guide the allocation of public resources in order to alleviate food insecurity among the most vulnerable children. The fact that households with a single head are more likely to experience low and very low food security among children suggests that policies designed to support the needs of these households, and especially households with single female heads, can have important effects on the well-being of children. Such policies could include supporting financial, labor market, transportation, and childcare program needs as well as educational efforts to enhance household resource management and coping skills. In addition, because having more children in the household places more demand on parent's time and increases food insecurity, programs that support the food needs of children, particularly school-age children (e.g., school lunches and breakfasts, and summer meals programs), are especially well targeted to the critical need for food assistance. Our findings go beyond the role of household-specific factors. In particular, we find evidence suggesting that the availability of low cost food (including fast food) in convenient and nearby locations (especially in the case of convenience stores and specialty food stores) may help mitigate food insecurity among children. Public policies and strategies aimed at encouraging businesses to open food stores of specific type (e.g., specialty food stores) in poorer neighborhoods are likely to alleviate food insecurity. Furthermore, our findings suggest that the effectiveness of food assistance programs may be enhanced by allowing for their requirements to vary across seasons in order to account for the differential opportunity cost of time. For example, restrictions on the use of SNAP program benefits may be relaxed during summer months so that participating households can spend part of the benefits on food away from home.

The Effect of Household Financial, Time and Environmental Constraints on Very Low Food Security among Children

1. Introduction

Food insecurity of low-income households, especially low-income households with children, is a matter of substantial public concern in the United States. Among households with children and income below 130% of the federal poverty level, 30% of households experienced low food security and 14% experienced very low food security in 2011 (Coleman-Jensen et al., 2012a; 2012b).[1] Food insecurity can be particularly detrimental to the well-being of children. It not only negatively affects children's current health but also has been linked to negative outcomes in their physical, intellectual, and social development (for reviews of the literature, see NRC, 2006; Nord and Parker, 2010; and Gundersen, Kreider, and Pepper, 2011).

Lack of financial resources is a critical factor that leads to food insecurity—the limited ability to access at all times enough food for an active, healthy life for all household members. Food insecurity is more likely at income levels near or below the poverty threshold. In particular, having low income (less than 130% or less than 185% of the federal poverty level) is consistently associated with higher levels of food insecurity.

Since not all poor households are food insecure, we expect that factors other than lack of income can significantly contribute to low and very low food security (see Bartfeld and Dunifon, 2006). However, identifying these factors is challenging. Household characteristics that are associated with greater food insecurity include single-headed household status (i.e., absence of a spouse in the household), presence of children, and householder being African American or Hispanic (Coleman-Jensen et al., 2012a). In addition, households with heads who are unemployed and have less formal education (especially less than a high school degree), and households lacking financial reserves and management skills are more likely than others to experience higher levels of food insecurity among children (Bartfeld and Dunifon, 2006; Nord and Parker, 2010; Gundersen, Kreider and Pepper, 2011). However, most of the referenced studies identify associations, rather than causal effects.

Moreover, households face resource constraints along dimensions other than income,

[1] For comparison, among all households with children, regardless of the household's poverty status, nearly 21% were food insecure in 2011 (Coleman-Jensen, McFall, and Nord, 2013).

including time constraints, as an example. Following Vickery's (1977) work on poverty measures that include both financial and time constraints, Rose (2007) highlights implications for low income households in meeting food needs (i.e., food shopping, meal preparation, and cleanup). Use of time resources can involve searching out lower prices, collecting coupons, traveling to food stores with lower prices, and shopping more frequently (Leibtag and Kaufman, 2003; Aguiar and Hurst, 2007). Evidence suggests that children in households with a single mother (such households may be more time-constrained than married-couple households, for example) are at a much greater risk of very low food security. In 2011, 5.8% of all households with children, but 11.5% of households with children and a single female head experienced very low food security (Coleman-Jensen et al., 2012a). In addition, differences in the ability to manage time (e.g., plan, monitor, and coordinate household activities) may help to explain varying ability to meet children's food needs, especially when work and childcare impose significant time demands on low income, single parents (Winker and Ireland, 2009).

Contextual factors that affect the local food environment determine access and affordability of food and can also influence food-related outcomes, including food insecurity (Bartfeld and Dunifon, 2006). Local food prices and other attributes of the food environment, such as the availability of various types of food business establishments in the neighborhood, are likely to have an effect on the ease of access to food and related costs of acquiring food, including the time cost of food shopping and related travel (Bartfeld and Dunifon, 2006). Lack of available food (and especially healthy foods) and limited access to grocery stores (i.e., in "food deserts," see Ver Ploeg, 2010) would increase search and transportation costs, and may be related to the level of local food prices through competition in the food market (Bitler and Haider, 2011). The types of food stores available to and used by low income households may also affect food security outcomes. Broda, Leibtag, and Weinstein (2009) find that although low income households invest time in order to shop in large stores (with lower prices), they also are more likely than higher income households to shop at higher-priced convenience stores. Perhaps lack of readily available transportation or time constraints result in this shopping pattern. The finding suggests that the food environment (i.e., availability and access to stores and level of food prices) may play an important role in influencing how households achieve food security. Still, relatively little is presently known (and much remains to be empirically learned) about effects of the local food environment on food insecurity specifically among children.

Developing a better understanding of factors associated with food insecurity and, in particular, with very low food security among children is the main objective of this report and critical to the design of policies and programs aimed at mitigating the negative consequences of households' limited access to food. We propose a relatively simple economic model that formalizes the use of constrained financial and time resources and accounts for impacts of other factors (including local food environment) on children's food security outcomes. By employing an empirical model specification that incorporates proxies for such factors and a large dataset assembled using several nationally representative surveys, we estimate the effects of a household's demographic and socioeconomic characteristics (household size and composition, income, race, education, etc.), and attributes of the place of residence, including local food prices and the availability of food business establishments, on food insecurity. We also estimate the effects of these factors and of attributes of the time-diary day on the amount of time devoted by householders and their spouses or unmarried partners to food preparation on the daily basis.

The estimation results indicate the importance of demographic, socioeconomic, and environmental factors contributing to food insecurity among children. For example, having a single household head (especially single female household head) and having a household with more children—are factors significantly increasing the likelihood of low and very low food security among children. As expected, we find that having less income and a lower educational attainment, which proxy for more limited household resources, resource management skills, and nutrition knowledge, negatively affect food security. In addition, being identified as a minority household significantly increases the incidence of low and very low food security among children. Beyond the demographic and socioeconomic characteristics, the estimation results suggest that the local food environment can affect food security. In particular, residing in a location with higher fast food prices tends to contribute to more food insecurity among children. In comparison, residing in a location with higher densities (i.e., number of stores per local population) of convenience stores and specialty food stores tends to mitigate food insecurity.

Furthermore, we find significant effects of demographic and socioeconomic characteristics as well as significant effects of attributes of the diary day on the time devoted by householders and their spouses or unmarried partners to food preparation, which includes food shopping and related travel. To illustrate, men spend substantially less time in food preparation than women. Children are associated with more time in food preparation. Also, adults tend to spend more time in food preparation if the householder is older or is Hispanic or foreign-born. We also find that the daily duration of food preparation is longer among households below 185% of the poverty level. As expected, adults spend relatively less time in food preparation on Friday, but more time on Sunday and a holiday. Moreover, time in food preparation tends to be lower during summer months in comparison to winter months.

Our approach enables a broad assessment of the effectiveness of a range of policies and programs aimed at reducing the incidence of low and very low food security among children in the United States. The contribution of household-specific factors to increased food insecurity may be mitigated by social policies that might strengthen the resiliency of households to avoid this negative outcome among their children. The fact that households with a single adult head are more likely to experience low and very low food security among children suggests that policies designed to support the needs of households with single heads, especially single female heads, will have important—and potentially, long-term—effects on the health and well-being of children. Such policies can include those to support the financial, labor market, transportation, and childcare program needs as well as educational efforts to enhance household resource management and coping skills, for example. Because having more children in the household places more demand on household time use in food preparation and increases food insecurity, programs that support the food needs of children, particularly school-age children, are especially well targeted to the critical need for food assistance. School meals (lunch and breakfast) and summer food service programs hold potential for reducing food insecurity (e.g., see Gundersen, Kreider, and Pepper, 2012). Programs that provide access to additional financial and food resources (e.g., the Supplemental Nutrition Assistance Program, SNAP; and indirectly, programs for education and job training) are likely to be effective at reducing food insecurity among children.

Our findings go beyond the role of household-specific factors. In particular, we find evidence suggesting that the availability of low cost food (including fast food) in convenient and nearby locations (especially in the case of convenience stores and specialty food stores) can help mitigate food insecurity among children. Strategies to encourage proximity of stores might also encourage availability of healthy foods through the local stores.

The remainder of this report is organized as follows. In Section 2, we propose a theoretical model of household decision-making with a focus on children's food insecurity and food preparation time, list the research hypotheses, describe the empirical specification of food insecurity and food preparation time equations, and outline the econometric estimation and inference approach. In Section 3, we describe data sources, discuss the construction of the analytical sample, and provide descriptive statistics for the characteristics of the sample. In Section 4, we describe the estimation results. In Section 5, we discuss the research findings and outline their policy implications. In Section 6, we conclude.

2. Research Methods

2.1. Overview

Our main research objective is to better understand household characteristics and circumstances that can ameliorate or exacerbate the likelihood of children's food insecurity, especially very low food security among children. We make use of a household production framework with constrained financial and time resources. Food security among children is conceptualized as a "commodity" produced in the household. Thus, children's food insecurity is viewed as an outcome of household decision-making subject to resource constraints. We also incorporate in the analysis another outcome—the amount of time in food preparation. Households can be heterogeneous with respect to their ability to utilize time when producing food security and other commodities. This unobservable (to the researcher) ability and other unobservable household-specific factors may affect all observed outcomes, including the children's food security status and the amount of time devoted by the householder, the householder's spouse, or the householder's unmarried partner (i.e., the most likely household decision-makers) to food preparation.[2] Common unobservable factors, if there are any, may induce a correlation between an error term in the empirical food insecurity equation and an error term in the empirical time in food preparation equation. This potential for correlation motivates estimating the two equations jointly, by using a seemingly unrelated regression (SUR) technique, and then testing for such correlation. The empirical analysis aims to address the following research questions:

(a) How do food prices affect low and very low food security among children?

(b) What is the importance of the local food environment in determining low and very low food

[2] In the empirical analysis in Section 3, we use the term "householder" interchangeably with the CPS term "reference person." A CPS reference person is an individual in the household in whose name the home is owned or rented and the one responding to questions in the CPS interview.

security among children?

(c) Which demographic and socioeconomic characteristics of households contribute to the risk of low and very low food security among children?

(d) Which factors affect the amount of time devoted to food preparation by householders, spouses, and unmarried partners?

2.2. Theoretical Framework

Our modeling approach draws on the economic theory of household production and time allocation, as originally formalized by Becker (1965) and extended by Pollak and Wachter (1975).[3] According to this theory, the household maximizes utility by consuming various "commodities" (e.g., meals and entertainment), which it produces by combining goods purchased in the marketplace with time, subject to constraints imposed by the household production technology and resource availability. Commodities can include attributes of child "quality" (Becker and Tomes, 1976)—for instance, how well-nourished the children are. In line with this theory, we conceptualize food security as a "commodity" produced by the household. Thus, we treat children's food insecurity as an outcome of household decision-making subject to resource constraints. Our approach is consistent with other existing research which treats child nutrition as an outcome of household decision-making in the presence of resource constraints (Chernichovsky and Coate, 1980; Bhattacharya et al., 2003). Also, by using the household as a unit of analysis, we follow the current standard of measuring children's food insecurity at the household level (NRC, 2006; Coleman-Jensen et al., 2012a, 2012b).

The importance of incorporating time in the analysis of household decision-making, poverty, and inequality is widely recognized, because income and expenditures on their own may not adequately reflect consumption and well-being in general (see Vickery, 1977; Douthitt, 2000; Aguiar & Hurst, 2007) and food consumption in particular (Aguiar & Hurst, 2005; Davis and You, 2011). Also, prior research identifies the cost of time as a large component of the total meal-

[3] Pollak and Wachter (1975) extended the original Becker's (1965) framework by allowing for possible "joint production" in the household. "Joint production" means that the time devoted to some household activities (e.g., cooking) can be both a direct source of utility (e.g., some individuals may enjoy the time they spend cooking) as well as an input into the household production of valuable "commodities" (e.g., cooking contributes to the production of meals at home).

preparation cost incurred by households (Raschke, 2012).[4] Therefore, we additionally incorporate in the analysis the time spent by the householder, the householder's spouse, or the householder's unmarried partner—the most likely household decision-makers—in food preparation (including food acquisition), and we treat the amount of such time as another outcome of household decision-making to explain.

2.3. Economic Model

First, let us outline the notation of the theoretical model and the main assumptions. We specify that a household decision-maker derives utility $U(\cdot)$ from the consumption of m ($m \geq 1$) different "commodities" whose quantities are denoted by a vector $Z = (z_1, \dots, z_m)'$. One of these commodities—for example, commodity 1—is the food security of children in the household; z_1 denotes its level. All else equal, the decision-maker prefers the children to be more food secure. Thus, $\frac{\partial U}{\partial z_1} > 0$, where we have assumed that the utility function is differentiable.[5] We often use the opposite term—"food *in*security." Its level, denoted as $\tilde{z}_1$, is defined as the negative of the level of food security: $\tilde{z}_1 = -z_1$. It follows that the decision-maker prefers the children to be *less* food insecure; that is, $\frac{\partial U}{\partial \tilde{z}_1} < 0$. Effectively, we assume that household decision-makers (e.g., parents) care about their children and internalize the detrimental consequences of food insecurity for the children.

Next, we specify that there are l ($l \geq 1$) different goods available for purchase in the marketplace. The quantities of these market goods are denoted by a vector $Y = (y_1, \dots, y_l)'$. To simplify matters, some of these goods could be composite goods. For example, good 1 could represent "groceries," in which case y_1 would denote the amount of groceries purchased (measured in terms of pounds per week, for example).

Also, the household's time endowment may be allocated across k ($k \geq 1$) different "activities." The times devoted to the activities are represented by a vector $T = (t_1, \dots, t_k)'$. For instance, activity 1 is "food preparation," and t_1 represents the amount of time in food preparation. The activities can include market work. In line with the household production framework,

[4] The literature has also investigated how the value of time and time use relate to the process of eating and health outcomes (e.g., Hamermesh, 2010).
[5] The differentiability assumption is not critical for the empirical analysis, however.

commodities Z are "produced" by combining market goods Y with the times in activities T according to a commodity production "technology." The corresponding decisions in the household give rise to the specific level of the children's food insecurity, $\tilde{z}_1$, and the amount of time in food preparation, t_1. In our analysis, we focus on factors affecting $\tilde{z}_1$ and t_1.[6]

The demographic and socioeconomic characteristics of the household—such as its size and composition, its income and poverty status, the educational attainment of the household decision-maker, etc.—are represented by a vector H. Components of this vector may affect the utility derived from commodities, the commodity production technology, the opportunity cost of time, or the resource constraints. For example, better educated householders may differ from others it terms of how much they value food security of children, how efficiently they can produce it, and how efficiently they are able to utilize the time endowment. In particular, higher education may be indicative of superior household management skills, which play a critical role in household production (Winkler and Ireland, 2009). Also, in comparison to poorer households, wealthier households may be able to purchase more (or higher quality) groceries for food production at home and more of "away from home" foods (e.g., restaurant meals).

In addition, we specify that household decision-making may be affected by various attributes of the household's place of residence, denoted here as a vector L. Such attributes may include local food prices, measures of the availability of local food establishments (e.g., densities of food stores and restaurants), and other location-specific characteristics (e.g., local poverty rate). The vector L may impact the resource constraints. As an example, grocery and fast food prices affect the budget constraint. In addition, L can impact the commodity production technology. To illustrate, individuals residing in a place with more sparsely located food stores may need to devote more time to food shopping than comparable individuals from a location with a higher store density—in order to produce the same level of children's food security.

Formally, consider a household i with a vector of demographic and socioeconomic characteristics H_i and residing in a location described by a vector of attributes L_i. The decision-maker in the household decides on purchasing a vector of market goods Y_i and on allocating the time endowment across a vector of activities T_i in order to maximize the utility U, by having the household produce and consume a vector of commodities Z_i. The utility is maximized subject to

[6] In the available data, food insecurity among children is recorded at a household level, whereas the time in food preparation is recorded at an individual level. These data features are accounted for in the empirical analysis.

constraints implied by the available commodity production technology, the time endowment, and financial resources. Formally, the problem is:

$$\max_{Z_i, Y_i, T_i} U(Z_i; H_i) \tag{1}$$

subject to a constraint implied by the commodity production technology:

$$F(Z_i, Y_i, T_i; H_i, L_i) = 0, \tag{2}$$

the time endowment constraint:

$$Q(T_i; H_i) = 0, \tag{3}$$

the budget constraint:

$$B(Y_i, T_i; H_i, L_i) = 0, \tag{4}$$

and non-negativity constraints:

$$Z_i, Y_i, T_i \geq 0. \tag{5}$$

To clarify, the production technology constraint $F(\cdot) = 0$ in Eq. (2) indicates which combinations of Z_i, Y_i, and T_i are feasible, given H_i and L_i. Thus, the technology is allowed to differ across households, depending on the vector of demographic and socioeconomic characteristics (H_i) and the vector of location-specific attributes (L_i). Also, the time constraint $Q(\cdot) = 0$ in Eq. (3) is affected by H_i, because the total time endowment depends on the household size, for example. In turn, the budget constraint $B(\cdot) = 0$ in Eq. (4) is allowed to depend on H_i and L_i, because H_i includes income and L_i incorporates local prices, for example. The specified theoretical model is very flexible. In particular, it can accommodate "joint production," as defined by Pollak and Wachter (1975), because vectors T_i and Z_i can have common elements (e.g., the time spent preparing food can be both in T_i and Z_i).[7]

This theoretical model is used to motivate our equations for food insecurity among children and the amount of time in food preparation. In particular, under suitable functional form restrictions, the model implies that the level of food insecurity and the amount of time in food preparation can be determined by solving the constrained maximization problem (1)–(5),[8] and moreover, that both of them are functions of the household characteristics H_i and location attributes L_i:

[7] Also, the model can accommodate secondary time-use activities.

[8] Recall that by definition, $\tilde{z}_1 = -z_1$, where $\tilde{z}_1$ denotes the level of food insecurity and z_1 denotes the level of food security among children. Also, note that the optimal level of z_1 is an element of the solution to the problem (1)–(5).

$$\tilde{z}_{1,i} = \tilde{z}_1(H_i, L_i), \quad (6)$$

$$t_{1,i} = t_1(H_i, L_i). \quad (7)$$

Eqs. (6) and (7) underlie empirical equation specifications for the children's food insecurity and the time devoted to food preparation by the householder/spouse/unmarried partner. Also, they serve as the basis for testing our research hypotheses regarding the effects of a household's demographic and socioeconomic characteristics and of food prices and densities of local food establishments on low and very low food security among children and on food preparation time.

It should be noted that not all household characteristics (H_i) and location-specific attributes (L_i) are observed and can be controlled for in the empirical analysis. Many potentially relevant factors are not reported in the surveys that we use or may simply be impractical to collect. For instance, we do not observe how good or bad household decision-makers are in terms of their ability to manage household activities and utilize the available time. As another example, we do not observe how far a household resides from local food stores and whether it owns a vehicle. Such unobservable factors underlie the error terms of the empirical counterparts to Eqs. (6) and (7). Since the relevant unobservable factors may or may not overlap between the two equations, the corresponding error terms may or may not be correlated. As such, it is important to estimate the equations jointly, while allowing for potential correlation between the error terms, and then test for non-zero correlation. We implement this approach in the empirical analysis by using a seemingly unrelated regression (SUR) estimation technique.[9]

2.4. Research Hypotheses

We test three groups of hypotheses (groups A, B, and C) related to household circumstances that can ameliorate or exacerbate low and very low food security among children, and an additional group of hypotheses (group D) related to potential effects of explanatory variables on the amount of time in food preparation.

Hypotheses in group A refer to how *prices of food* influence food insecurity:

- *Hypothesis A.1:* Higher prices of food at home (i.e., of food items purchased for further processing and consumption at home) are associated with increased food insecurity. In particular, households with children in locations with higher food at

[9] By estimating the two equations jointly, we may also increase the efficiency of parameter estimates.

home prices are more likely to report experiencing low and very low food security among children.

- *Hypothesis A.2:* Higher prices of food away from home (i.e., for consumption outside of the home, such as restaurant meals)—more specifically, higher fast food prices—are associated with increased food insecurity. In particular, households with children in locations with higher fast food prices are more likely to report experiencing low and very low food security among children.

Hypotheses in group B refer to the relative importance of such neighborhood circumstances as the *local food environment* in affecting food insecurity. We would expect that more densely located supermarkets, food stores, and other food service establishments in the area would be associated with more readily available food and lower travel cost to obtain food, holding prices constant, and hence, with less food insecurity. Related hypotheses include:

- *Hypothesis B.1:* Higher density of supermarkets and other types of food stores in the household's place of residence is associated with decreased food insecurity. In particular, households with children in locations with higher densities of food stores are less likely to report experiencing low and very low food security among children.
- *Hypothesis B.2:* Higher density of full-service restaurants and limited-service eating places in the household's place of residence is associated with decreased food insecurity. In particular, households with children in locations with higher densities of restaurants are less likely to report experiencing low and very low food security among children.

Hypotheses in group C refer to *demographic and socioeconomic characteristics*—including measures of household financial resources and proxies for resource management skills and nutrition knowledge—that are likely to affect food insecurity. Limited financial resources or management skills constrain the household's ability to acquire food and increase food insecurity. Larger households (e.g., households with more children) put additional demands on resources, because household members share in the available food supply. In addition, the age composition of children in the household may affect the relative needs of households. For instance, households with older children may be relatively more likely to report experiencing low and very low food security. This could be due, in part, to the household response to limited food supply: feeding older children may require more financial resources, or parents may make more effort to protect younger children from experiencing adverse long-term effects of food deprivation. The available resources, management skills, and relative needs measured through the demographic and socioeconomic factors affect food insecurity of children in the households as expressed in related hypotheses:

- *Hypothesis C.1:* Household income decreases food insecurity. In particular, higher-income households are less likely to report experiencing low and very low food security among children.
- *Hypothesis C.2:* Higher educational attainment decreases food insecurity. In particular, households are less likely to report experiencing low and very low food security among children if the householder has higher educational attainment.[10]
- *Hypothesis C.3:* Households of larger size face greater food insecurity. In particular, households are more likely to report experiencing low and very low food security among children when there are more children in the household.
- *Hypothesis C.4:* The impact of an additional child in the household on food insecurity varies with the child's age. In particular, younger children increase the likelihood of the household reporting low and very low food security among children by less than do older children.

Hypotheses in group D refer to individual and household characteristics and circumstances that are likely to affect the amount of time devoted to food preparation by the householder/spouse/unmarried partner. Traditional gender roles and household structure can influence the allocation of time between market work and household production and affect the degree of specialization among household members. For instance, women may spend more time in food preparation relative to men. Also, having more children, especially younger children, may require more time to prepare meals and snacks for family consumption at home. Characteristics such as educational attainment of the householder and household income can affect the opportunity cost of time and ability to substitute market goods for time in home production. For example, members of poorer households may spend more time in food preparation, as such households are less able to pay for increased convenience/time-saving embedded in some food products (e.g.,

[10] Education could be a proxy for wealth. It may also proxy for the ability to efficiently manage financial and time resources and for the stock of nutrition knowledge. In an empirical setting, the different sources of possible effects of educational attainment on food insecurity may be difficult to disentangle.

bagged lettuce) and less able to purchase restaurant meals as a substitute for preparing food at home. In addition, the time in food preparation on a given day may depend on whether the day falls on a weekend or a holiday, as opposed to a regular workday. To illustrate, individuals may spend relatively more time in food preparation on a Sunday or on a holiday due to a lower opportunity cost of time on these days relative to a workday. In addition, the time in food preparation may be affected by seasonal activity patterns (i.e., differential opportunity cost of time across seasons). We summarize all these expected effects in related hypotheses:

- *Hypothesis D.1:* Traditional gender roles affect the reported amount of time in food preparation. In particular, men tend to spend less time in food preparation relative to women.
- *Hypothesis D.2:* Household structure affects the degree of possible specialization in household production and the resulting amount of time in food preparation. In particular, householders in single female- and male-headed households report spending less time in food preparation than wives in married couples and female partners in unmarried couples.
- *Hypothesis D.3:* Children are associated with more time spent by householders/spouses/unmarried partners in food preparation. In particular, the reported amount of time in food preparation increases when there are more children in the household. Also, younger children increase the reported time in food preparation by relatively more than do older children.[11]
- *Hypothesis D.4:* Household financial resources affect the reported amount of time in food preparation. In particular, householders/spouses/unmarried partners spend more time in food preparation when the household is relatively poor (e.g., when household income is below 185% of the federal poverty level).
- *Hypothesis D.5:* The reported (daily) amount of time in food preparation varies with the day of the week and season. More time in food preparation is spent on a Sunday and a holiday relative to a workday. Also, less time in food preparation is

[11] Feeding younger children may require preparing specialized meals that are less suitable for consumption by older children and adults. Thus, parents of younger children may be less able to take advantage of scale economies in food preparation. Also, feeding younger children may require additional time spent in clean-up after meals. Moreover, younger children are less likely than older children to be able to prepare meals and snacks for themselves.

spent (on a daily basis) during summer months relative to winter months.[12]

2.5. Empirical Specification

To facilitate the discussion of empirical specifications of the food insecurity Eq. (6) and the food preparation time Eq. (7) for a household i, we collect all observed explanatory variables expected to affect children's food insecurity into a vector X_i^z and all those anticipated to influence the time in food preparation by the householder/spouse/unmarried partner into a vector X_i^t. The vectors X_i^z and X_i^t include selected demographic and socioeconomic characteristics (H_i), attributes of the household's place of residence (L_i), and additional variables needed to account for the specifics of the data collection, as described below.

The vectors X_i^z and X_i^t partly overlap. In particular, among demographic variables that are common between X_i^z and X_i^t, we include the number of children in the household, differentiated by age (0–4, 5–12, and 13–17 years); number of adults other than the householder, spouse, or unmarried partner; indicators for race, Hispanic origin, and educational attainment of the householder; age of the householder; and an indicator for a foreign-born householder.

Differences between X_i^z and X_i^t in terms of other demographic variables are intended to account for specific aspects of the available data. In particular, since food security data are collected at the household level, X_i^z includes such household structure controls as indicators for an unmarried couple household, single female-headed household, and single male-headed household (married couple households are the base category). In turn, the time use data are available at an individual (rather than household) level. Thus, X_i^t includes indicators for the respondent being a male in a married couple, female in an unmarried couple, male in an unmarried couple, a single female householder, or a single male householder (females in married couples comprise the base category).[13] We distinguish between married and unmarried couple cases, because unmarried (i.e., cohabiting) couples may be relatively less stable or have fewer resources at their disposal than married couples (there may be other differences between married and unmarried couples in terms of unobservable characteristics and preferences).

[12] The opportunity cost of time in food preparation may be higher during summer months because of more possibilities for outdoor leisure activities in comparison to winter months, for example. Also, food preparation may be less pleasurable per se during warmer months.

[13] As discussed in Section 3, we focus on cases where ATUS respondents are householders, spouses of householders, or unmarried partners of householders.

In turn, all household economic characteristics are common between X_i^z and X_i^t. They include real family income; an indicator for missing income; and an indicator for income below 185% of the federal poverty level.

Among location-specific variables, all of which are common between X_i^z and X_i^t, we include an indicator for the household's place of residence in a metropolitan area; indicators for region; local poverty rate; price indices for food at home and fast food; and densities of various types of food establishments expressed as the number of establishments per 10,000 residents in the area. While the price indices and the food establishment densities are specifically included as attributes of the local food environment, indicators for the metropolitan area and region and the local poverty rate variable are introduced to help control for other potentially relevant aspects of the place of residence, such as location-specific population preferences, climate, amenities, etc.—all of which may be important for the production of food security and the pattern of time use in the household.

Additional control variables included to account for the specifics of data collection can somewhat differ between X_i^z and X_i^t. In both cases, the vectors contain indicators for the year of data collection, which may help to control for potential survey-design effects and macroeconomic shocks. X_i^t also contains a set of indicators describing the reference day of the time use data, including day-of-week indicators; an indicator for a holiday; and indicators for the month on which the reference day falls. Time use patterns may substantially differ between weekends/holidays and workdays (due to differences in the opportunity cost of time, for example), and they can also substantially vary across seasons.

We employ categorical data on food insecurity among children, with categories ordered from the least severe to the most severe form of insecurity: (1) high/marginal food security; (2) marginal food security; (3) low food security; and (4) very low food security. Due to the nature of these data, it is convenient to adopt an ordered probit approach to modeling food insecurity. In particular, let $\tilde{z}_{1,i}^*$ be a continuous latent variable underlying the food insecurity of children in household i. We model $\tilde{z}_{1,i}^*$ as a linear index in the explanatory variables:

$$\tilde{z}_{1,i}^* = X_i^{z\prime} \cdot \beta + \epsilon_i, \tag{8}$$

where β is a vector of coefficients to estimate, and ϵ_i is an error term representing the effect of factors that are unobservable to the researcher. Instead of the latent variable $\tilde{z}_{1,i}^*$, we observe an ordered categorical "response" $\tilde{z}_{1,i}$, indicating the food security status of children in household i.

The value of $\tilde{z}_{1,i} \in \{1,2,3,4\}$ places the household in one of the four food security categories listed earlier. We assume that $\tilde{z}_{1,i}$ and $\tilde{z}^*_{1,i}$ are linked as follows:

$$\tilde{z}_{1,i} = k \text{ if and only if } \mu_k < \tilde{z}^*_{1,i} \leq \mu_{k+1}, \tag{9}$$

where $k \in \{1,2,3,4\}$ and "thresholds" μ_k's are such that $\mu_1 = -\infty < \mu_2 < \mu_3 < \mu_4 < \mu_5 = +\infty$. The thresholds μ_2, μ_3, and μ_4 are model parameters to estimate.[14]

In turn, the time in food preparation is reported in minutes per day. This time could be convenient to model as a continuous variable, except that we must account for a substantial fraction of observations with zero time. Thus, we adopt a Tobit approach here. Let $t^*_{1,i}$ be a continuous latent variable underlying the reported time in food preparation by the householder/spouse/partner in household i. We model $t^*_{1,i}$ as a linear index in the explanatory variables:

$$t^*_{1,i} = X_i^{t\prime} \cdot \gamma + \eta_i, \tag{10}$$

where γ is a vector of coefficients to estimate, and η_i is an error term representing the effect of factors that are unobservable to the researcher. We assume that the latent variable $t^*_{1,i}$ and the actually reported time in food preparation $t_{1,i}$ are linked as follows:

$$t_{1,i} = 0, \text{ if } t^*_{1,i} \leq 0; \text{ and } t_{1,i} = t^*_{1,i}, \text{ if } t^*_{1,i} > 0. \tag{11}$$

2.6. Estimation and Inference Approach

It may or may not be the case that a common set of unobservable factors underlies the error term in Eq. (8), ϵ_i, and the error term in Eq. (10), η_i. If, in fact, there is an unobservable factor (e.g., unobservable ability to manage household resources) that affects both the children's food insecurity and the time spent in food preparation by the householder/spouse/partner in household i, then the error terms ϵ_i and η_i may be mutually correlated. In that case, efficiency gains could result from estimating Eqs. (8) and (10) jointly, by using a SUR approach.[15] Because we do not know a priori whether ϵ_i and η_i are correlated with each other, we choose to first estimate the two equations jointly as a system, and then test for the presence of the correlation.

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[14] One of these thresholds would not be identifiable if the linear index $X_i^{z\prime} \cdot \beta$ were to include a constant term. We choose to suppress the constant term in the linear index, and estimate μ_2, μ_3, and μ_4 along with the vector β.

[15] It should be noted that if ϵ_i and η_i are correlated, parameters of the model, such as β and γ, may still be consistently (though not efficiently) estimated by estimating each of the two equations in isolation from the other. If there is indeed no correlation, then the joint and the separate estimations are both consistent, and there is no efficiency gain from performing the joint estimation relative to the separate one.

To be able to estimate the econometric model given by Eqs. (8)–(11), we must specify a few distributional assumptions. In order to simplify the notation, let us combine all explanatory variables for household i into a vector X_i: $X_i = X_i^z \cup X_i^t$. In that case, the data for household i comprise the children's food security status $\tilde{z}_{1,i}$, the amount of time devoted to food preparation by the householder/spouse/partner $t_{1,i}$, and the vector of explanatory variables X_i. Given random sampling, we assume that the data vector, $\left(\tilde{z}_{1,i}, t_{1,i}, X_i\right)'$, is independent and identically distributed (i.i.d.) across i. Next, we specify that the vector of the error terms $(\epsilon_i, \eta_i)'$ is i.i.d. across i as a normal random vector, conditional on X_i:

$$\begin{pmatrix}\epsilon_i \\ \eta_i\end{pmatrix} | X_i \sim i.i.d.N\left(\begin{pmatrix}0 \\ 0\end{pmatrix}, \begin{pmatrix}1 & \rho\cdot\sigma \\ \rho\cdot\sigma & \sigma^2\end{pmatrix}\right), \tag{12}$$

where ρ is the correlation coefficient between ϵ_i and η_i and σ is the standard deviation of η_i (both ρ and σ are model parameters to estimate). The standard deviation of ϵ_i is normalized to one because it is not identifiable in view of the ordered probit approach to modeling food security status (see Maddala, 1983). Eq. (12) implies ϵ_i and η_i have the following joint probability density function, conditional on X_i (see Bartoszyński and Niewiadomska-Bugaj, 1996, p. 395–396):

$$f(\epsilon, \eta) = \frac{1}{2\pi\sigma\sqrt{1-\rho^2}} \cdot \exp\left(-\frac{1}{2(1-\rho^2)} \cdot \left[\epsilon^2 - 2\frac{\rho}{\sigma}\epsilon\eta + \frac{\eta^2}{\sigma^2}\right]\right). \tag{13}$$

By the properties of the normal distribution, the conditional distribution of ϵ_i, given η_i and X_i, is normal: $\epsilon_i | \eta_i, X_i \sim N(\frac{\rho}{\sigma}\eta_i, (1-\rho^2))$; the conditional probability density function here is:

$$f_{\epsilon|\eta}(\epsilon) = \frac{1}{\sqrt{2\pi(1-\rho^2)}} \cdot \exp\left(-\frac{1}{2(1-\rho^2)} \cdot \left[\epsilon - \frac{\rho}{\sigma}\eta\right]^2\right). \tag{14}$$

In turn, the (marginal) distribution of η_i, given X_i, is normal: $\eta_i | X_i \sim N(0, \sigma^2)$; the marginal probability density function is:

$$f_\eta(\eta) = \frac{1}{\sqrt{2\pi}\sigma} \cdot \exp\left(-\frac{1}{2\sigma^2} \cdot \eta^2\right). \tag{15}$$

We estimate the econometric model by the maximum likelihood (ML) method. Let θ stand for the vector of all identifiable parameters:

$$\theta = (\beta', \gamma', \mu_2, \mu_3, \mu_4, \rho, \sigma)'. \tag{16}$$

To express the likelihood contribution of observation i, it is helpful to separately consider two cases: $t_{1,i} = 0$ and $t_{1,i} > 0$. When $t_{1,i} = 0$ (first case), the likelihood contribution is:

$$L_i(\theta) = \tag{17}$$

$$\Pr\left[\mu_{\tilde{z}_{1,i}} < \tilde{z}_{1,i}^* \le \mu_{\tilde{z}_{1,i}+1}, t_{1,i}^* \le 0 | X_i; \theta\right] =$$

$$\Pr\left[\mu_{\tilde{z}_{1,i}} < X_i^{z\prime}\beta + \epsilon_i \le \mu_{\tilde{z}_{1,i}+1}, X_i^{t\prime}\gamma + \eta_i \le 0 | X_i; \theta\right] =$$

$$\Pr\left[\mu_{\tilde{z}_{1,i}} - X_i^{z\prime}\beta < \epsilon_i \le \mu_{\tilde{z}_{1,i}+1} - X_i^{z\prime}\beta, \eta_i \le -X_i^{t\prime}\gamma | X_i; \theta\right] = \int_{\mu_{\tilde{z}_{1,i}} - X_i^{z\prime}\beta}^{\mu_{\tilde{z}_{1,i}+1} - X_i^{z\prime}\beta} \int_{-\infty}^{-X_i^{t\prime}\gamma} f(\epsilon, \eta) d\eta d\epsilon,$$

where the formula for the joint probability density function $f(\epsilon, \eta)$ is given by Eq. (13).

When $t_{1,i} > 0$ (second case), it is convenient to represent the joint probability of $\tilde{z}_{1,i}$ and $t_{1,i}$ as a product of the marginal density of η_i and a conditional probability of ϵ_i given η_i. More specifically, the likelihood contribution can be expressed as follows:

$$L_i(\theta) = \tag{18}$$

$$f_\eta\left(t_{1,i} - X_i^{t\prime}\gamma\right) \cdot \Pr\left[\mu_{\tilde{z}_{1,i}} < \tilde{z}_{1,i}^* \le \mu_{\tilde{z}_{1,i}+1} | t_{1,i} = X_i^{t\prime}\gamma + \eta_i, X_i; \theta\right] =$$

$$f_\eta\left(t_{1,i} - X_i^{t\prime}\gamma\right) \cdot \Pr\left[\mu_{\tilde{z}_{1,i}} - X_i^{z\prime}\beta < \epsilon_i \le \mu_{\tilde{z}_{1,i}+1} - X_i^{z\prime}\beta | \eta_i = t_{1,i} - X_i^{t\prime}\gamma, X_i; \theta\right] =$$

$$f_\eta\left(t_{1,i} - X_i^{t\prime}\gamma\right) \cdot \int_{\mu_{\tilde{z}_{1,i}} - X_i^{z\prime}\beta}^{\mu_{\tilde{z}_{1,i}+1} - X_i^{z\prime}\beta} f_{\epsilon | t_{1,i} - X_i^{t\prime}\gamma}(\epsilon) d\epsilon,$$

where the formula for the conditional probability density function $f_{\epsilon | t_{1,i} - X_i^{t\prime}\gamma}(\epsilon)$ is obtained from the expression for $f_{\epsilon|\eta}(\epsilon)$ in Eq. (14) by replacing η with $t_{1,i} - X_i^{t\prime}\gamma$.[16]

By using Eq. (17) or Eq. (18), when appropriate, to calculate $L_i(\theta)$, the model parameters can be estimated by the ML method:

$$\hat{\theta}_{MLE} = \arg\max_\theta \sum_{i=1}^n \ln L_i(\theta), \tag{19}$$

where $\hat{\theta}_{MLE}$ denotes the ML estimator (MLE) and n stands for the sample size.

As a technical matter, we should note that since the children's food security status is modeled using an ordered probit approach and the time in food preparation is modeled using a Tobit approach, the computation of $\hat{\theta}_{MLE}$ in Eq. (19) involves estimating a mixed-process model in a SUR framework. Roodman (2011) discusses estimation of such models in Stata with a "CMP"

[16] The bivariate integral in Eq. (17) and univariate integral in Eq. (18) can be computed numerically by using existing algorithms for evaluating bivariate normal and univariate normal rectangle probabilities.

package, which we use. He also provides details on model reparameterization and computation of analytical derivatives of the log-likelihood contribution. Once our model is estimated, statistical inference and hypothesis testing can be performed using conventional MLE techniques (see Greene, 2012, Ch. 14).

Finally, we note that the vector of coefficients β in Eq. (8) and the vector of coefficients γ in Eq. (9) are specified in terms of corresponding latent variable scales. Although the signs of these coefficients should be informative as to the direction of impacts of explanatory variables on the children's food insecurity and on the time in food preparation, the magnitudes of the coefficients can be difficult to interpret. Therefore, in order to facilitate the interpretation of the estimation results, we compute average marginal effects (*AME*) associated with the explanatory variables. More specifically, in the case of the children's food insecurity, we calculate average marginal effects representing the impact of a change in an explanatory variable on the probability of each categorical food security status, as implied by the estimated model:

$$AME(\tilde{z}_1 = k) = \frac{1}{n}\sum_{i=1}^{n} \frac{\partial}{\partial X_i} \Pr[\tilde{z}_{1,i} = k | X_i; \hat{\theta}_{MLE}] \,, \tag{20}$$

where $k \in \{1,2,3,4\}$ denotes a food insecurity outcome of interest. Thus, the magnitude of an element of the vector $AME(\tilde{z}_1 = k)$ may be interpreted as an average change in the probability of children's food security status k that is associated with a unit change in the corresponding explanatory variable.

In the case of the time in food preparation, we calculate average marginal effects representing the impact of a change in an explanatory variable on the expected value of the amount of time in food preparation, as implied by the estimated model:

$$AME(t_1) = \frac{1}{n}\sum_{i=1}^{n} \frac{\partial}{\partial X_i} \mathrm{E}[t_{1,i} | X_i; \hat{\theta}_{MLE}] \,. \tag{21}$$

Greene (2012, pp. 848–850) discusses marginal effects of a form similar to Eq. (21) in the context of a conventional Tobit model. Notably, unlike the values of coefficients γ in Eq. (10) specified in terms of the latent variable $t^*_{1,i}$, the magnitudes of the averages marginal effects in Eq. (21) account for the fact that the observed amount of time in food preparation $t_{1,i}$ cannot be negative.[17] Thus, the magnitude of an element of the vector $AME(t_1)$ may be interpreted as an average change in

[17] Recall from Eq. (11) that $t_{1,i} = 0$ if $t^*_{1,i} \leq 0$, and $t_{1,i} = t^*_{1,i}$ if $t^*_{1,i} > 0$. Thus, the latent variable $t^*_{1,i}$, which underlies the observed time in food preparation $t_{1,i}$, can be negative; but the observed time in food preparation itself is always nonnegative: $t_{1,i} \geq 0$. The left-censoring at zero here gives rise to the difference between the values of coefficients γ and the magnitudes of the average marginal effects $AME(t_1)$.

the expected amount of time in food preparation (specified in minutes per day) that is associated with a unit change in the corresponding explanatory variable.

3. Data

3.1. Overview

The two main sources of data for this research project are the Food Security Supplement (FSS) of the Current Population Survey (CPS), 2002–2010, and the American Time Use Survey (ATUS), 2003–2011. These two datasets are pooled across the years and cross-linked to construct a matched analytical sample (N = 13,474). Direct linking of observations is possible here owing to the fact that the ATUS is collected on a subsample of CPS participants soon after their households exit the CPS. An advantage to pooling the data across the years is that we are able to compile a sufficiently large sample in order to investigate a relatively rare phenomenon of very low food security among children. Also, the approach allows us to utilize both the spatial (cross-sectional) and the time variation in the data to identify parameters of the empirical model. The matched ATUS–FSS data are supplemented with location-specific variables (e.g., local food price indices, food establishment densities, and local poverty rate values) obtained using data from other sources, such as the Quarterly Food-at-Home Price Database (QFAHPD), a price database of the American Chamber of Commerce Researchers Association (ACCRA), the County Business Patterns (CBP) database, the Small Area Income and Poverty Estimates (SAIPE) program's database, and the American FactFinder database. As described in more detail below, the matching of the ATUS–FSS data to the location-specific variables is performed using geographic identifiers provided in the core CPS. Also, to account for the impact of inflation across the years, we deflate all nominal price and income measures into real dollar values (1982–1984 dollars) by using the Consumer Price Index (CPI) series (BLS, 2013).

3.2. Main Data Sources

3.2.1. Food Security Supplement (FSS) of Current Population Survey (CPS)

Presently, the FSS of the CPS is administered every calendar year in December on a nationally representative probability sample of households who completed the core CPS in that month.[18] While the FSS collects, among other data, the information on household food spending and participation in a number of federal food assistance programs, the main objective of the supplement is to help policymakers and researchers assess the severity of food insecurity experienced in U.S. households.

For purposes of this research project, the FSS has a key advantage over other nationally representative surveys collecting food insecurity data (e.g., the National Health and Nutrition Examination Survey, or NHANES). Namely, it provides us with a sufficiently large sample of households to investigate the phenomena of low and very low food security among children in the United States, especially when the FSS data are pooled across multiple years. Having a large sample size is critical for studying the relatively rare phenomenon of very low food security among children.

In the FSS, food security measures are based on the 18-item Household Food Security Survey Module (HFSSM). Eight of the HFSSM items are child-specific (for details on the measures, see NRC, 2006; Coleman-Jensen et al., 2012a; 2012b). It should be noted that the module contains questions referenced to the last 12 months and the last 30 days before the interview. We focus on child-specific food security items and measures referenced to the last 12 months.[19] We pool the FSS data across the years 2002–2010. The decision to start with the year 2002 is motivated by the time frame of the available ATUS data (the years 2003–2011), which are linked to FSS records when creating an analytical sample (see Section 3.3). Notably, the investigated period covers the time of substantial economic change, including the most recent recession. Also, by pooling the data across the years, we are able to utilize both the spatial (cross-sectional) and the time variation in the data in order to identify parameters of the empirical model.

3.2.2 American Time Use Survey (ATUS)

The ATUS is a nationally representative time use survey conducted by the U.S. Census Bureau for the Bureau of Labor Statistics (BLS). Its main purpose is to quantify the amount of time Americans

[18] The CPS is a monthly survey of about 50,000 households, conducted by the U.S. Census Bureau (see U.S. Census Bureau, 2011). By design, it is representative of the U.S. civilian noninstitutional population. Although the main purpose of the CPS is to collect employment data, its notable secondary goal is to obtain demographic and socioeconomic information. CPS supplements, such as the FSS, are periodically added to the core CPS in order to collect more specialized data on the U.S. population.

[19] The FSS is also the source of demographic and socioeconomic variables controlled for in the analysis.

devote to non-market activities, such as food preparation, childcare, and various leisure activities. The data have been collected continuously since January 2003, using randomly selected respondents (15 or more years of age) from a subsample of households exiting the CPS.[20] Only one respondent per household is interviewed. For purposes of this research project, an important aspect of the ATUS is that its records can be linked directly to records in the core CPS (and therefore, also to records in the FSS, which is a supplement to the core CPS administered in December), which allows us to construct a matched ATUS–FSS sample for analysis (for details, see Section 3.4).

The reference period for time use comprises 24 hours, starting at 4am on the day before an ATUS interview and ending at 4am on the day of the interview. For this reference period, a respondent reports his or her daily activities and their starting and ending times.[21] The responses are subsequently coded by the ATUS staff using an activity lexicon with three layers of detail.[22] Notably, except in the case of childcare, the ATUS collects time use data only for "primary" activities. If a respondent was engaged in more than one activity at a time, the choice as to which of the activities to classify as primary is made by the respondent himself or herself (rather than assigned by the interviewer). Additional data are collected on childcare performed as a "secondary" activity. Interviews in the ATUS are scheduled throughout an entire calendar year and all seven days of the week (i.e., including workdays and weekend days), which motivates including corresponding indicator variables in the empirical specification so as to account for potentially systematic variation in the time in food preparation by calendar season and day-of-the-week. Additional details on the ATUS design can be found in the user guide (BLS, 2012).

3.3. Construction of ATUS–FSS Analytical Sample

The ATUS–FSS sample for the empirical analysis is constructed in two stages. First, since ATUS respondents are recruited from among CPS participants, and the FSS itself is administered as part of the CPS, we construct an initial FSS sample of households with children. Second, we link records from this FSS sample to respondent records in the ATUS and prepare the ATUS–FSS analytical sample on the basis of the matched data. The main steps of our two-stage data processing

[20] The average time gap between a final CPS interview and an ATUS interview is roughly three months.
[21] Additional information is often collected on the location of activities and identities of other individuals present.
[22] Each such layer is coded using two digits. Thus, the most detailed description of an activity in the ATUS is represented by a six-digit code.

procedure are outlined below.

In the first stage, we download December CPS–FSS merged data files for each year between 2002 and 2010 from the website of the Interuniversity Consortium for Political and Social Research (ICPSR): http://www.icpsr.umich.edu/icpsrweb/landing.jsp. Each file contains roughly 150,000–160,000 individual records. We clean and process the data in a sequence of steps, as described in Table 1. First, we delete all records without administered CPS interviews. An interview could not be administered if no one was home or the house was found demolished, for example. Second, we delete all records without administered FSS interviews (some households declined to participate in the FSS after having completed the core CPS). Third, because our main research objective is to investigate circumstances of food-insecure children, we delete all records from households *without* children. We apply the same child definition as that in the FSS: a child is an individual who is not a household reference person (we often refer to CPS reference persons as "householders," because the home is rented or owned in their name) or the spouse of the reference person, and who is at most 17 years of age. Fourth, we only retain records from households who responded to the FSS as part of their *second* four-month period in the CPS.

The CPS employs a complex survey design. A newly recruited household is interviewed every month during the first four months in the survey. Then, it is out of the CPS sample during the following eight months. Finally, it is brought back into the CPS sample and interviewed every month during the following four months. As such, it is possible for a household to respond to the FSS twice, with an interval of one year. By focusing only on households in their last four months in the CPS, we avoid introducing a complicated data dependence pattern in the sample when the data are pooled across years (each household in the resulting FSS sample is unique). Moreover, the approach facilitates the matching of the FSS records to those in the ATUS. In particular, because the ATUS respondents are recruited from among members of households exiting the CPS and are interviewed at least a couple of months after the household participated in the CPS for the last time, the approach is aimed at minimizing the time gap between the data collection points in the FSS and the ATUS. Fifth, two out of eight household rotations in the December 2007 CPS—namely, households in their third and eighth months in the CPS (roughly one-fourth of the full December 2007 sample)—were administered an experimental FSS questionnaire with changed wording on some questions. The proposed tested wording change did not perform adequately (Nord, 2009, p. 2). As a result, all food security categorical and raw score variables for the affected households are missing. We exclude such households from further consideration. Because households in their third month in the CPS are dropped at the previous data processing stage, we now only delete records from all households in the 8th-month CPS rotation (as of December 2007). Sixth, we delete all records with missing responses to food security questions. Some households who participated in the FSS failed to answer all questions necessary to determine the food security status of children (the number of such cases is small relative to the overall sample size).

Table 1 shows that after applying the above data processing steps, we are left with about 28,000–34,000 individual FSS records per year (except in the case of the year 2007, when the number of records is less, at approximately 22,000). Of these records, roughly 53% contain information on adults and 47% on children. We employ both adult and child records to construct explanatory variables for use in the empirical analysis. Table 1 also shows the distribution, by year, of household records comprising the FSS sample (N = 68,381). Except in the case of the year 2007, each annual period provides between 7,068 and 8,616 household observations. The year 2007 is an exception in that it provides only 5,627 observations.

In the second stage, we download all ATUS data files for each year between 2003 and 2011 from a webpage maintained by the BLS: http://www.bls.gov/tus/#data. To construct the ATUS–FSS analytical sample, we match, whenever possible, an individual FSS record from December of year t to a corresponding ATUS record from year t+1. Table 2 outlines the procedure. First, we follow the instructions in Appendix K "Linking ATUS files to CPS files" of the ATUS User's Guide (BLS, 2012) and link individual records in the FSS sample to records of prospective ATUS participants in ATUS–CPS files. Since ATUS respondents comprise a proper subsample of the CPS sample, we retain less than half (roughly 45%) of the FSS sample at this linking step.[23] The fraction of the retained records declines between 2003 and 2004, consistent with a reduction in the monthly ATUS sample size implemented in December 2003 (BLS, 2012, p. 12). Second, not all designated individuals were actually interviewed in the ATUS (e.g., a prospective respondent could still be deemed ineligible for the ATUS, could not be contacted, or could simply refuse to participate). Such cases are dropped from the sample, resulting in a further decline in the retained records. Third, to ensure that researchers would be able to work with high quality data, after each ATUS interview (conducted over the phone) an interviewer recorded whether the interview should

[23] To clarify, only a fraction of households exiting the CPS are designated to be contacted by the ATUS staff. Also, only one member per household is designated to be interviewed in the ATUS.

or should not be used. In the latter case, the interviewer also provided a reason: for example, whether he or she thought that the respondent intentionally provided wrong answers, tried to provide correct answers but could not correctly remember the activities, or deliberately reported very long duration activities. All such records are deleted from the sample (the number of such deletions is relatively small). Fourth, by design, an ATUS respondent need not be the same person as the CPS reference person, but could be the spouse, unmarried partner, child, grandchild, etc. of the CPS reference person. We choose to focus on records of ATUS respondents who are the CPS reference person, the reference person's spouse, or the reference person's unmarried partner ("householder/spouse/partner"), because their time use—in particular, the time they devote to food preparation—is likely to be most relevant for understanding the provision of food for at-home consumption in the household.[24] Records of the other types of respondents (children, grandchildren, etc.) are excluded from further consideration (matched FSS household records in such instances are likewise dropped). This step leads to a moderate reduction in the sample size.

Table 2 shows that each annual period contributes between 1,058 and 2,274 observations to the ATUS–FSS analytical sample. The FSS year 2002 (ATUS year 2003) and the FSS year 2007 (ATUS year 2008) are exceptional in that they provide considerably more and considerably fewer observations, respectively, than the other years. The total number of observations in the analytical sample is 13,474, which represents both the number of ATUS respondents and the number of matched households. This sample is the focus of subsequent empirical work.

3.4. Additional Data Sources

3.4.1. Quarterly Food-at-Home Price Database (QFAHPD)

The QFAHPD is a source of comprehensive estimates of food-at-home prices in the United States (see Todd et al., 2010; Zhylyevskyy et al., 2013). The database is provided for public use by the Economic Research Service (ERS) of the U.S. Department of Agriculture (USDA). It contains nominal quarterly prices, specified in dollars per 100 grams of food as purchased by consumers (for consumption at home), for over 50 different food groups. The food group prices are available separately for 35 distinct geographical areas covering the contiguous United States and for every

[24] All unmarried partners in our sample are at least 18 years old.

quarter between 1999 and 2010.[25] Thus, the data can help to account for spatial and time variation in U.S. food prices.

The QFAHPD is based on Nielsen Homescan survey data, which contain information on food purchases by a demographically balanced panel of metropolitan and nonmetropolitan households. The households report transactions from a wide variety of store types, including grocery, drug, mass-merchandise, club, supercenter, and convenience stores. The ERS classified household-level purchases by food group and aggregated information on the purchases to obtain household-level quarterly prices for each food group. Then, the household-level quarterly prices were aggregated to obtain quarterly, market-area food-group prices. The ERS created market areas using geographical information in Nielsen Homescan and aggregated the data into 26 metropolitan and 9 nonmetropolitan areas, for a total of 35 areas. See Todd et al. (2010) for additional details.

We use the QFAHPD to construct an index of prices for food consumed at home. More specifically, we first calculate a quarterly index as an expenditure-weighted average of quarterly real food group prices available in the database (real prices, expressed in 1982–1984 dollars, are obtained by deflating nominal prices by the CPI). The weight of a food group in the index represents annual U.S. expenditures on the group as a fraction of annual U.S. expenditures on all food groups covered in the database in 2004 (the expenditure data are available). We then compute an annual price index as an average of corresponding quarterly index values. The data are merged with the ATUS–FSS records according to the household's place of residence, by using a matching procedure similar to that of Gregory and Coleman-Jensen (2013), in which each record from the sample is mapped to a particular market area covered in the QFAHPD.

3.4.2. American Chamber of Commerce Researchers Association (ACCRA) Database

Although less comprehensive than the QFAHPD in terms of the coverage of food-at-home items, the ACCRA database is the only publicly available, extensive source of location- and time-specific fast food prices in the United States.[26] In particular, the database provides nominal prices for the following three fast food items: (1) a McDonald's quarter-pounder hamburger with cheese, (2) an

[25] Presently, the ERS provides two versions of the database: QFAHPD-1 (covering the years 1999 through 2006), which is based on UPC-coded and random-weight purchases, and QFAHPD-2 (2004 through 2010), which is based only on UPC-coded purchases. We employ QFAHPD-2 as the main source of food-at-home price data for 2004–2010, and supplement it with data for 2002–2003 from QFAHPD-1. We account for small differences in the food group coverage between the two database versions by appropriately adjusting weights in the price index.

[26] In the mid-2000s, the ACCRA was renamed as the Council for Community and Economic Research (C2ER).

11–12” thin crusted cheese pizza at Pizza Hut or Pizza Inn, and (3) fried chicken (thigh and drumstick) at Kentucky Fried Chicken or Church’s. During 2002–2010, the data are available on a quarterly basis, for approximately 350–400 different metropolitan areas (coverage slightly varies over time).

We follow an approach due to Chou et al. (2004) and Powell (2009) and compute a fast food price index as a simple average of prices of the three indicated items. More specifically, we first calculate real prices (in 1982–1984 dollars) of the items by deflating their nominal prices by the CPI. Next, we compute an average of the real prices separately for each quarter and metropolitan area and obtain quarterly fast food price index values. Lastly, we average these quarterly index values over four corresponding quarters of a calendar year and compute the annual fast food price index.[27] The data are merged with the ATUS–FSS records according to the household’s place of residence. We are able to match about two-thirds of the sample directly by a CBSA FIPS code. In the remaining cases, we match a sample record to an average of the fast food price index values across metropolitan areas covered by the ACCRA in the household’s state of residence, by using a state FIPS code.

3.4.3. American FactFinder Database

American FactFinder (http://factfinder2.census.gov) is an online resource maintained by the U.S. Census Bureau to provide access to publicly available data in the Decennial Census, the American Community Survey, the Economic Census, etc. We use this resource to extract annual population counts for every county in the United States during 2002–2010, and employ the counts to construct local poverty rate and food establishment density measures.

3.4.4. Small Area Income and Poverty Estimates (SAIPE) Program Database

The U.S. Census Bureau’s SAIPE program (http://www.census.gov/did/www/saipe/) provides more current estimates of selected income and poverty statistics than those available from the most recent Decennial Census. The estimates combine data from administrative records, postcensal population estimates, and the Decennial Census with direct estimates from the American Community Survey. We use the program’s database to obtain annual counts of people in poverty (below 100% of the federal poverty level) for every country in the United States during 2002–

[27] Starting in 2007, the ACCRA also contains annual price averages, which we employ directly.

2010. We then compute a local poverty rate measure (location- and year-specific) representing the number of people of all ages in poverty as a fraction of total population in the household's place of residence. To accommodate the specifics of geographical identifiers available for the ATUS–FSS analytical sample, we construct the local poverty rate variable separately at three levels of geographical aggregation: (1) county, (2) MSA (prior to the year 2004) or CBSA (starting in 2004), and (3) state. The poverty rate data are merged with the sample records according to the place of residence at the most detailed geographical level available. Approximately 45% of the records are matched by the county FIPS code. Of the remaining 55%, roughly one-half are matched by the CBSA (MSA) FIPS code, and the rest are matched by the state FIPS code. It should be noted that measures of community poverty are often used in the literature on local food availability (e.g., see Lee, 2012).

3.4.5. County Business Patterns (CBP) Database

The U.S. Census Bureau's CBP (http://www.census.gov/econ/cbp/) is an annual series that provides selected county-level economic data by industry, including the number of local business establishments, employment, and payroll. Businesses are classified by a six-digit code in accordance with the North American Industry Classification System (NAICS). We extract raw counts of local food establishments, while sorting the establishments into the following five groups: (1) supermarkets and other general line grocery stores, (2) convenience stores (including gasoline stations with convenience stores), (3) specialty food stores, (4) full-service restaurants, and (5) limited-service eating places. The group of "Supermarkets and other general line grocery stores" comprises establishments with NAICS codes 445110 "Supermarkets and other grocery (except convenience) stores" and 452910 "Warehouse clubs and supercenters." The group of "Convenience stores" includes establishments with codes 445120 "Convenience stores" and 447110 "Gasoline stations with convenience stores." The group of "Specialty food stores" represents establishments with codes 445210 "Meat markets," 445220 "Fish and seafood markets," 445230 "Fruit and vegetable markets," 445291 "Baked goods stores," 445292 "Confectionery and nut stores," 445299 "All other specialty food stores," and 311811 "Retail bakeries." The group of "Full-service restaurants" comprises establishments with a code 722110 "Full-service restaurants." The group of "Limited-service eating places" is composed of establishments with codes 722211 "Limited-service restaurants," 722212 "Cafeterias, grill buffets, and buffets," and 722213 "Snack and nonalcoholic beverage bars."

We use the extracted counts to construct food establishment density measures, expressed as the number of establishments of a particular type per 10,000 local residents. Analogous to the local poverty rate variable, the density measures are first created at three different levels of geographical aggregation (county, MSA/CBSA, and state), and then merged with the ATUS–FSS records according to the most detailed geographical level available. It should be noted that population-based densities of food stores and restaurants are commonly used in the literature to account for differential availability of food and potentially varying time cost of acquiring food across neighborhoods (e.g., see Chou et al., 2004; Moore and Diez Roux, 2006; Auld and Powell, 2009; Powell, 2009; An and Sturm, 2012; Bonanno and Goetz, 2012; and Lee, 2012). Also, Rose and Richards (2004, p. 1081) indicate that "environmental factors are importantly related to dietary choice in a nationally representative sample of low-income households."

3.5. Characteristics of ATUS–FSS Analytical Sample

3.5.1. Children's Food Insecurity

We employ a categorical measure of children's food insecurity that is referenced to the last 12 months. It is based on the FSS variable HRFS12M6 ("Children's Food Security Raw Score, 12-Month Recall"). The labels for the categories follow the official USDA labels (see Nord and Hopwood, 2007, p. 535; also, see Nord, 2009). However, we split the USDA category "High or marginal food security" (a raw score of 0–1) into two categories: "High/marginal food security" (a raw score of 0) and "Marginal food security" (score of 1). We prefer to use the label "High/marginal food security," because among the eight child-specific items in the HFSSM, there is no item with low enough severity of food insecurity among children to reliably differentiate "high food security" from "marginal food security" among children.

Table 3 provides the distribution of households in the ATUS–FSS analytical sample by the children's food security status (the listed fractions of households are computed using the ATUS sample weights). The predominant majority of households (85.91%) indicate high/marginal food security among children, and seven percent (6.80%) indicate marginal food security. Slightly over seven percent of households indicate that children are food insecure, with low (6.73%) or very low (0.57%) food security among children.

3.5.2. Time in Food Preparation

We use the ATUS data to construct a measure of time in food preparation. It encompasses activities such as food preparation, presentation, and clean-up as well as grocery shopping and related travel. The measure is analogous to the one employed by Davis and You (2011). More specifically, we calculate the time devoted to food preparation by an individual as the sum of his or her reported time (in minutes on the ATUS diary day) in the following seven distinct activities defined by the ATUS lexicon:

- 020201 "Food and drink preparation,"
- 020202 "Food presentation,"
- 020203 "Kitchen and food clean-up,"
- 020299 "Food and drink preparation, presentation, and clean-up, n.e.c.,"
- 070101 "Grocery shopping,"
- 180202 "Travel related to food and drink preparation, clean-up, and presentation,"
- 180701 "Travel related to grocery shopping."[28]

Table 4 lists descriptive statistics for the constructed measure, including statistics that are specific to the respondent's gender (the descriptive statistics in this table and all following tables are calculated using the ATUS sample weights). Among the individuals in the ATUS–FSS analytical sample, 34.26% do not report having been engaged in a food preparation activity on the diary day (the time in food preparation for these individuals is zero). A substantial difference is observed here with respect to the gender of respondent, as 53.26% of men but only 18.33% of women in the sample indicate no time in food preparation. Among those with a positive time in food preparation, the mean duration of food preparation is 79.20 minutes (on the diary day) and the median duration is 60 minutes. Expectedly, we see a substantial difference between men and women who were engaged in food preparation: the mean (median) time is 56.15 (40) minutes for men and 90.26 (70) minutes for women. Thus, among the respondents in the analytical sample, women are more likely than men to do food preparation. Moreover, among those reporting a positive time in food preparation, women tend to devote more time to the activity than men.[29]

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[28] Activities in the ATUS lexicon are identified by a six-digit code. Also, an ATUS lexicon abbreviation "n.e.c." stands for "not elsewhere classified."

[29] We perform tests (not reported in Table 4) to check if the indicated differences between men and women are statistically significant. In a test of equal proportions, the null hypothesis of the equality between the proportion of men who report a positive time in food preparation and the corresponding proportion of women is rejected at less than 0.01% significance level. Also, in a test of equal means, the null hypothesis of the equality between the mean duration

To provide an additional, graphical illustration for the difference between the genders, Figure 1 plots kernel densities of the amount of time in food preparation for men and women among those reporting the activity on the diary day. As can be seen, while both distributions have a long right tail (i.e., they are both skewed to the right), there is a substantial difference between the density for men and that for women. In particular, shorter durations of food preparation are relatively less frequent and longer durations are relatively more frequent among women, indicating that women tend to spend more time in food preparation than men.

3.5.3. Demographic and Socioeconomic Characteristics

Table 5 shows descriptive statistics for demographic and socioeconomic characteristics of the ATUS–FSS analytical sample. To prevent confusion, we note that data in the sample consist of linked ATUS respondent–FSS household records, with exactly one individual ATUS respondent per an FSS household.[30] Thus, the number of individuals in the sample (n = 13,474) is identically equal to the number of households.

We distinguish among cases of married couples, unmarried (i.e., cohabiting) couples, and single-headed households; and we additionally differentiate between males and females, as needed. In the analytical sample, 40.59% of the individuals are females in married couples (i.e., wives), 40.68% are males in married couples (husbands), 2.64% are females in unmarried couples, 2.52% are males in unmarried couples, 11.17% are single female householders, and 2.40% are single male householders. It follows that 81.27% of the households in the sample are married couple households, 5.16% are unmarried couple households, 11.17% are single female-headed households, and 2.40% are single male-headed households.

We consider a range of household "background" characteristics in addition to the household structure (to clarify, all these characteristics refer to the time of the FSS data collection for the household). Households in the sample contain up to five children of age 0–4 years, with 0.53 children in this age category on average; up to seven children of age 5–12 years, with 0.86 children in this category on average; and up to five children of age 13–17 years, with 0.50 such

of food preparation for men and the corresponding mean duration for women (conditional on positive time in food preparation in each case) is rejected at less than 0.01% significance level. Thus, the indicated differences are, indeed, statistically significant.

[30] Also, recall that due to specific aspects of the available data, the analysis of children's food insecurity is performed at the household level, while the analysis of food preparation time is conducted at the individual level.

children on average. Also, the households contain up to six adults other than the householder himself or herself and other that the householder's spouse or unmarried partner, with 0.30 such adults on average. These 'other' adults can include the householder's children who are eighteen years of age or older.

In a large majority (82.76%) of the cases in the sample, the householder is White; and in 10.75% and 6.50% of the cases he or she is African American and of some other race, respectively. Also, 16.88% of the householders are Hispanic. The age of the householders ranges from 16 to 85 years, with an average age of 39.86 years. Nearly twelve percent (11.91%) of them have no high school degree, 27.66% have a high school degree or GED, 26.63% have some college education (including, among other possibilities, vocational and academic associate degrees), 22.19% have a bachelor's degree, and 11.61% have a graduate degree (i.e., a master's, professional, or doctorate degree). The education categories here are mutually exclusive and exhaustive and describe the highest education level attained. Nearly eighteen percent (17.88%) of the householders are foreign-born, which includes individuals who are U.S. citizens by naturalization and non-U.S. citizens.

The available income measure in the December CPS represents the combined income of all family members who are fifteen years of age or older during the last twelve months, including money from jobs; net income from business, farm, or rent; pensions; dividends; interest; Social Security payments; and any other money income. These income data are collected using nominal income brackets (the specification of the brackets slightly varies over time). We set nominal income at the midpoint of the reported bracket and then convert the value into real dollars using the CPI series (BLS, 2013). In addition, we create a dummy variable indicating a case of missing income information, and we employ a poverty indicator provided in the FSS for income below 185% of the federal poverty level (FSS variable "HRPOOR"). Among households with non-missing income data, real family income ranges between $2,293 and $81,522, with an average value of $32,680. The information on income is missing for 9.36% of the households in the sample. Also, 31.45% of the cases have income below 185% of the poverty level.

3.5.4. Location-Specific Characteristics

Table 6 lists descriptive statistics for attributes of the household's place of residence (as of the time of the FSS interview). Among the households in the ATUS–FSS analytical sample, 82.11% live in a metropolitan area. Also, 17.68% reside in the Northeast region, 25.42% in the Midwest region, 33.73% in the South region, and 23.18% in the West region.

The local poverty rate measure represents the fraction of local residents living in poverty, based on estimates compiled by the SAIPE program (for details, see Section 3.4.4). For the households in the sample, the local poverty rate ranges from 2.35% to 40.93%, with an average value of 12.37%.

The local food-at-home price index is an average of local food prices, expressed in real dollars per 100 grams of food as purchased. It is based on the food price data in the QFAHPD (see Section 3.4.1). For the households in the sample, the value of the index is between 0.21 and 0.32, with an average value of 0.24 (real $/100g of food at home). In turn, the local fast food price index is an average of real prices of three fast food items (hamburger, cheese pizza, and fried chicken), based on the price data in the ACCRA database (Section 3.4.2). The value of the index ranges from 2.13 to 3.95, with an average value of 2.66 (real $).

The last set of location-specific characteristics controlled for in the empirical analysis comprises the densities of five distinct types of local food business establishments. Each density is calculated as the number of local food establishments of a given type per 10,000 local residents (for details, see Section 3.4.5). The statistics presented in Table 6 suggest that the households in the sample face different local food environments. In particular, the density of supermarkets and other general line grocery stores ranges from 0.69 to 8.34, with an average value of 2.17 (supermarkets per 10,000 local residents). The density of convenience stores, including gas stations with convenience stores, is between 0.74 and 10.38, with an average value of 3.80 (convenience stores per 10,000 local residents). The density of specialty food stores ranges from 0.10 to 4.89, with an average value of 1.11 (specialty food stores per 10,000 local residents). In turn, the density of full-service restaurants is between 2.48 and 26.40, with an average value of 7.00 (restaurants per 10,000 local residents). The density of limited-service eating places ranges from 3.34 to 20.12, with an average value of 8.68 (eating places per 10,000 local residents).

3.5.5. Temporal Characteristics

The households in the ATUS–FSS analytical sample were administered the FSS questionnaire in different years during the period covered in this report.[31] Also, the ATUS respondents in these households were surveyed regarding their time use on different days throughout a year. To prevent confusion, we emphasize that while the FSS data for a particular household are collected during a calendar year *t*, the corresponding ATUS respondent data are collected during a year *t* + 1. On average, the time gap between the corresponding FSS and ATUS data collection dates in the analytical sample is 4.5 months.

Table 7 provides descriptive statistics for dummy variables indicating the specific time of data collection. In the case of the FSS household data, we create dummies representing the calendar year of the data collection (namely, the years 2002, 2003,…, 2010). In the case of the ATUS respondent data, we create dummies representing the year (2003, 2004,…, 2011—these years are shifted by one relative to the year of the corresponding FSS household data), day of the week, holiday status, and month of the ATUS diary day.

In the empirical analysis, the year dummies may help to account for impacts of macroeconomic shocks as well as for potential survey design effects. The weighted fractions of the sample observations originating in different years range from 8.77% for the year 2007 to 12.08% for the year 2003 in the case of the FSS household data (the years 2008 and 2004, respectively, in the case of the ATUS respondent data). In most instances, the fraction of observations coming from a given year is roughly 11%. The year 2007 (2008) is an exception in that it provides fewer observations because of a reduced usable sample in the 2007 FSS.[32]

The empirical analysis of food preparation time additionally includes dummies characterizing the ATUS diary day, namely: the specific day of the week on which the diary day falls, whether the diary day is a federal holiday, and the specific calendar month of the diary day. These dummies may help to account for a variation in time use due to systematic differences in the opportunity cost of time across days and seasons. The weighted fractions of the sample observations originating on different days of the week are similar, with roughly 14% of the observations falling on each day of the week (Sunday through Saturday). Slightly more than two

[31] Recall that each FSS questionnaire is administered in December, following the core CPS interview in that month. In addition, recall that we pool FSS data across multiple years—2002 through 2010—to obtain a sufficiently large sample size in order to investigate the relatively rare phenomenon of very low food security among children.

[32] Recall that about one-fourth of the full sample of the 2007 FSS of the CPS could not be employed for food security estimates, because a proposed FSS questionnaire wording change tested in those cases did not perform adequately (Nord, 2009, p. 2). We excluded all such cases from consideration when constructing the ATUS–FSS analytical sample (see Section 3.3).

percent (2.11%) of the sample cases fall on a holiday. Also, the predominant majority of the time use records comprising our analytical sample were collected during spring and early summer: 20.33% of the cases fall on March, 26.65% on April, 25.55% on May, and 21.30% on June. Substantially fewer observations come from February (2.13%) and from July and August (4.05%).[33] There are no time use observations in the sample referenced to other calendar months.

4. Results

4.1. Overview

As a preliminary step of the empirical analysis, we performed an exploratory estimation of a model similar to that described in Section 2.5, except that no explanatory variables were included in the specification of the model's two equations.[34] The estimation results for this model (not presented here) suggested that the error terms in the two equations could be correlated. In particular, we obtained a correlation coefficient estimate of 0.0700 (std. error of 0.0134); the estimate is statistically significant at the 1% level. Given the potential for a similar correlation between the error terms in the full model (i.e., with all of the explanatory variables included), we proceeded to estimate Eqs. (8) and (10) as a SUR system.[35] In the case of the full model, the estimate of the correlation between the equation error terms is -0.0030 (std. error of 0.0153); the estimate is not statistically significant at a conventional significance level. The finding of a practically zero correlation here suggests that any correlation between food insecurity among children in the household and the time in food preparation by a decision maker may be attributed to effects of the observed explanatory variables (rather than to factors unobservable by the researcher).[36] The estimated children's food insecurity equation, with the coefficients given on the latent variable scale, is shown in Table 8. The estimated food preparation time equation (also on the latent variable scale) is presented in Table 9. To facilitate the interpretation of the estimation results, we calculate average marginal effects associated with the explanatory variables (see Section 2.6 for the formulas). The marginal effects for food insecurity and time in food preparation, which are

[33] The number of the records with the ATUS diary day in August is very small (28 observations in total). Thus, we did not create a separate dummy for August, but rather we grouped such observations together with the July cases.
[34] To clarify, we specified that the coefficients on all of the explanatory variables in the food insecurity and food preparation time equations were zero, but we allowed for and estimated the other parameters of the model: the threshold levels for the latent food insecurity variable, covariance matrix of the error terms, etc.
[35] To perform the estimation, we use the CMP package in Stata (see Roodman, 2011).
[36] This finding also implies that the joint estimation of the two equations as a SUR system provides no efficiency gains relative to estimating each equation separately.

calculated using the estimated model parameters, are discussed in detail in Sections 4.2 and 4.3, respectively.

4.2. Children's Food Insecurity

Table 10 presents average marginal effects (AMEs) of the explanatory variables on the probability of each of the four food insecurity outcomes—(1) high/marginal food security, (2) marginal food security, (3) low food security, and (4) very low food security among children—as implied by the estimated model parameters. These effects are calculated according to Eq. (20). While some of the effects may appear to be numerically small, especially in the case of the very low food security outcome, they are often substantial in magnitude in comparison to the incidence of a given outcome in the analytical sample (we provide the fraction of households with each of the four food insecurity outcomes in the sample in the last row of the table). To illustrate, a marginal effect associated with the unmarried-couple household dummy is calculated to be 0.0014 in the case of very low food security; the magnitude of this estimate is almost 25% of the incidence of very low food security in the sample (0.0057).

In comparison to the base category of married-couple households, children in unmarried-couple households and in households with a single head (male or female) are less likely to experience high/marginal food security and more likely to experience marginal, low, and very low food security. The calculated AMEs are statistically significant at the 10% significance level in the case of unmarried couples and significant at the 1% level in the case of single female- or male-headed households. These effects are substantial in magnitude. To illustrate, in the case of single female-headed households, the probability of high/marginal food security among children is lower by 5.19 percentage points (p.p.), or 6% of the sample incidence of high/marginal food security, while the probability of very low food security among children is higher by 0.38 p.p., or 67% of the incidence of very low food security. The direction of the effects is intuitive, because married-couple households are likely to have relatively more, and other types of households are likely to have relatively less resources to produce food security among children.

The estimates show that children in households containing more children (i.e., larger households) are less likely to experience high/marginal food security and more likely to experience marginal, low, and very low food security. All of the calculated AMEs are statistically significant at the 1% level. Notably, we find that the magnitude of the impact on food insecurity tends to be larger if a household contains more of older, rather than of younger, children. To illustrate, the probability of very low food security increases by 0.09 p.p. with an additional child of age 0–4 years in the household, but it increases by 0.18 p.p. with an additional child of age 5–12 or 13–17 years. We test and reject (at the 1% level) a null hypothesis of equality between the coefficient on the number of children of age 0–4 years and the coefficient on the number of children of age 5–12 years. We also reject (at the 5% level) a null hypothesis of equality between the coefficient on the number of children of age 0–4 years and that on the number of children of age 13–17 years. However, we are unable to reject equality between the effect of children of age 5–12 and that of children of age 13–17 years. All else equal, we can expect children in larger households to be relatively more food-insecure, because an increase in the number of children puts more strain on household resources, making it more difficult for the parents (or other caregivers) to produce food security. The fact that the relative magnitude of the impact appears to vary with respect to child age suggests that younger children (i.e., under 5 years) may require fewer resources to feed than older children.[37]

The AMEs of race variables indicate that in comparison to the base category of households with White householders, those with African American householders and householders of a race other than White or African American ("other race") are less likely to report experiencing high/marginal food security and more likely to report experiencing marginal, low, and very low food security among children. To illustrate, if a householder is African American, the probability of the high/marginal food security outcome decreases by 2.95 p.p., while the probability of the very low food security outcome increases by 0.21 p.p. (or 37% of the incidence of very low food security in the sample). In the case of African American householders, the calculated AMEs are statistically significant at the 1% level; in the case of "other race," they are significant at the 10% level. In addition, children are more likely to be food-insecure if the householder is Hispanic: the probability of high/marginal food security decreases by 3.42 p.p., and the probability of very low food security increases by 0.25 p.p. (or 44% of the incidence of very low food security), for example. While these results are not surprising, they suggest that children in minority households are more likely to be food-insecure than children in comparable non-minority households—for

[37] In addition, some argue that households may be more "protective" of younger children, and that parents take extra measures to shield such children from the effects of limited financial resources on food insecurity (see Nord and Hopwood, 2007).

reasons that cannot be fully attributed to discrepancies in income, household size/composition, educational attainment of the householder, and other factors controlled for in the empirical specification. Perhaps minority households are resource-poor along dimensions that are not fully captured by the econometric model. In comparison, Burke et al. (2012) find that African American households with children have the highest prevalence of persistent and non-persistent food insecurity—relative to other racial groups (including Whites)—using data from the Early Childhood Longitudinal Study-Kindergarten (ECLS-K).

The estimated effects of educational attainment show that more education among householders tends to alleviate children's food insecurity. To illustrate, in comparison to the case of a householder with less than a high school degree, if the householder has a high school degree, it increases the probability of high/marginal food security by 1.67 p.p. and decreases the probability of very low food security by 0.12 p.p. (these estimates are statistically significant at the 5% level). Also, if the householder has a bachelor's degree, it increases the probability of high/marginal food security by 5.79 p.p. and decreases the probability of very low food security by 0.42 p.p. (or 74% of the incidence of very low food security in the sample; the estimates are statistically significant at the 1% level). The AMEs of a graduate degree are similar to those of a bachelor's degree (also, the null of equality between corresponding coefficients cannot be rejected in a formal test). In addition, the magnitudes of the estimates suggest that the "effectiveness" of a householder's education in the production of food security among children may increase with the level of educational attainment. For instance, absolute magnitudes of the AMEs of a bachelor's degree are larger than those of a high school degree (also, we test and reject at the 1% level the null of equality between corresponding coefficients). Overall, the direction of the effects is as expected, since higher educational attainment can proxy for more wealth (and therefore, less stringent household resource constraints) and may also be an indicator of the household's ability to more efficiently manage available resources.

Higher real family income is associated with a higher likelihood of high/marginal food security and lower likelihood of marginal, low, and very low food security among children (the calculated AMEs are statistically significant at the 1% level). In turn, if a household is below 185% of the federal poverty level, children are less likely to experience high/marginal food security and more likely to experience marginal, low, and very low food security (the effects are significant at the 1% level). For example, the probability of the high/marginal food security outcome decreases by 4.33 p.p. and that of the very low food security outcome increases by 0.31 p.p. (or 54% of the incidence of very low food security in the sample) when the household is below 185% of the poverty level. The direction of the AMEs here is as expected, because higher income implies that the household has more financial resources to acquire market goods to produce food security among children.

Lastly, the results indicate several statistically significant effects associated with the place of residence and attributes of the local food environment. In particular, if a household resides in a metropolitan area, the children are more likely to be food-insecure. To illustrate, the probability of the high/marginal food security outcome decreases by 1.30 p.p. and probability of the very low food security outcome increases by 0.09 p.p. (the estimated AMEs are statistically significant at the 10% level). This result may be due to differential living costs, which can affect the cost of producing children’s food security, especially if living costs are higher in metropolitan relative to non-metropolitan areas. Notably, we find that higher fast food prices are associated with a lower incidence of high/marginal food security and higher incidence of marginal, low, and very low food security among children (the estimated effects are significant at the 10% level). The direction of the fast food price effects is intuitive. In addition, higher densities of convenience stores (including gas stations with convenience stores) and of specialty food stores (including meat markets, fish and seafood markets, fruit and vegetable markets, etc.) are associated with a higher probability of the high/marginal food security outcome and lower probabilities of the marginal, low, and very low food security outcomes (the estimated AMEs are significant at the 10% level in both store type cases). In other words, a higher number of such stores per local population tends to ameliorate food insecurity among children, which could be because convenience and specialty food stores increase the overall availability (or accessibility) of foods to purchase. It is also possible that specialty food stores offer more (and a higher variety) of lower-cost foods; thus, they can help to reduce the cost of producing children’s food security. There is some evidence that minority neighborhoods tend to have more stores, and especially specialty food stores, although the mix of foods and whether they offer healthy food choices varies across locations (Moore and Diez Roux, 2004). Overall, in contrast to many previous studies that do not find significant effects associated with the attributes of the local food environment, our results suggest that the local food environment may be a significant contributor to children's food security.[38]

4.3. Food Preparation Time

Table 11 presents AMEs of the explanatory variables on the expected duration of food preparation (including food shopping and related travel), as implied by the estimated model parameters. The effects are calculated according to Eq. (21). The magnitude of each effect is specified in minutes per day and accounts for the fact that the time in food preparation cannot be negative (unlike in the case of the coefficients reported in Table 9, for example). The relative magnitude of an effect may be assessed by comparing the estimate to the average duration of food preparation in the sample at 52.05 minutes per day (see the last row of Table 11).[39]

We find that the gender and relationship status of an individual can affect his or her time in food preparation. In comparison to the base category of women in married couples, the time in food preparation among men in married couples and men in unmarried couples is lower by 48.28 and 47.94 minutes per day, respectively. These two estimates are statistically significant at the 1% significance level and large in magnitude relative to the average duration of food preparation in the sample (52.06 minutes per day). We also find in a formal test that these two estimates are not significantly different from each other, indicating similar impacts of a marital and a cohabiting relationship on the duration of food preparation among men. In a similar vein, a small and not statistically significant AME estimate for women in unmarried couples shows that the duration of food preparation does not significantly differ between married and cohabiting women. Next, in comparison to women in married couples, single female householders spend 13.07 minutes less per day in food preparation (estimate is significant at the 1% level). Also, we test and reject (at the 1% level) equality between this estimate and that for women in unmarried couples. The findings suggest that single women are less able to specialize in food preparation than women in a relationship (married or cohabiting). Lastly, in comparison to women in married couples, single male householders spend 31.23 minutes less per day in food preparation (estimate is significant at

[38] The associations reported here should be interpreted cautiously, because they need not indicate *causal* effects of the local food environment on children's food security. In principle, it is possible that parents with relatively stronger unobservable preferences for food security among children choose to live in places with lower fast food prices or with higher densities of such food establishments as convenience and specialty food stores. It is also possible that food establishments choose their location depending on unobservable (to us) food-security preferences of local residents. In these cases, the estimated associations would not represent causal effects.

[39] The unit of observation for the results reported in Table 11 is an individual—such as the householder or the spouse or unmarried partner of the householder—rather than a household.

the 1% level). We compare this estimate to that for women in unmarried couples and that for single female householders and reject equality (at the 1% level) in both cases using formal tests. Overall, the results indicate that men tend to devote less time to food preparation than women regardless of the relationship status (i.e., married, cohabiting, or single). Furthermore, using formal tests we find that the estimate for single male householders is significantly different (at the 1% level) from that for married men and that for cohabiting men. Thus, single male householders tend to spend more time in food preparation than men in a relationship (married or cohabiting).

As expected, the presence of children in the household is associated with more time in food preparation among householders and their spouses or unmarried partners. In particular, a child of age 0–4 years is associated with 6.43 minutes more per day in food preparation, whereas a child of age 5–12 years and a child of age 13–17 years are associated with 4.36 and 4.30 additional minutes, respectively. The three estimates here are statistically significant at the 1% level and represent eight to twelve percent of the average duration of food preparation in the sample. The effect appears to be somewhat larger for younger children, as we test and reject (at the 5% level) equality between the estimate for a child of age 0–4 years, on the one hand, and estimates for children of age 5–12 and 13–17 years, on the other hand.[40] It is possible that younger children are associated with relatively more added time in food preparation because feeding them requires preparing specialized meals and spending more time in clean-up after meals. It is also conceivable that older children are associated with comparatively less added time in food preparation because they have some of their meals at school rather than at home.

If the householder is of a race other than White or African American, we estimate the expected duration of food preparation to increase by 4.99 minutes per day (the AME estimate is significant at the 5% level). If the householder is Hispanic, the expected duration is estimated to increase by 5.07 minutes (significant at the 1% level). We also find a positive and statistically significant (at the 1% level) association between the time in food preparation and the age of the householder. Thus, it appears that older individuals tend to spend more time in food preparation than younger individuals, which could be an indication of the presence of a cohort effect in time use preferences.[41] In turn, the time in food preparation is estimated to decrease by 3.67 (significant

[40] In a test, the estimate for a child of age 5–12 years is not significantly different from that for a child of age 13–17 years.

[41] In a cross-sectional study such as ours, it is not possible to disentangle cohort effects from the effects of age on the time in food preparation.

at the 10% level) and 4.18 minutes (significant at the 5% level) if the householder has a high school degree and some college education, respectively, relative to the base category of householders with less than a high school degree. The AMEs for a bachelor's and a graduate degree are smaller in magnitude and not statistically significant. Hence, we do not find a robust negative association between the time in food preparation and the level of educational attainment of the householder. Also, if the householder is foreign-born, the expected duration of food preparation is estimated to increase by 10.32 minutes per day; this AME estimate is statistically significant at the 1% level and constitutes 20% of the average daily duration of food preparation in the sample. Perhaps individuals in households with a foreign-born householder tend to spend more time in food preparation because their preferred foods as well as ingredients to prepare such foods are less readily available locally or in pre-prepared form. Also, it could be that individuals in these households have different preferences regarding time use than native-born individuals. In addition, we estimate that the time in food preparation increases by 4.15 minutes per day if the household is below 185% of the federal poverty level. This result is expected, because the literature indicates that individuals with fewer financial resources or those experiencing a negative income shock may substitute time for expenditures when preparing food (Aguiar and Hurst, 2005). In particular, individuals in lower-income households may utilize 'time-intensive' strategies aimed at reducing monetary expenditures related to food consumption, including strategies such as "coupon shopping," visiting food stores more frequently (i.e., to take advantage of sales or price discounts), and purchasing less expensive food items that require more time to process when preparing meals (e.g., random-weight items and raw food ingredients rather than packaged and ready-to-eat items). For more on these strategies, see Leibtag and Kaufman (2003) and Aguiar and Hurst (2007).

We find few effects associated with the place of residence and attributes of the local food environment. More specifically, if the household resides in a metropolitan area, the expected duration of food preparation is estimated to increase by 3.18 minutes per day (the AME estimate is statistically significant at the 5% level). Also, if the household resides in the South (rather than in the Northeast), the expected duration is estimated to decrease by 6.34 minutes (significant at the 1% level). This finding may reflect regional differences in time use preferences or types of foods prepared. Also, we estimate a positive and statistically significant (at the 5% level) coefficient on the dummy for the year 2006, which may be reflective of a survey design effect.

Lastly, the AME estimates show that the duration of food preparation varies in an expected manner depending on the characteristics of the ATUS diary day. More specifically, in comparison to Wednesday, the expected duration of food preparation is higher by 5.64 minutes on Sunday (the AME estimate is statistically significant at the 1% level) and lower by 8.59 minutes on Friday (significant at the 1% level). This pattern of the estimates is expected and intuitive because many individuals traditionally spend Sunday in home- and family-centered activities, including food preparation, and also traditionally go out on Friday after work. In other words, the opportunity cost of time in food preparation may be relatively low on Sunday, but relatively high on Friday, which would explain the direction of the effects. In addition, we estimate that the expected duration of food preparation is higher by 10.69 minutes on a holiday; this AME estimate is statistically significant at the 1% level and constitutes nearly 21% of the average daily duration of food preparation in the sample. It is possible that the duration of food preparation is longer on holidays due to a relatively low opportunity cost of time in food preparation on these days (i.e., holidays are similar to Sunday in this respect). Perhaps also individuals spend more time in food preparation on holidays because there are few options to eat out on these days due to business closures. In addition, the AMEs show that relative to February, the expected daily duration of food preparation is lower by 6.62 minutes in May (significant at the 5% level), by 7.27 minutes in June (significant at the 5% level), and by 13.21 minutes in July (significant at the 1% level). These results seem to suggest that the opportunity cost of time in food preparation is higher during summer months, which may be because there are more possibilities for outdoor leisure activities in the summer relative to winter. It may also be that food preparation (e.g., cooking) is a relatively less pleasurable activity during warmer months.

5. Discussion

For the most part, our estimation results for food insecurity among children are in line with intuition and results reported in the literature. We also find support for many of our research hypotheses (for reference, see Section 2.4). More specifically, our results on food prices offer little evidence to support *Hypothesis A.1*, because the effect of local food-at-home prices on children's food security is not found to be statistically significant (at a conventional significance level). However, our estimates support *Hypothesis A.2*, since we find that higher fast food prices are, indeed, associated with a higher incidence of low food security and higher incidence of very low food security among children (at the 10% significance level). Thus, we find partial support for hypotheses in group A (effects of food prices) overall.

We also find partial support for hypotheses in group B (effects of availability of local food business establishments). In particular, the results show that higher densities of convenience stores and specialty food stores are associated with a lower incidence of low food security and lower incidence of very low food security among children (at the 10% significance level), which supports *Hypothesis B.1*. These results are important because they suggest that the attributes of local food environment (other than food prices) may affect the production of children's food security in the household. Also, they differ from the results in many previous empirical studies, which tend to find little or no impact of local food environment on food security and diets of youths (e.g., see An and Sturm, 2012). In contrast, we find little evidence to support *Hypothesis B.2*, because our estimates on the densities of full-service restaurants and limited-service eating places are not statistically significant and of opposite signs. This result seems to suggest that the availability of various types of restaurants in the neighborhood has limited impact on the production of children's food security in the household, or that there may be other dimensions of food outlets that are not well-measured using the density variables.

We find strong support for all hypotheses in group C (effects of demographic and socioeconomic characteristics). The results indicate that real family income is strongly associated with more food security among children (at the 1% significance level). Moreover, children in households with low income (below 185% of the federal poverty level) are less likely to be high/marginally food secure and more likely to experience marginal, low, and very low food security. Thus, higher-income households are less likely to report experiencing low and very low food security among children, which confirms *Hypothesis C.1*.

We also find support for *Hypothesis C.2*. Relative to the baseline group of households with householders who have no high school degree, those with householders who have more education (a high school degree, a bachelor's degree, or a graduate degree) are less likely to experience low and very low food security among children. Thus, higher educational attainment of householders tends to alleviate food insecurity. Although we do not find statistically significant effects associated with some college education (less than a bachelor's degree), the direction of the estimates in this case is generally consistent with the hypothesis.

As expected, household composition affects the food security status of children. Our estimates indicate that households with more children (regardless of the child age) are more likely to experience low and very low food security, confirming *Hypothesis C.3*. At the same time, the presence of more adults in the household is not found to be associated with children's food security outcomes. Both results are intuitive, since additional children likely put more strain on the existing household financial resources, whereas additional adults can bring with them extra resources (e.g., adults may have sources of income such as earnings, pensions, etc.). We also find support for *Hypothesis C.4* in that the magnitude of the impact of additional children of age 0–4 years on the incidence of low and very low food security is found to be smaller than (and roughly half of) that of additional children of age 5–12 and 13–17 years. Thus, the age composition of children in the household may matter for food security, as hypothesized.

Individual and household characteristics also have statistically significant effects on the amount of time devoted to food preparation by the householder or the householder's spouse or unmarried partner. We find strong support for all corresponding research hypotheses. In particular, the results show that men tend to spend significantly less time than women in food preparation (the difference is statistically significant at the 1% level), regardless of the household type. This finding is consistent with *Hypothesis D.1* in that traditional gender roles can impact the allocation of time across household production activities (including food preparation, in particular). The estimates also suggest that single female and single male householders spend significantly less time in food preparation (at the 1% level) than wives in married-couple households and female partners in unmarried-couple households. Thus, we are able to affirm *Hypothesis D.2*, which says that the household structure influences the extent of individual specialization in various household production activities, including food preparation.

As expected, we find that children in the household are associated with more time in food preparation (all estimated effects for children are statistically significant at the 1% level). Moreover, children of age 0–4 years are found to have a larger impact on the duration of food preparation than children of age 5–12 and 13–17 years. Thus, the estimates support *Hypothesis D.3*, although we do not find a statistically significant difference between the magnitude of the effect of children of age 5–12 years and that of children of age 13–17 years.

Furthermore, we find partial support for *Hypothesis D.4* regarding the impact of household financial resources on time in food preparation. While we do not estimate a statistically significant effect of real family income per se, the results indicate that households with income below 185% of the federal poverty level tend to spend more time in food preparation. This finding is consistent with a hypothesis that householders and spouses/unmarried partners in lower-income households devote more time to food preparation (including food shopping) in comparison to higher income households—as a way to reduce the monetary cost of food consumption.[42] For example, lower-income individuals may be more likely to use "time-intensive" strategies such as "coupon shopping" and purchasing cheaper food items with less embedded convenience/time-saving in order to lower the household's monetary expenditures on food (see Leibtag and Kaufman, 2003; Aguiar and Hurst, 2007).

Finally, we find support for *Hypothesis D.5* in that the amount of time in food preparation is estimated to systematically vary across days of the week and months of the year. The direction of the effects is consistent with households spending more time in food preparation at home in times when the opportunity cost of time is lower. Householders and their spouses/unmarried partners spend relatively more time in food preparation on Sunday, but relatively less time on Friday; and more time in food preparation on holidays. In addition, we find that the amount of time in food preparation decreases during summer months, which is consistent with the hypothesis.

Our results for associations between socioeconomic and demographic characteristics and children's food security have implications for the design of public policies and programs targeting food insecurity. The results suggest that when all else (e.g., family income) is equal, children are more likely to be food insecure in households with more children, a single adult head, and in households with a householder who has less formal education (e.g., no high school degree). These findings can guide the allocation of public resources in order to alleviate food insecurity among the most vulnerable children. Policies and programs that provide financial and other resources to support the needs of households with children that have a single adult head—and especially single female heads—are likely to be particularly important. Such programs might include programs to provide transportation services or childcare, or other skills to help the householder better manage available resources.

In recent years, there has been substantial public interest in potential effects of "food deserts" (see Ver Ploeg, 2010) on food security, but the academic literature has thus far been unable to detect strong effects. In comparison, our finding of statistically significant associations (in the

[42] Also, adults in lower-income households may engage relatively more in food preparation (i.e., a household production activity) because the opportunity cost of their time in household production could be lower than that of adults in higher income households.

expected direction) between the availability of convenience and specialty food stores and the incidence of low and very low food security among children indicates the potential importance of local food environment to the production of children's food security in the household: more stores in the neighborhood are associated with lower incidence of food insecurity among children. At the same time, we do not estimate a statistically significant association for supermarkets and other grocery stores (though the estimated effect in this case is in the expected direction). It is possible that the availability of convenience and specialty food stores matters substantially for lower-income households without easy access to transportation (e.g., households without personal vehicles). Specialty food stores (e.g., fruit and vegetable markets) may contribute to the production of food security in that they can increase the overall variety of available foods and also decrease the monetary cost of foods. There is some evidence that minority neighborhoods tend to have more stores, and particularly specialty food stores, although the mix of foods and whether they offer healthy food choices varies across locations (Moore and Diez Roux, 2004). Overall, the results suggest that public policies aimed at encouraging businesses to open food stores of specific type—e.g., specialty food stores—in poorer neighborhoods may help alleviate food insecurity among children.

We also find that local food prices may matter for children's food security, although we only find a statistically significant association (in the expected direction) in the case of fast food prices.[43] While fast food is not necessarily the healthiest type of food that a household may purchase to feed children, it still may be a critically important source of food for lower-income households facing stringent time constraints (e.g., single-headed households with children). Thus, changes to public policy aimed at increasing taxes on fast food—in order to promote healthy eating, for example—may actually have a counter-productive effect in terms of increasing the incidence of low and very low food security among children.

The results for time in food preparation may also help inform the design of public policies and programs. SNAP benefit amounts are linked to food cost calculations based on the Thrifty Food Plan, which is known to require substantial meal preparation time in order to attain an adequate diet (Davis and You, 2011). Moreover, SNAP participants are not allowed to spend

[43] It is possible that our measure of local food-at-home prices is "too coarse" in terms of geographical specificity, and therefore, it does not allow us to detect a food-at-home price effect. In other words, we may need to have a price measure at a lower level of geographical aggregation than is presently available.

program benefits on prepared (hot) meals outside of the home, a restriction that may require shifting time use toward food preparation (at home) among participating households. Our estimates reveal significant differences in the daily duration of food preparation across different household types, with time in food preparation among single-headed households (especially female single-headed households) less than that among married-couple and cohabiting couple households. Vickery (1977) argues that public assistance programs that ignore time differentials across different household types tend to "underestimate" the time constraint faced by single-headed households. It may be difficult for such households, especially for those in poverty, to effectively utilize federal food assistance and meet their food needs. The design of food assistance programs may need to take into account that increasing food preparation time among these households—in line with the requirements of the Thrifty Food Plan—may not be feasible, due to binding time constraints.[44]

In addition, our results indicate that low income households (households with income below 185% of the federal poverty level) and households that have more children tend to devote more time to food preparation. For these households, a further increase in food preparation time may be unproductive or infeasible. Thus, the design of food assistance programs may need to account for household structure (e.g., the number and the ages of children present in the household), as it affects the allocation of time in household production. Although perhaps relatively obvious, our results suggest that providing food and meals to low income children is likely to alleviate food insecurity. This occurs both through the value of added resources to obtain food as well as potentially through reduced time in food preparation. Providing food through school meals, after school programs, and during the summer is likely to be especially effective for reducing food insecurity among children.

Finally, our estimates indicate a significant variation in food preparation time across seasons, which is likely due to systematic differences in the opportunity cost of time. In particular, less time on the daily basis is devoted to food preparation during summer months in comparison to winter months. To increase the effectiveness of federal food assistance programs, their design may need to account for systematic differences in the opportunity cost of time across seasons. For example, restrictions on the use of program benefits could be relaxed during summer months by

[44] Moreover, lower-income households may be subject to work requirements of public assistance programs, which can further limit their ability to spend time in food preparation.

allowing households to spend part of the benefits on food away from home.

6. Conclusion

Low and very low food security can be detrimental to the physical, intellectual, and social well-being of children. Thus, developing a better understanding of factors that may contribute to the low and very low food security outcomes is important for public policy and the design of federal food assistance programs. Becker's household production approach provides a useful framework to account for the use of constrained financial and time resources in the household and for potential impacts of demographic, socioeconomic, and other factors, including local food environment attributes, on food insecurity among children. We find evidence suggesting that demographic, socioeconomic, and environmental factors do contribute to the demand for time in food preparation and to food insecurity among children. Some households with children, especially those with a single head and those with lower income, can be particularly challenged in their ability to meet children's food needs and effectively utilize federal food assistance.

The fact that households with a single head are more likely to experience low and very low food security among children suggests that policies and programs designed to support the needs of these households, and especially those with a single female head, are particularly important for reducing food insecurity and improving the well-being of children in the short- and long-run. In addition, we find evidence suggesting that the availability of low cost food in convenient and nearby locations (especially in the case of convenience stores and specialty food stores) may help mitigate food insecurity among children. In fact, our results suggest that lower fast food prices tend to reduce the incidence food insecurity. It is important to note that the demand on the time resources devoted to food preparation in the household (including meal preparation at home, as well as food shopping and related travel) is likely to be met in ways most efficient to the household production, which may involve the use of fast food. In addition, public policies and strategies aimed at encouraging viable neighborhoods and supporting local food stores of specific type (e.g., specialty food stores) in poorer neighborhoods are likely to help address the needs of low-income households with children and alleviate children's food insecurity among these households.

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Table 1. FSS Data Processing Steps and FSS Sample Construction

FSS Year Description of Data Processing Step	*2002*	*2003*	*2004*	*2005*	*2006*	*2007*	*2008*	*2009*	*2010*
Extract all data from December CPS–FSS merged file; total records	159,657	156,967	155,845	153,049	152,962	151,431	149,687	152,260	152,384
Delete records without CPS interviews (HRINTSTA = 2, 3, 4); records deleted	16,406	17,603	16,942	16,875	17,687	17,759	18,661	17,903	18,000
Delete records without FSS interviews (HRSUPINT = 2); records deleted	16,425	20,680	17,674	16,936	19,499	20,456	21,662	20,999	22,768
Delete records from households without children; records deleted	56,866	53,064	55,180	54,930	54,230	53,318	52,220	54,167	53,400
Delete records from households in their first four months in CPS (HRMIS $\leq$ 4); records deleted	35,828	32,340	32,814	32,278	30,638	30,027	28,835	29,956	28,797
Delete records from households in their eighth month in CPS (HRMIS = 8) as of December 2007;[a] records deleted	—	—	—	—	—	7,490	—	—	—
Delete records with missing responses to food security questions; records deleted:	93	148	98	102	126	123	61	89	108
Total records to construct FSS sample	34,039	33,132	33,137	31,928	30,782	22,258	28,248	29,146	29,311
Of these:									
Records with information on adults	*17,830*	*17,377*	*17,365*	*16,637*	*16,265*	*11,788*	*14,939*	*15,441*	*15,597*
Records with information on children	*16,209*	*15,755*	*15,772*	*15,291*	*14,517*	*10,470*	*13,309*	*13,705*	*13,714*
Total number of households in FSS sample (=68,381), by year:	8,616	8,386	8,337	8,043	7,754	5,627	7,068	7,252	7,298

Source: Data from FSS, 2002–2010.

Notes:

This table describes data processing steps to prepare the FSS sample of households with children.

[a] A proposed FSS wording change tested in these households did not perform adequately (Nord, 2009, p. 2).

Table 2. ATUS Data Processing Steps and ATUS–FSS Analytical Sample Construction

FSS Year *ATUS Year* Description of Data Processing Step	*2002* *2003*	*2003* *2004*	*2004* *2005*	*2005* *2006*	*2006* *2007*	*2007* *2008*	*2008* *2009*	*2009* *2010*	*2010* *2011*
Total number of households in FSS sample (see the last row of Table 1) [a]	8,616	8,386	8,337	8,043	7,754	5,627	7,068	7,252	7,298
Link FSS records to records of prospective ATUS respondents in ATUS-CPS files; records retained	5,112	3,112	3,489	3,580	3,362	2,453	3,104	3,217	3,204
Delete records of prospective ATUS respondents who were not interviewed in ATUS; records deleted	2,307	1,379	1,537	1,647	1,648	1,165	1,355	1,408	1,600
Delete records of potentially low quality as designated by interviewer; records deleted	21	4	5	15	13	3	6	8	3
Delete a record when an ATUS respondent is not a CPS reference person, spouse, or unmarried partner; records deleted	510	314	346	348	325	227	304	342	319
Total number of records comprising ATUS–FSS analytical sample (=13,474), by year:	2,274	1,415	1,601	1,570	1,376	1,058	1,439	1,459	1,282

Source: Merged data from FSS, 2002–2010, and ATUS, 2003–2011.

Notes:

This table describes data processing steps implemented when matching the ATUS respondent records to the records in the FSS sample of households with children (see Table 1) in order to construct the ATUS–FSS sample for empirical analysis.

[a] At most one member per an FSS household can be designated to be interviewed in the ATUS.

Table 3. Distribution of Households in ATUS–FSS Analytical Sample by Children's Food Security Status

Food Security Category	Count	Weighted Fraction, % [a]	Description[b]
(1) High/marginal food security	11,600	85.91	Raw score of 0
(2) Marginal food security	911	6.80	Raw score of 1
(3) Low food security	897	6.73	Raw score of 2–4
(4) Very low food security	66	0.57	Raw score of 5–8
Total	13,474	100.00	

Source: Merged data from FSS, 2002–2010, and ATUS, 2003–2011.

Notes:

This table presents the distribution of households in the ATUS–FSS analytical sample with respect to the children's food security status.

[a] Weighted fractions are computed using the ATUS sample weights (the ATUS variable TUFINLWGT "ATUS final weight" [based on the 2006 weighting methodology]).

[b] Children's food security status is based on the FSS variable HRFS12M6 ("Children's Food Security Raw Score, 12-Month Recall"). The labels for the categories follow the official USDA labels (see Nord and Hopwood, 2007, p. 535), except that we split the USDA category "High or marginal food security" (a raw score of 0–1) into "High/marginal food security" and "Marginal food security." In the former case, we use the label "High/marginal food security," because the FSS does not contain an item with low enough severity of food insecurity among children to reliably differentiate "high" from "marginal" food security.

Table 4. Descriptive Statistics for Time in Food Preparation (Minutes/Day) in ATUS–FSS Analytical Sample

(Sub)sample[a]	Fraction of Cases with Zero Time[b]	Among Cases with Non-Zero Time (minutes/day)[c]				
		Mean	Std. Dev.	Median	Min	Max
All respondents	34.26%	79.20	69.33	60	1	995
Men only	53.26%	56.15	54.84	40	1	660
Women only	18.33%	90.26	72.76	70	1	995

Source: Merged data from FSS, 2002–2010, and ATUS, 2003–2011.

Notes:

This table presents descriptive statistics for the time in food preparation, in minutes per day, reported by the respondents in the ATUS–FSS analytical sample. "Food preparation" comprises the following time use categories from the ATUS lexicon: 020201 "Food and drink preparation," 020202 "Food presentation," 020203 "Kitchen and food clean-up," 020299 "Food and drink preparation, presentation, and clean-up, not elsewhere classified (n.e.c.)," 070101 "Grocery shopping," 180202 "Travel related to food and drink preparation, clean-up, and presentation," and 180701 "Travel related to grocery shopping." The descriptive statistics are computed using the ATUS sample weights (the ATUS variable TUFINLWGT "ATUS final weight" [based on the 2006 weighting methodology]).

[a] The ATUS–FSS analytical sample includes a total of 13,474 respondents (see Table 2). Of them, 5,528 are men (weighted 45.62% of the sample) and 7,946 are women (54.38%).

[b] A weighted fraction of respondents who do not report having been engaged in food preparation on the reference day.

[c] The descriptive statistics are provided for respondents who report non-zero time in food preparation on the reference day.

Table 5. Demographic and Socioeconomic Characteristics of ATUS–FSS Analytical Sample

Characteristic	Mean	Std. Dev.	Min	Max
Individual characteristics				
Female in married couple, dummy[a]	0.4059	0.4911	0	1
Male in married couple, dummy	0.4068	0.4913	0	1
Female in unmarried couple, dummy	0.0264	0.1603	0	1
Male in unmarried couple, dummy	0.0252	0.1567	0	1
Single female householder, dummy[b]	0.1117	0.3150	0	1
Single male householder, dummy	0.0240	0.1532	0	1
Household characteristics				
Married couple household, dummy	0.8127	0.3902	0	1
Unmarried couple household, dummy	0.0516	0.2212	0	1
Single female-headed household, dummy	0.1117	0.3150	0	1
Single male-headed household, dummy	0.0240	0.1532	0	1
Children of age 0–4 years, count	0.5349	0.7308	0	5
Children of age 5–12 years, count	0.8598	0.8991	0	7
Children of age 13–17 years, count	0.5009	0.7008	0	5
Adults other than householder/spouse/partner, count[c]	0.3033	0.6683	0	6
Householder is White, dummy	0.8276	0.3778	0	1
Householder is African American, dummy	0.1075	0.3097	0	1
Householder is of race other than White or African American, dummy	0.0650	0.2465	0	1
Householder is Hispanic, dummy	0.1688	0.3746	0	1
Age of householder, years	39.86	9.77	16	85
Householder has no high school degree, dummy[d]	0.1191	0.3239	0	1
Householder has high school degree, dummy[d]	0.2766	0.4473	0	1
Householder has some college education, dummy[d]	0.2663	0.4421	0	1
Householder has bachelor's degree, dummy[d]	0.2219	0.4155	0	1
Householder has graduate degree, dummy[d]	0.1161	0.3203	0	1
Householder is foreign-born, dummy	0.1788	0.3832	0	1
Real family income, thousands of 1982–1984 dollars[e]	32.680	20.376	2.293	81.522
Information on income is missing, dummy	0.0936	0.2912	0	1
Income is below 185% of federal poverty level, dummy[f]	0.3145	0.4643	0	1

Source: Merged data from FSS, 2002–2010, and ATUS, 2003–2011.

Notes:

This table reports descriptive statistics for demographic and socioeconomic characteristics of the ATUS–FSS analytical sample (at the time of the FSS data collection). These descriptive statistics are computed using the ATUS sample weights (the ATUS variable TUFINLWGT "ATUS final weight" [based on the 2006 weighting methodology]). The number of observations is 13,474.

[a] A "dummy" variable takes the value of 1 if the condition specified by a characteristic is true, and the value of 0 otherwise.

[b] For brevity, the term "householder" refers to an individual identified as the "reference person" (i.e., the person who owns or rents the home) of a household in the core CPS interview immediately preceding the FSS questionnaire.

[c] The number of adults (age 18 years or older) in the household who are not the householder, the spouse of the householder, or the unmarried partner of the householder.

[d] The categories are mutually exclusive and exhaustive and refer to the highest level of educational attainment.

[e] Nominal income is set at the midpoint of the reported income category (the CPS variable HUFAMINC "Family Income"). Real income is obtained by deflating this value by the CPI. The descriptive statistics are reported for the subsample with non-missing income.

[f] This poverty indicator (variable HRPOOR in the FSS) is based on the CPS variable HUFAMINC "Family Income" and information on the household composition.

Table 6. Location-Specific Characteristics of ATUS–FSS Analytical Sample

Characteristic	Mean	Std. Dev.	Min	Max
Household resides in a metropolitan area, dummy[a]	0.8211	0.3833	0	1
Household resides in the Northeast region, dummy	0.1768	0.3815	0	1
Household resides in the Midwest region, dummy	0.2542	0.4354	0	1
Household resides in the South region, dummy	0.3373	0.4728	0	1
Household resides in the West region, dummy	0.2318	0.4220	0	1
Local poverty rate, fraction of residents[b]	0.1237	0.0404	0.0235	0.4093
Local food price indices:				
Food-at-home price index, real dollars[c]	0.2445	0.0186	0.2113	0.3228
Fast food price index, real dollars[d]	2.6604	0.1723	2.1319	3.9478
Densities of local food business establishments, number of establishments per 10,000 local residents:[e]				
Supermarkets and other general line grocery stores	2.1747	0.7758	0.6868	8.3403
Convenience stores	3.7975	1.2977	0.7445	10.3750
Specialty food stores	1.1084	0.5079	0.0975	4.8940
Full-service restaurants	7.0047	1.7291	2.4772	26.4003
Limited-service eating places	8.6837	1.3854	3.3362	20.1199

Source: Merged data from FSS, 2002–2010, and ATUS, 2003–2011.

Notes:

This table presents descriptive statistics for attributes of the place of residence of the ATUS–FSS analytical sample (at the time of the FSS data collection). The reference period for the local poverty rate, local food prices, and densities of local food establishments is the calendar year of the FSS data collection. The descriptive statistics are computed using the ATUS sample weights (the ATUS variable TUFINLWGT “ATUS final weight” [based on the 2006 weighting methodology]). The number of observations is 13,474.

[a] A “dummy” variable takes the value of 1 if the condition specified by a characteristic is true, and the value of 0 otherwise.

[b] Local poverty rate refers to the number of people of all ages living in poverty (i.e., below 100% of the federal poverty level) as a fraction of total population in the household’s place of residence. Annual counts of people in poverty come from the U.S. Census Bureau’s SAIPE program’s database. Annual population counts come from the U.S. Census Bureau’s American FactFinder database. We construct the poverty rate variable separately at each of the following three levels of geographical aggregation: county, MSA (prior to the year 2004) or CBSA (starting in 2004), and state. The poverty rate data are merged with the ATUS–FSS sample records according to the place of residence at the most detailed geographical level available. Approximately 45% of the records are matched by the county FIPS code; of the remaining 55%, roughly one-half are matched by the CBSA (MSA) code and the rest by the state code.

[c] The index represents an expenditure-weighted average of food group prices in the QFAHPD,

expressed in real dollars. The QFAHPD provides nominal quarterly prices for 54 different food groups. These prices are separately available for 35 distinct geographical market areas covering the contiguous United States. Each individual food group price refers to the dollar cost of 100 grams of food as purchased by consumers. Real prices, expressed in 1982–1984 dollars, are obtained by deflating nominal prices by the CPI. The weight of a food group in the index represents annual U.S. expenditures on the food group as a fraction of annual U.S. expenditures on all food groups covered in the QFAHPD in 2004 (the expenditure data are available in the QFAHPD). We first compute quarterly price index values and then average out values for the four quarters of a year. The data are merged with the household records according to the place of residence, by using a matching procedure similar to that of Gregory and Coleman-Jensen (2013).

[d] We construct the fast food price index of Chou et al. (2004) and Powell (2009). It is calculated as an average of real prices for the following three items tracked by the ACCRA: (1) a McDonald's quarter-pounder hamburger with cheese, (2) an 11–12" thin crusted cheese pizza at Pizza Hut or Pizza Inn, and (3) fried chicken (thigh and drumstick) at Kentucky Fried Chicken or Church's. Real prices, expressed in 1982–1984 dollars, are obtained by deflating nominal prices by the CPI. The ACCRA database separately provides quarterly prices for approximately 350–400 metropolitan areas (coverage varies over time). We first compute quarterly price index values and then average out values for the four quarters of a year. The data are merged with the household records according to the place of residence by the CBSA FIPS code whenever possible (about two-thirds of the sample). For the remainder of the sample, we first calculate an average of the price index values across all metropolitan areas covered by the ACCRA in a given state and then match the state average to a record by the state FIPS code.

[e] Annual business establishment counts are extracted from the CBP database. Annual population counts are obtained from the U.S. Census Bureau's American FactFinder database. We create all density measures separately at each of the following three levels of geographical aggregation: county, MSA (prior to the year 2004) or CBSA (starting in 2004), and state. The data are merged with the ATUS–FSS sample records according to the place of residence at the most detailed geographical level available. Approximately 45% of the records are matched by the county FIPS code; of the remaining 55%, roughly one-half are matched by the CBSA (MSA) code and the rest by the state code. Business establishments in the CBP are classified using a six-digit NAICS code. The group of "Supermarkets and other general line grocery stores" comprises establishments with NAICS codes 445110 "Supermarkets and other grocery (except convenience) stores" and 452910 "Warehouse clubs and supercenters." The group of "Convenience stores" includes establishments with codes 445120 "Convenience stores" and 447110 "Gasoline stations with convenience stores." The group of "Specialty food stores" represents establishments with codes 445210 "Meat markets," 445220 "Fish and seafood markets," 445230 "Fruit and vegetable markets," 445291 "Baked goods stores," 445292 "Confectionery and nut stores," 445299 "All other specialty food stores," and 311811 "Retail bakeries." The group of "Full-service restaurants" comprises establishments with a code 722110 "Full-service restaurants." The group of "Limited-service eating places" is composed of establishments with codes 722211 "Limited-service restaurants," 722212 "Cafeterias, grill buffets, and buffets," and 722213 "Snack and nonalcoholic beverage bars."

Table 7. Temporal Characteristics of ATUS–FSS Analytical Sample

Characteristic	Mean	Std. Dev.	Min	Max
FSS/ATUS data collection year is 2002/2003, dummy [a,b]	0.1137	0.3175	0	1
FSS/ATUS data collection year is 2003/2004, dummy	0.1208	0.3259	0	1
FSS/ATUS data collection year is 2004/2005, dummy	0.1160	0.3202	0	1
FSS/ATUS data collection year is 2005/2006, dummy	0.1177	0.3222	0	1
FSS/ATUS data collection year is 2006/2007, dummy	0.1136	0.3173	0	1
FSS/ATUS data collection year is 2007/2008, dummy [c]	0.0877	0.2829	0	1
FSS/ATUS data collection year is 2008/2009, dummy	0.1122	0.3156	0	1
FSS/ATUS data collection year is 2009/2010, dummy	0.1123	0.3158	0	1
FSS/ATUS data collection year is 2010/2011, dummy	0.1060	0.3078	0	1
ATUS diary day is Sunday, dummy[d]	0.1475	0.3546	0	1
ATUS diary day is Monday, dummy	0.1379	0.3448	0	1
ATUS diary day is Tuesday, dummy	0.1484	0.3556	0	1
ATUS diary day is Wednesday, dummy	0.1401	0.3471	0	1
ATUS diary day is Thursday, dummy	0.1407	0.3477	0	1
ATUS diary day is Friday, dummy	0.1427	0.3498	0	1
ATUS diary day is Saturday, dummy	0.1428	0.3499	0	1
ATUS diary day is a holiday, dummy[e]	0.0211	0.1437	0	1
ATUS diary day falls on February, dummy	0.0213	0.1445	0	1
ATUS diary day falls on March, dummy	0.2033	0.4024	0	1
ATUS diary day falls on April, dummy	0.2665	0.4421	0	1
ATUS diary day falls on May, dummy	0.2555	0.4361	0	1
ATUS diary day falls on June, dummy	0.2130	0.4095	0	1
ATUS diary day falls on July, dummy[f]	0.0405	0.1970	0	1

Source: Merged data from FSS, 2002–2010, and ATUS, 2003–2011.

Notes:

This table presents descriptive statistics for characteristics of the ATUS–FSS analytical sample related to the timing of the data collection. These descriptive statistics are computed using the ATUS sample weights (the ATUS variable TUFINLWGT "ATUS final weight" [based on the 2006 weighting methodology]). The number of observations is 13,474.

[a] A "dummy" variable takes the value of 1 if the condition specified by a characteristic is true, and the value of 0 otherwise.

[b] The FSS household data are collected in December of year *t*, and the ATUS respondent data are collected in year *t* + 1. On average, the time gap between the FSS and the ATUS data collection dates in the sample is 4.5 months.

[c] The number of observations is less than that in the other years because of a smaller size of the underlying FSS sample. About one-fourth of the household sample in the 2007 FSS of the CPS

was not used for food security estimates, since a proposed FSS wording change tested in those households did not perform adequately (Nord, 2009, p. 2). Such cases are excluded from consideration when constructing the ATUS–FSS analytical sample.

[d] An ATUS respondent reported his or her time use for a 24-hour period starting at 4am on the diary day and ending at 4am on the following day.

[e] Holidays include New Year's Day, Easter, Memorial Day, the Fourth of July, Labor Day, Thanksgiving Day, and Christmas Day.

[f] This dummy variable takes the value of 1 if the ATUS diary day falls on July or August, and the value of 0 otherwise. The number of ATUS respondents with a diary day falling on the month of August (28 respondents in the sample) is too small to warrant a creation of a separate dummy. Also, due to the specifics of the ATUS–FSS sample construction, there are no observations with a diary day falling on the months of January, September, October, November, and December.

Table 8. Estimated Equation for Children's Food Insecurity (Latent Variable Scale)

Explanatory Variable	Coefficient	(Std. Error)
Unmarried couple household[a]	0.1160*	(0.0655)
Single female-headed household[a]	0.3025***	(0.0390)
Single male-headed household[a]	0.2302***	(0.0814)
Number of children, age 0–4 years	0.0748***	(0.0244)
Number of children, age 5–12 years	0.1462***	(0.0174)
Number of children, age 13–17 years	0.1455***	(0.0255)
Number of adults other than householder/spouse/partner	0.0120	(0.0292)
African American householder[b]	0.1719***	(0.0471)
Householder of race other than White or African American[b]	0.1203*	(0.0662)
Hispanic householder	0.1993***	(0.0519)
Age of householder (years)	-0.0009	(0.0017)
Householder has high school degree[c]	-0.0972**	(0.0475)
Householder has some college education[c]	-0.0594	(0.0490)
Householder has bachelor's degree[c]	-0.3378***	(0.0607)
Householder has graduate degree[c]	-0.3451***	(0.0794)
Householder is foreign-born	0.0253	(0.0513)
Real family income ($, thousands)	-0.0300***	(0.0020)
Missing income (indicator)	-0.8442***	(0.0851)
Income < 185% of poverty level	0.2522***	(0.0511)
Metropolitan area	0.0756*	(0.0434)
Midwest region[d]	0.0289	(0.0599)
South region[d]	-0.0312	(0.0646)
West region[d]	0.0338	(0.0658)
Local poverty rate	0.2990	(0.5024)
Food-at-home price index	-0.9384	(1.4447)
Fast food price index	0.2106*	(0.1155)
Density of supermarkets and other general line grocery stores[e]	-0.0067	(0.0316)
Density of convenience stores[e]	-0.0323*	(0.0191)
Density of specialty food stores[e]	-0.1013*	(0.0603)
Density of full-service restaurants[e]	0.0035	(0.0123)
Density of limited-service eating places[e]	-0.0174	(0.0155)
FSS year 2003[f]	-0.0590	(0.0597)
FSS year 2004[f]	0.0355	(0.0579)
FSS year 2005[f]	0.0085	(0.0579)
FSS year 2006[f]	-0.0482	(0.0626)
FSS year 2007[f]	-0.0269	(0.0689)
FSS year 2008[f]	0.0918	(0.0626)
FSS year 2009[f]	-0.0191	(0.0673)
FSS year 2010[f]	-0.0572	(0.0705)

Table 8—*Continues over*

Table 8—*Continued*

Parameter	Estimate	(Std. Error)
Threshold between ‘high/marginal’ and ‘marginal’ food security	0.7276	(0.4921)
Threshold between ‘marginal’ and ‘low’ food security	1.2124**	(0.4923)
Threshold between ‘low’ and ‘very low’ food security	2.5599***	(0.4946)

Source: Estimation results on merged data from FSS, 2002–2010, and ATUS, 2003–2011.

Notes:

This table presents an estimated equation for the children’s food insecurity, based on data from the ATUS–FSS analytical sample. The equation is estimated jointly with an equation for the time in food preparation (see Table 9 for that other equation and additional estimation results). The estimation is performed by the maximum likelihood method, using a SUR technique implemented in the CMP package in Stata (Roodman, 2011). Standard errors (given in parentheses) are computed using the Hessian of the sample log-likelihood function. Observed categorical outcomes for the children’s food security status are ordered and labeled as follows: (1) high/marginal food security, (2) marginal food security, (3) low food security, and (4) very low food security. The children’s food security status is modeled using an ordered probit approach. Parameter magnitudes are specified in terms of the corresponding latent variable scale. Qualitatively, a positive estimated coefficient on a variable implies that the variable tends to exacerbate children’s food insecurity. Conversely, a negative coefficient implies that the variable alleviates food insecurity. To assess these effects quantitatively, see Table 10 for the estimates of marginal effects associated with the explanatory variables. The value of the joint sample log-likelihood function at the parameter estimates is -62,402.76. The number of observations is 13,474. Statistical significance is denoted as: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

[a] The base category comprises married couple households.

[b] The base category comprises households in which the householder is White.

[c] The base category comprises households in which the householder has no high school degree.

[d] The base category comprises cases with the place of residence in the Northeast region.

[e] Density is measured as the number of local food establishments per 10,000 local residents.

[f] The base category comprises cases with the FSS administered in 2002.

Table 9. Estimated Equation for Time in Food Preparation (Latent Variable Scale)

Explanatory Variable	Coefficient	(Std. Error)
Male in married couple[a]	-75.3023***	(1.8247)
Female in unmarried couple[a]	-5.8962	(5.0883)
Male in unmarried couple[a]	-74.7760***	(6.1382)
Single female householder[a]	-20.3837***	(2.5081)
Single male householder[a]	-48.7107***	(4.9340)
Number of children, age 0–4 years	10.0229***	(1.3510)
Number of children, age 5–12 years	6.8014***	(0.9754)
Number of children, age 13–17 years	6.7027***	(1.4121)
Number of adults other than householder/spouse/partner	-2.4446	(1.6425)
African American householder[b]	-1.2179	(2.9518)
Householder of race other than White or African American[b]	7.7791**	(3.5826)
Hispanic householder	7.9016***	(3.0746)
Age of householder (years)	0.7842***	(0.0987)
Householder has high school degree[c]	-5.7264*	(3.1967)
Householder has some college education[c]	-6.5261**	(3.2393)
Householder has bachelor's degree[c]	-4.2058	(3.4894)
Householder has graduate degree[c]	0.9739	(3.8642)
Householder is foreign-born	16.0899***	(2.8467)
Real family income ($, thousands)	-0.0906	(0.0653)
Missing income (indicator)	-1.4539	(3.8899)
Income < 185% of poverty level	6.4800**	(2.6226)
Metropolitan area	4.9541**	(2.3852)
Midwest region[d]	-3.0327	(2.9959)
South region[d]	-9.8848***	(3.2102)
West region[d]	-3.4643	(3.3284)
Local poverty rate	-7.6251	(27.4181)
Food-at-home price index	54.4782	(72.7731)
Fast food price index	5.8650	(6.0179)
Density of supermarkets and other general line grocery stores[e]	1.2785	(1.7220)
Density of convenience stores[e]	1.1045	(0.9864)
Density of specialty food stores[e]	-1.6629	(3.1104)
Density of full-service restaurants[e]	0.7191	(0.6409)
Density of limited-service eating places[e]	-0.0616	(0.8083)
ATUS year 2004[f]	1.1649	(3.1485)
ATUS year 2005[f]	-1.2476	(3.1294)
ATUS year 2006[f]	6.9283**	(3.1048)
ATUS year 2007[f]	-3.3225	(3.2749)
ATUS year 2008[f]	-1.5649	(3.6455)
ATUS year 2009[f]	0.2257	(3.4123)
ATUS year 2010[f]	0.1762	(3.5550)
ATUS year 2011[f]	4.9506	(3.7315)

Table 9—*Continues over*

Table 9—*Continued*

Explanatory Variable	Coefficient	(Std. Error)
Sunday[g]	8.8017***	(2.9074)
Monday[g]	-1.7134	(3.5005)
Tuesday[g]	-1.4949	(3.4741)
Thursday[g]	-2.0903	(3.5267)
Friday[g]	-13.3931***	(3.5563)
Saturday[g]	0.3743	(2.9281)
Holiday	16.6702***	(5.1068)
March[h]	-6.4053	(5.1394)
April[h]	-7.4131	(5.1384)
May[h]	-10.3188**	(5.1403)
June[h]	-11.3462**	(5.1736)
July[h]	-20.6081***	(6.3756)
Constant term	-6.2311	(25.7131)

Source: Estimation results on merged data from FSS, 2002–2010, and ATUS, 2003–2011.

Notes:

This table presents an estimated equation for the time in food preparation, based on data from the ATUS–FSS analytical sample. The equation is estimated jointly with an equation for the children's food insecurity (see Table 8 for that other equation and additional estimation results). The estimation is performed by the maximum likelihood method, using a SUR technique implemented in the CMP package in Stata (Roodman, 2011). Standard errors (given in parentheses) are computed using the Hessian of the sample log-likelihood function. The time in food preparation is measured in minutes per day and comprises the following time use categories from the ATUS lexicon: 020201 "Food and drink preparation," 020202 "Food presentation," 020203 "Kitchen and food clean-up," 020299 "Food and drink preparation, presentation, and clean-up, not elsewhere classified (n.e.c.)," 070101 "Grocery shopping," 180202 "Travel related to food and drink preparation, clean-up, and presentation," and 180701 "Travel related to grocery shopping." To account for a substantial fraction of cases with zero time in food preparation, the dependent variable in the equation is modeled using a Tobit approach (with left censoring at zero). Parameter magnitudes are specified in terms of the corresponding latent variable scale. Qualitatively, a positive estimated coefficient on a variable implies that the variable is associated with an increase in the amount of time in food preparation. Conversely, a negative coefficient implies that the variable is associated with a decrease in the amount of time in food preparation. To facilitate the interpretation of the estimation results, Table 11 provides the estimates of marginal effects of the explanatory variables on the expected amount of time in food preparation, specified in terms of minutes per day. The estimated standard deviation (std. error) of the error term of the equation is 85.3426*** (0.6691). The estimated correlation (std. error) between the error terms of the two equations is -0.0030 (0.0153). The number of observations is 13,474. Statistical significance is denoted as: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

[a] The base category comprises females in married couples (i.e., wives in married couple households).

[b] The base category comprises cases when the householder is White.

[c] The base category comprises cases when the householder has no high school degree.

[d] The base category comprises cases with the place of residence in the Northeast region.

[e] Density is measured as the number of local food establishments per 10,000 local residents.

[f] The base category comprises cases with the ATUS administered in 2003.

[g] The base category comprises cases with the ATUS diary day falling on a Wednesday.

[h] The base category comprises cases with the ATUS diary day falling on the month of February.

Table 10. Marginal Effects of Explanatory Variables on Incidence of Children's Food Insecurity

Food Security Outcome	*(1) High/Marginal*		*(2) Marginal*		*(3) Low*		*(4) Very Low*	
Explanatory Variable	Estimate	(Std. Error)	Estimate	(Std. Error)	Estimate	(Std. Error)	Estimate	(Std. Error)
Unmarried couple hh[a]	-0.0199*	(0.0112)	0.0074*	(0.0042)	0.0110*	(0.0062)	0.0014*	(0.0008)
Single female-headed hh	-0.0519***	(0.0066)	0.0194***	(0.0025)	0.0288***	(0.0037)	0.0038***	(0.0006)
Single male-headed hh	-0.0395***	(0.0139)	0.0147***	(0.0052)	0.0218***	(0.0077)	0.0029***	(0.0011)
# of children, age 0–4	-0.0128***	(0.0042)	0.0048***	(0.0016)	0.0071***	(0.0023)	0.0009***	(0.0003)
# of children, age 5–12	-0.0251***	(0.0030)	0.0094***	(0.0011)	0.0139***	(0.0017)	0.0018***	(0.0003)
# of children, age 13–17	-0.0250***	(0.0044)	0.0093***	(0.0016)	0.0138***	(0.0024)	0.0018***	(0.0004)
# of other adults	-0.0021	(0.0050)	0.0008	(0.0019)	0.0011	(0.0028)	0.0001	(0.0004)
African American hh	-0.0295***	(0.0081)	0.0110***	(0.0030)	0.0163***	(0.0045)	0.0021***	(0.0006)
Other race hh	-0.0206*	(0.0114)	0.0077*	(0.0042)	0.0114*	(0.0063)	0.0015*	(0.0008)
Hispanic hh	-0.0342***	(0.0089)	0.0128***	(0.0033)	0.0190***	(0.0049)	0.0025***	(0.0007)
Age of hh (years)	0.0002	(0.0003)	-0.0001	(0.0001)	-0.0001	(0.0002)	-0.0000	(0.0000)
High school degree	0.0167**	(0.0081)	-0.0062**	(0.0030)	-0.0092**	(0.0045)	-0.0012**	(0.0006)
Some college education	0.0102	(0.0084)	-0.0038	(0.0031)	-0.0057	(0.0047)	-0.0007	(0.0006)
Bachelor's degree	0.0579***	(0.0104)	-0.0216***	(0.0039)	-0.0321***	(0.0058)	-0.0042***	(0.0009)
Graduate degree	0.0592***	(0.0136)	-0.0221***	(0.0051)	-0.0328***	(0.0076)	-0.0043***	(0.0011)
Foreign-born hh	-0.0043	(0.0088)	0.0016	(0.0033)	0.0024	(0.0049)	0.0003	(0.0006)
Real family income ($, thousands)	0.0051***	(0.0003)	-0.0019***	(0.0001)	-0.0028***	(0.0002)	-0.0004***	(0.0000)
Missing income	0.1448***	(0.0146)	-0.0540***	(0.0056)	-0.0803***	(0.0083)	-0.0105***	(0.0015)
Income < 185% of poverty level	-0.0433***	(0.0087)	0.0161***	(0.0033)	0.0240***	(0.0049)	0.0031***	(0.0007)
Metropolitan area	-0.0130*	(0.0074)	0.0048*	(0.0028)	0.0072*	(0.0041)	0.0009*	(0.0005)
Midwest region	-0.0050	(0.0103)	0.0019	(0.0038)	0.0028	(0.0057)	0.0004	(0.0007)
South region	0.0054	(0.0111)	-0.0020	(0.0041)	-0.0030	(0.0061)	-0.0004	(0.0008)
West region	-0.0058	(0.0113)	0.0022	(0.0042)	0.0032	(0.0063)	0.0004	(0.0008)
Local poverty rate	-0.0513	(0.0862)	0.0191	(0.0322)	0.0284	(0.0478)	0.0037	(0.0063)
Food-at-home price index	0.1610	(0.2478)	-0.0601	(0.0925)	-0.0893	(0.1374)	-0.0117	(0.0180)
Fast food price index	-0.0361*	(0.0198)	0.0135*	(0.0074)	0.0200*	(0.0110)	0.0026*	(0.0015)

Table 10—*Continues over*

Table 10—*Continued*

Food Security Outcome	*(1) High/Marginal*		*(2) Marginal*		*(3) Low*		*(4) Very Low*	
Explanatory Variable	Estimate	(Std. Error)	Estimate	(Std. Error)	Estimate	(Std. Error)	Estimate	(Std. Error)
Density of supermarkets	0.0012	(0.0054)	-0.0004	(0.0020)	-0.0006	(0.0030)	-0.0001	(0.0004)
Density of convenience stores	0.0055*	(0.0033)	-0.0021*	(0.0012)	-0.0031*	(0.0018)	-0.0004*	(0.0002)
Density of specialty food stores	0.0174*	(0.0104)	-0.0065*	(0.0039)	-0.0096*	(0.0057)	-0.0013*	(0.0008)
Density of full-serv. restaurants	-0.0006	(0.0021)	0.0002	(0.0008)	0.0003	(0.0012)	0.0000	(0.0002)
Density of lim.-serv. eating places	0.0030	(0.0027)	-0.0011	(0.0010)	-0.0017	(0.0015)	-0.0002	(0.0002)
FSS year 2003	0.0101	(0.0102)	-0.0037	(0.0038)	-0.0056	(0.0057)	-0.0007	(0.0007)
FSS year 2004	-0.0061	(0.0099)	0.0023	(0.0037)	0.0034	(0.0055)	0.0004	(0.0007)
FSS year 2005	-0.0015	(0.0099)	0.0005	(0.0037)	0.0012	(0.0055)	0.0001	(0.0007)
FSS year 2006	0.0083	(0.0107)	-0.0031	(0.0040)	-0.0046	(0.0060)	-0.0006	(0.0008)
FSS year 2007	0.0046	(0.0118)	-0.0017	(0.0044)	-0.0026	(0.0066)	-0.0003	(0.0009)
FSS year 2008	-0.0157	(0.0107)	0.0059	(0.0040)	0.0087	(0.0060)	0.0011	(0.0008)
FSS year 2009	0.0033	(0.0115)	-0.0012	(0.0043)	-0.0018	(0.0064)	-0.0002	(0.0008)
FSS year 2010	0.0098	(0.0121)	-0.0037	(0.0045)	-0.0054	(0.0067)	-0.0007	(0.0009)
Fraction of households[b]	0.8591		0.0680		0.0673		0.0057	

Source: Estimation results on merged data from FSS, 2002–2010, and ATUS, 2003–2011.

Notes:

This table presents average marginal effects of explanatory variables on children's food insecurity, as implied by parameter estimates. An estimate measures the impact of a change in a variable on the probability of a given categorical food security outcome. All probability changes are first evaluated for each observation separately and then averaged across the ATUS–FSS analytical sample. Standard errors (presented in parentheses) are computed by the delta method. Marginal effects of explanatory variables that do not enter the children's food insecurity equation (see Table 8) are identically zero and omitted. Statistical significance is denoted as: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

[a] The abbreviation "hh" stands for "household" or "householder" as appropriate. See the unabbreviated variable names and descriptions of base categories in Table 8.

[b] A weighted fraction of households in the ATUS–FSS analytical sample with a specified children's food security status (see Table 3).

Table 11. Marginal Effects of Explanatory Variables on Expected Amount of Time in Food Preparation (Minutes per Day)

Explanatory Variable	Estimate	(Std. Error)
Male in married couple[a]	-48.2817***	(1.1342)
Female in unmarried couple	-3.7805	(3.2624)
Male in unmarried couple	-47.9443***	(3.9253)
Single female householder	-13.0695***	(1.6064)
Single male householder	-31.2319***	(3.1580)
Number of children, age 0–4 years	6.4264***	(0.8654)
Number of children, age 5–12 years	4.3608***	(0.6250)
Number of children, age 13–17 years	4.2976***	(0.9052)
Number of adults other than householder/spouse/partner	-1.5674	(1.0531)
African American householder	-0.7809	(1.8926)
Householder of race other than White or African American	4.9878**	(2.2971)
Hispanic householder	5.0663***	(1.9712)
Age of householder (years)	0.5028***	(0.0632)
Householder has high school degree	-3.6716*	(2.0496)
Householder has some college education	-4.1843**	(2.0770)
Householder has bachelor's degree	-2.6966	(2.2373)
Householder has graduate degree	0.6244	(2.4776)
Householder is foreign-born	10.3164***	(1.8250)
Real family income ($, thousands)	-0.0581	(0.0419)
Missing income (indicator)	-0.9322	(2.4941)
Income < 185% of poverty level	4.1548**	(1.6814)
Metropolitan area	3.1764**	(1.5292)
Midwest region	-1.9445	(1.9208)
South region	-6.3378***	(2.0580)
West region	-2.2212	(2.1340)
Local poverty rate	-4.8890	(17.5797)
Food-at-home price index	34.9299	(46.6591)
Fast food price index	3.7605	(3.8585)
Density of supermarkets and other general line grocery stores	0.8197	(1.1041)
Density of convenience stores	0.7082	(0.6324)
Density of specialty food stores	-1.0662	(1.9942)
Density of full-service restaurants	0.4611	(0.4109)
Density of limited-service eating places	-0.0395	(0.5183)
ATUS year 2004	0.7469	(2.0187)
ATUS year 2005	-0.7999	(2.0065)
ATUS year 2006	4.4422**	(1.9905)
ATUS year 2007	-2.1303	(2.0997)
ATUS year 2008	-1.0034	(2.3374)
ATUS year 2009	0.1447	(2.1879)
ATUS year 2010	0.1130	(2.2794)
ATUS year 2011	3.1742	(2.3925)

Table 11—*Continues over*

Table 11—*Continued*

Explanatory Variable	Estimate	(Std. Error)
Sunday	5.6434***	(1.8640)
Monday	-1.0986	(2.2444)
Tuesday	-0.9585	(2.2275)
Thursday	-1.3403	(2.2612)
Friday	-8.5873***	(2.2794)
Saturday	0.2400	(1.8774)
Holiday	10.6885***	(3.2740)
March	-4.1069	(3.2952)
April	-4.7531	(3.2945)
May	-6.6161**	(3.2956)
June	-7.2748**	(3.3168)
July	-13.2133***	(4.0870)
Average amount of time in food preparation (minutes per day)[b]	52.0620	

Source: Estimation results on merged data from FSS, 2002–2010, and ATUS, 2003–2011.

Notes:

This table presents average marginal effects of explanatory variables on the time in food preparation, as implied by parameter estimates. The magnitude of a marginal effect represents an average change in the expected amount of time in food preparation, specified in terms of minutes per day. In contrast to the coefficient estimates on the latent variable scale presented in Table 9, the estimates here account for the fact that the amount of time cannot be negative (for additional details, see Greene, 2012, pp. 848–850). All marginal effects are first evaluated for each observation separately and then averaged across the ATUS–FSS analytical sample. Standard errors (presented in parentheses) are computed by the delta method. Marginal effects of explanatory variables that do not enter the time in food preparation equation (see Table 9) are identically zero and omitted. Statistical significance is denoted as: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

[a] For a description of base categories, see Table 9.

[b] A weighted average for the reported amount of time in food preparation (in minutes per day) in the ATUS–FSS analytical sample, including cases with zero time.

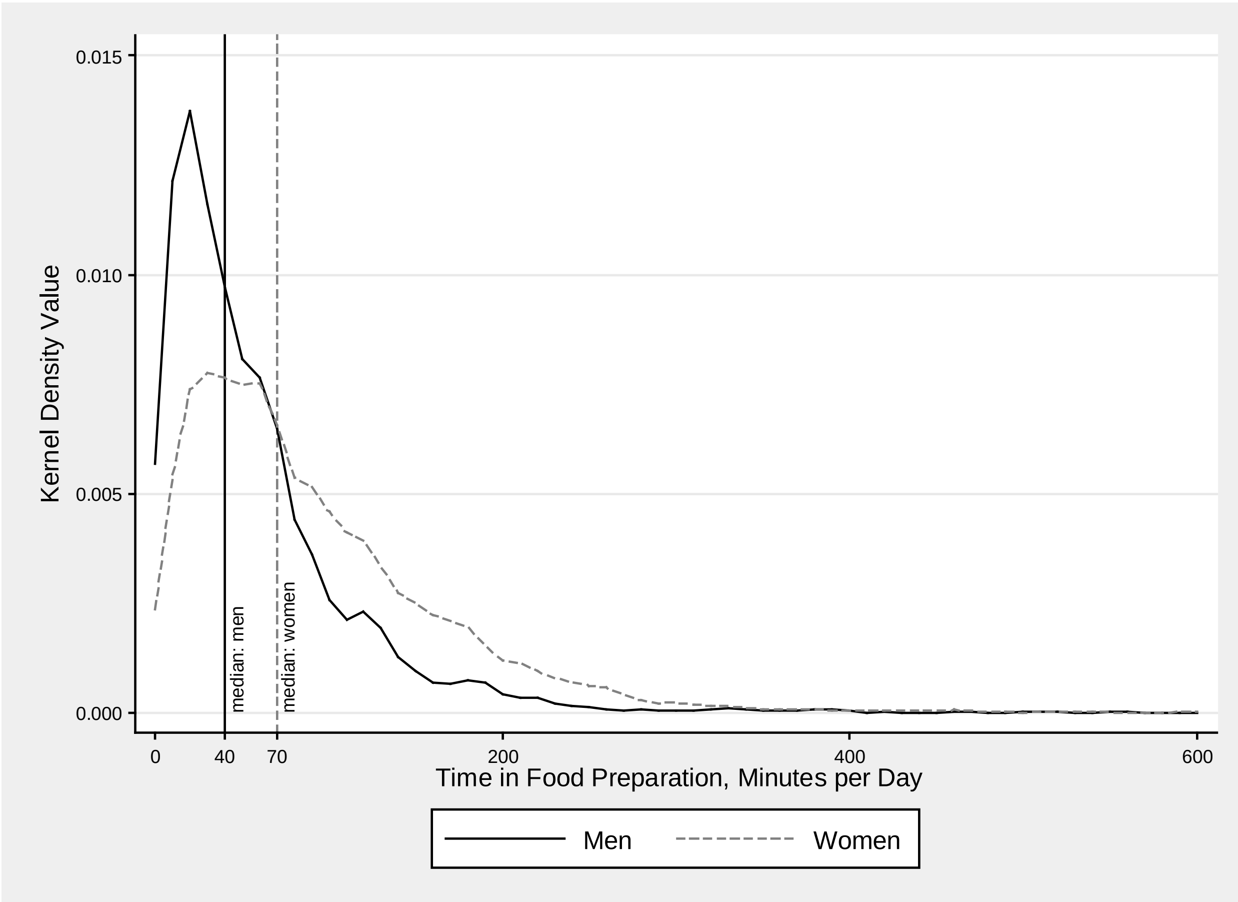

Figure 1. Kernel Densities of Time in Food Preparation (Conditional on Time > 0).

Notes:

This figure plots kernel densities of the amount of time in food preparation, in minutes per day, for men and women from the ATUS–FSS analytical sample who report non-zero time in food preparation. These densities are computed using Epanechnikov's kernel (with a bandwidth set at 7.00) and the ATUS sample weights. To facilitate a comparison of the densities between the subsample of men and the subsample of women, the horizontal axis is truncated at 600 minutes.