Received: 3 September 2018 | Revised: 20 February 2019 | Accepted: 19 April 2019

DOI: 10.1111/agec.12506

AGRICULTURAL ECONOMICS The Journal of the International Association of Agricultural Economists IAAE WILEY

ORIGINAL ARTICLE

Life cycle models of women's body mass index and probability of being obese: Evidence from panel data

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Abstract

The objective of this paper is to develop a multiperiod, finite-life, life cycle models of household decisions on food, leisure, and health (body mass index [BMI] or being obese) and to estimate econometric versions of these models treating SNAP (Supplemental Nutrition Assistance Program) participation as endogenous. A key insight from the economic models is that households allocate their wealth over the multiperiod life cycle to equalize the marginal utility of wealth in each period. The observations for this study are a balanced panel of over 1,600 women from the National Longitudinal Survey of Youth, 1979 Cohort (NLSY79). We focus on the 20-year period starting in 1986, when SNAP data first became available. Women of all ages are included in the study because at the beginning of adulthood women cannot accurately predict over their life cycle labor and marriage market and health shocks that can thrust them into an economic position where they would qualify for SNAP. New findings include that a woman's household SNAP participation with or without updating for last periods health status and higher local dairy product prices reduce significantly her BMI and probability of being obese.

KEYWORDS

Frisch model, food and drink prices, life-cycle decision making, panel data analysis, Supplemental Nutrient Assistance Program, United States, women

JEL CLASSIFICATION

D91, D12, Q18, C33

1 | INTRODUCTION

Over the past 35 years, the U.S. adult obesity rate has more than doubled from roughly 15–35%, reflecting a general diffusion of obesity across all segments of the adult population (Fryar, Carroll, & Ogden, 2018). Obesity is a concern because it increases the risk for cardiovascular diseases, diabetes, and most forms of cancer, except for lung. In addition, when adults are obese, their labor productivity and quality of life decline, medical expenditures increase dramatically, and many die prematurely. The U.S. obesity rate is the highest in the world, and obese adults are a major financial burden to families and also the U.S. Medicare and Medicaid Programs. In 2008, medical costs associated with obesity were estimated at $147 billion; the per capita medical costs paid by third-party payers for people who are obese were $1,429 higher than for those of normal weight (Ogden & Carroll, 2010).

Food (and drink) purchased for at home uses is targeted by the USDA's Supplemental Nutrition Assistance Program (SNAP), formerly known as the Food Stamp Program (FSP). The FSP was initiated in the 1960s when the major concern among low-income households was inadequate calories and nutrition, sometimes called food insecurity (Caswell & Yaktine, 2013). In addition, over this time period family structure has changed; single parenting has become an increasing

U.S. phenomena (Duncan, Sweeny, & Murname, 2011; Heckman & Masterov, 2007; Heckman, Stixrud, & Urzua, 2006; Phillips, 2011), and Currie and Grogger (2001) show that single-parent households are roughly three times as likely to be SNAP participants as two-parent households. Roughly 87% of these households are headed by women (U.S. Census Bureau, 2013). In an attempt to reduce the transactions costs associated with SNAP benefit usage, in 2004 the Food and Nutrition Service started to implement electronic benefits transfer (see Food and Nutrition Service, 2018).

The amount of benefits is low before 1970, but it trended steadily upward to 1995 with a short-term peak of about $26 billion (see Supplemental Figure A1). Following some reforms, SNAP benefits dipped to 2000 with about $14 billion (Wilde, Cook, Gundersen, Nord, & Tiehen, 2000) and then rose more or less steadily until 2012 with total benefits of about $80 billion, before declining to about $72 billion in 2015. The onset of the Great Recession in 2007 was a major factor in the rapid rise in SNAP benefits from 2007 to 2013, and benefits have been slow to decline since then. In 2014, SNAP food expenditures accounted for about 10% of total expenditures on food for consumption at home (Economic Research Service, 2016).

Currently, SNAP benefits can be used to purchase most foods and beverages sold in grocery stores and supermarkets for home consumption, including nutrient-rich whole grains, fruit, and vegetables, as well as nutrient-poor salty snacks, sweets, baked goods, sugar-sweetened beverages, milk and dairy products, and processed and raw meats.[1] However, deli, hot or prepared foods, dietary supplements, alcohol, and tobacco are excluded (Food and Nutrition Service, 2019).

Related research provides mixed evidence of the effects of SNAP on women's health.[2] Leung et al. (2012) report that SNAP participants have higher consumption of fruit juices, potatoes, red meat, and sugar-sweetened beverages and lower consumption of whole grains than other adults from low-income households. They also report that SNAP participants have a lower frequency of daily dietary intakes meeting two or more of ten food and nutrient intake guidelines than adults in other low-income households.

Although the FSP was launched with the aim to improve food security of low-income people, it is now sometimes criticized for causing overweight and obesity in participants, including women who are or who have been participants in the program (Gunderson, 2013; Ver Ploeg & Ralston, 2008). Although Meyerhoefer and Yang (2011) provide a review of the relationship between food assistance and health, their review of economic and econometric models in the literature only covers static models presumably because they did not find anyone undertaking life cycle analysis of obesity and SNAP participation. Empirical cross-sectional studies include Chen, Yen, and Eastwood (2005), who used the data from the 1994–1996 Continuing Survey of Food Intakes by Individuals and found that FSP participation was positively related to body weight and to the likelihood of women being obese. Meyerhoefer and Pylypchuk (2008), using the 2000–2003 Medical Expenditure Panel Survey (MEPS) and information on state-level FSP characteristics, found that when a woman's household participates in the FSP, she was 5.9% more likely to be overweight or obese and also to have higher medical expenditures. Gibson (2003, 2004), using a short panel and a static model, found that both current and long-term FSP participation were significantly related to the obesity of women. Baum (2011) used models assuming one period decision making and the NLSY data, subsample of low-income men and women, to explain weight changes over time and relate it to current and past participation in the FSP. He found that FSP participation has a significant positive effect on obesity, but the effect is relatively small.[3] Zhang, Chen, Diawara, and Wang (2011) examine the interactive between the price of unhealthy foods and SNAP participation on body weight status among low-income women in the United States. Using a static model and observations on the NLSY 79 cohort over 1985–2002, the authors found that higher prices for unhealthy food could partially offset the positive association between SNAP participation and body weight among low-income women. Herring and Moffitt (2018) study whether SNAP mediates the effect of food insecurity on future health (and health care utilization). They use relatively recent data from the National Health Interview Survey and MEPS. The MEPS provides information on SNAP participation starting in 2011. Their results include that SNAP significantly reduces BMI for (nonelderly) adults that are extremely poor, but not for other (non-elderly) adults.

In contrast to the above studies, Gundersen and Ziliak (2003) consider the effects of the FSP on income and food consumption stabilization. They used data from the Panel Study of Income Dynamics over 1980–1999 and find that FSP benefits reduce income volatility by about 3% and consumption volatility by about 4%. Not surprising is that for families at high ex ante risk of food stamp participation, the reductions were by 12 and 14%, respectively. However, they conclude that the role of FSP in smoothing income and food consumption by the early 1990s was reduced by two-thirds relative to

[1] SNAP can also be used to purchase seeds and plants that produce food for the household to eat. Soft drinks candy, cookies, snack crackers, ice cream, seafood, steak, and bakery cakes are also eligible foods (USDA, 2018).

[2] The model can be applied to men, too.

[3] In related research, Mancino and Guthrie (2014) report analyzing dietary intake data from the 2003–2010 NHANES to assess the diet of adult SNAP participants and other adult respondents relative to the 2010 Healthy Eating Index (HEI). They concluded that HEI scores for adult SNAP participants averaged 46 (out of 100 maximum points), compared to 50 for income-eligible adults not receiving SNAP benefits, and 53 for higher income adults. Differences were most pronounced for whole fruits and empty calories. However, SNAP participants showed lower sodium intake.

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the 1980s. This is, the relative role of FSP smoothing consumption and income seems to have declined.

Major shortcomings of the literature on the impacts of SNAP participation on health status (BMI and being obese) include that some studies do not include an economic model of participation, or if they do, it is a static model. However, Gundersen and Ziliak (2003) did introduce the distinction between permanent and transitory components of income, including FSP benefits and their effects on food consumption, but their model is not one of optimization over a finite-life life cycle where delaying an investment 1 year eliminates one period of benefits. Other studies use simpler economic models. From a finite-life life cycle perspective, a young adult woman has a number of important decisions that need to be made in each period including time allocation, health production, and consumption. One possible source of income is from the SNAP program, but due to random shocks in the labor market (layoffs and permanent loss of jobs), marriage market, and health outcomes, she is unsure about these outcomes. Hence, all young adult women have positive probability of being eligible for SNAP at some point in their life cycle, and past studies that focus only on currently low-income women creates a select sample for researching the impact of SNAP on women's health.

Over the past 30 years, some have alleged that falling real prices of food, increased consumption of processed and fast foods, reduced exercise, and rising incomes have resulted in a general problem in the United States and Western Europe of people consuming too many calories. Some others suggest that altered birthing modes and human host–bacterial interactions, which are related to more than diet or exercise, are to blame, for example, Nicholson et al. (2012). What is clear is that there is a growing obesity problem. For example in our data set, over a 20 year period, the average BMI of women increased by over 19% from 22.6 to 27, whereas their obesity rate increased by over 20 percentage points.[4]

The objective of this paper is to develop multiperiod, finite-life, life cycle models of household decisions on food, leisure, and health (BMI or being obese) and to estimate econometric versions of these models treating SNAP participation as endogenous. We develop models without and with updating for health status in the previous period. The observations for this study are a balanced panel of over 1,600 women who were in their teens or early twenties when they entered the National Longitudinal Survey of Youth, 1979 Cohort (NLSY79). These women were a nationally representative sample of women (and men) 14–22 years of age when they were first interviewed in 1979. The individuals were interviewed annually from 1979 to 1994 and then biennially after 1996. However, data on household FSP/SNAP participation did not start until 1986. Our data set is a balanced panel of women over 20 years of age starting in 1986, but sampled at 4-year intervals over the next 20 years. Women of all ages are included in the study because at the beginning of adulthood, women cannot accurately predict adulthood life cycle labor and marriage market and health shocks that can thrust them into an economic position where they would qualify for SNAP.

We obtained special permission from the U.S. Department of Labor to access geocode information for each woman and household, allowing us to link an individual and household to area level data on prices of food, drink, and simple health care items obtained from the American Chamber of Commerce Research Association (ACCRA) Cost of Living Index.[5] New findings include that a woman's SNAP participation with or without updating for her health status in the previous period and higher local dairy product prices reduces significantly her BMI and probability of being obese.

The rest of the paper is organized as follows. In Section 2, we develop two theoretical models of an individual's life cycle decision making on health, SNAP participation, leisure, and food consumption without updating and with updating. Section 3 summarizes the data, Section 4 presents the econometric model. Section 4 presents the empirical results from fitting both models. The final section presents conclusions from the study.

2 | LIFE CYCLE MODELS OF HOUSEHOLD DECISION MAKING

Our economic model is one of a forward-looking adult woman who makes multiperiod, finite-life life cycle decisions on a number of behaviors. Two scenarios are considered: Model I where a woman makes lifetime decisions at the beginning of (adult) life and does not update, and Model II where she updates decisions each period based on last period's health outcome (BMI and probability of being obese). The first model is simpler, and we consider it first and in considerable detail. These models build on earlier research by McCurdy (1981) and Blundell and McCurdy (1999).

2.1 | Model I

Households have an identical strictly concave utility function for each year in the life cycle t:

$$U_t = U(F_t, C_t, H_t, LP_t, LO_t, Z_t, \phi) + S(FS_t; Z_t, \phi) \quad (1)$$

where F_t is the quantity of food and drink, C_t is quantity of other purchased goods, except health care, LP_t is hours of

[4] An international perspective on diet, food, obesity, and satisfaction can be found in Just and Gabrielyan (2016), Staudigel (2012), and Huffman and Rizov (2018).

[5] One important fact is that over the study period, U.S. households do their main grocery shopping at supermarkets and supercenters regardless of income level (Ver Ploeg, Mancino, Todd, Clay, & Scharadin, 2015).

physically active leisure, and LO_t is hours of other leisure time. Z_t includes observable measures of the household, that is, age, race, education, family structure, and geographic location. ϕ represents household-specific unobservable.

An additional dimension of household utility is the disutility from stigma obtained from participating in the SNAP program (Barnhill, 2011; Moffitt, 1983). This disutility is represented by $S(\cdot)$. Specifically, with FS_t representing the quantity of food purchased with the SNAP income, SNAP-use disutility function satisfies the conditions:

$$\begin{cases} S(0; Z_t, \varphi) = 0, \quad S(FS_t; Z_t, \varphi) \to c_1 < 0 \text{ if } FS_t \to 0, \\ \dfrac{dS}{dFS_t} \to c_2 > 0 \text{ if } FS_t \to 0, \quad \dfrac{d^2S}{dFS_t^2} \leq 0 \end{cases} \tag{2}$$

In other words, if the household does not participate in the program, the disutility associated with SNAP participation is 0. If the household participates in the SNAP program, the disutility associated with participation is lower, bounded by a constant $c_1 < 0$, and increases as the quantity of food purchased from SNAP payments increases, which implies a positive marginal disutility.[6] To permit a corner solution for FS_t, we also impose an upper bound, $c_2 > 0$, for marginal disutility.

Households have an identical strictly concave health production function that applies in each year of the life cycle t:

$$H_t = H(F_t, LP_t, M_t; H_e, Z_t, \varphi) \tag{3}$$

where M_t is a medical care input. Production of health is conditioned by H_e, her individual-specific and unvarying over the life cycle health endowment, Z_t, which represents observable characteristic of the household, for example, age, race, education, family structure, geographic location, and φ, which represents household specific health-related unvarying unobservables.

In each year, a woman has a time endowment T, say 8,760 hr, that is allocated among work for pay L_t, physically active leisure LP_t, and passive leisure LO_t:

$$L_t + LP_t + LO_t = T. \tag{4}$$

She also has additional resources, household assets A_t, and she faces a market wage W_t, price of food, drink of P_{Ft}, and of health care P_{Mt}.

[6] The USDA has taken steps to reduce the stigma of SNAP use, including changing the name of the program in 2008 from the FSP to the SNAP, and replacing paper coupons with EBT cards that work like debit cards (Barnhill, 2011).

To simplify the analysis in Model 1, the woman is assumed to operate in an environment of perfect certainty, including length of finite life, and choose the quantity of current food and drink (F_t), other consumption, excluding medical care (C_t), physically active leisure time (LP_t), other leisure time (LO_t), purchased medical care (M_t), and SNAP participation (FS_t), conditional on Z_t, ϕ, and φ, by maximizing the value function:

$$V(A_t, t) = \max \big[U(F_t, C_t, H(F_t, LP_t, M_t; Z_t, \phi), LP_t, LO_t; Z_t, \varphi) + S(FS_t; Z_t, \varphi) + \kappa V(A_{t+1}, t+1)\big] \tag{5}$$

subject to the law of motion for a woman's household assets:

$$A_{t+1} = (1 + r_{t+1})(A_t + B_t + P_{F,t}FS_t + W_tT - W_tLP_t - W_tLO_t - C_t - P_{F,t}F_t - P_{M,t}M_t). \tag{6}$$

When the price of C_t, the numeraire good, is set to 1; P_{F_t} and P_{M_t} denotes the local real price of food and drink and purchased medical care, respectively, and W_t denotes the real wage rate. Note that since SNAP is used to purchase food and drink, $(F_t - FS_t)$ is the amount of food and drinks that the household purchases out of its own pre-SNAP resources.

Application of standard dynamic programming techniques produces the first-order conditions (7a)–(7g) below. *Equations* (7a)–(7f) *are the first-order conditions for optimal household decisions in a standard static productive household model, but equation* (7g) *is new and it contains* λ_t, *the marginal utility of wealth* ($\partial V/\partial A_t$). These first-order conditions imply that the woman's decisions are made such that the marginal returns from each choice equals it marginal (opportunity) cost. Specifically, the first-order condition with respect to FS_t indicates that the household would not participate in SNAP when the marginal return from participation $\lambda_t P_{F,t}$ is less than the marginal disutility $-(dS/dFS_t)$, and vice versa.

$$\frac{\partial U_t}{\partial F_t} + \frac{\partial U_t}{\partial H_t} \cdot \frac{\partial H_t}{\partial F_t} = \lambda_t P_{F,t} \tag{7a}$$

$$\frac{\partial U_t}{\partial C_t} = \lambda_t \tag{7b}$$

$$\frac{\partial U_t}{\partial H_t} \cdot \frac{\partial H_t}{\partial M_t} = \lambda_t P_{M,t} \tag{7c}$$

$$\frac{\partial U_t}{\partial LP_t} + \frac{\partial U_t}{\partial H_t} \cdot \frac{\partial H_t}{\partial LP_t} = \lambda_t W_t \tag{7d}$$

$$\frac{\partial U_t}{\partial LO_t} = \lambda_t W_t \tag{7e}$$

$$\frac{dS}{dFS_t} + \lambda_t P_{F,T} \le 0,\ FS_t \ge 0,$$

$$FS_t\left(\frac{dS}{dFS_t} + \lambda_t P_{F,T}\right) = 0 \tag{7f}$$

$$\frac{\partial V_{t+1}}{\partial A_{t+1}} = \frac{\lambda_t}{\kappa(1+r_{t+1})} = \lambda_{t+1}. \tag{7g}$$

Equation (7g) provides key information associated with the dynamic features of the model of household decision making. It is the Euler equation of dynamic programming, and it provides the optimal conditions for allocating wealth over time in the finite-life, life cycle as represented in the condition: $\lambda_t = \lambda_{t+1}\ \kappa(1+r_{t+1})$, that is, she chooses savings (dissavings) so that her marginal utility of wealth in year t equals the discounted value of the marginal utility of her wealth in year $t + 1$; the rate of discount is $\kappa(1+r_{t+1})$.

Given the multiperiod, finite-life life cycle model, the conditions in (7) can be solved to provide the optimal quantity demanded of goods (F^*, C^*, M^*), time allocation of adults (LP^*, LO^*, L^*), demand for food stamps FS_t, and adult health status (H^*). These Frisch marginal-utility-of-wealth-constant demand functions for goods (F^*, FS^*, C^*), medical services (M^*), hours (LP^*, LO^*, L^*), and health status (H^*) are of the form summarized below in Equations (8a)–(8h).

$$F_t^* = F(\lambda_t, P_{F,t}, P_{M,t}, W_t; Z_t, H_e, \phi, \varphi) \tag{8a}$$

$$C_t^* = C(\lambda_t, P_{F,t}, P_{M,t}, W_t; Z_t, H_e, \phi, \varphi) \tag{8b}$$

$$M_t^* = M(\lambda_t, P_{F,t}, P_{M,t}, W_t; Z_t, H_e, \phi, \varphi) \tag{8c}$$

$$L_t^* = L(\lambda_t, P_{F,t}, P_{M,t}, W_t; Z_t, H_e, \phi, \varphi) \tag{8d}$$

$$LP_t^* = LP(\lambda_t, P_{F,t}, P_{M,t}, W_t; Z_t, H_e, \phi, \varphi) \tag{8e}$$

$$LO_t^* = LO(\lambda_t, P_{F,t}, P_{M,t}, W_t; Z_t, H_e, \phi, \varphi) \tag{8f}$$

$$FS_t^* = FS(\lambda_t, P_{F,t}, P_{M,t}, W_t; Z_t, H_e, \phi, \varphi) \tag{8g}$$

$$\begin{aligned} H_t^* &= H(F_t^*, LP_t^*, M_t^*; Z_t, H_e, \phi) \\ &= H(\lambda_t, P_{F,t}, P_{M,t}, W_t; Z_t, H_e, \phi, \varphi). \end{aligned} \tag{8h}$$

These equations reveal the very important set of variables that determine individual's finite-life life cycle choices. They are the marginal utility of wealth (λ_t), contemporaneous prices of local food and drink and medical care, the individual's opportunity cost of time or her wage conditional on observable attributes of the household (Z_t), household-specific health-related fixed (over the life time) unobservables (φ), and unobservable other effects affecting household utility (ϕ).

In contrast to static household models, for example, Meyerhoefer and Yang (2011) and Zhang et al. (2011), current income is not a determinant of the demand for good health in Equation (8h). The reason is that in this multiperiod, finite-life, life cycle model, assets are allocated over years according to Equation (7g), which provides intertemporal smoothing of consumption. However, we do not observe λ_t, but Blundell and MaCurdy (1999) suggest that in these circumstance we use the following logic to measure it. First, rearrange Equation (7g) to obtain the following relationship:

$$\ln \lambda_{t+1} = -\ln(\kappa(1+r_{t+1})) + \ln \lambda_t = b_t + \ln \lambda_t, \tag{9}$$

then apply repeat substitution and working backward to obtain the following relationship:

$$\ln \lambda_t = \sum_{j=0}^{t-1} b_j + \ln \lambda_0, \tag{10}$$

where $b_t = -\ln(\kappa(1+r_{t+1}))$. From (10), λ_t can be partitioned into λ_0, which is treated as an unobservable household fixed effect, plus b_t, which is related to the household's interest rate (r_t) and utility discount rate (κ). Hence, in our empirical model we replace λ_t in the set of choice equations (8a)–(8h) by the individual's age and age-squared and an individual fixed effect. The effects of (ϕ, φ), which do not change over time, are also included in the individual fixed effect.

2.2 | Model II

The multiperiod, finite-life, life cycle decision making of a woman might include updating, for example, current decisions respond to shocks in her health in the previous year. For example, her health in the last year may affect her ability to conduct some activities, for example, plan and produce meals, engage in physically active leisure, and to produce good health in the current period. Second, her current health status is a result of an especially complex process, including genetic endowment at birth, long-term habits, past health shocks, and accumulated past health investments.

In our dynamic model with updating, the following equations are modified:

$$H_t = H(F_t, LP_t, M_t, H_{t-1}; Z_t, \phi). \tag{3$'$}$$

$$\begin{aligned} V(A_t, H_{t-1}, t) = \max[&U(F_t, C_t, H(F_t, LP_t, M_t, H_{t-1}; \\ &Z_t, \phi), LP_t, LO_t; Z_t, \varphi) \\ &+ S(FS_t; Z_t, \varphi) \\ &+ \kappa V(A_{t+1}, H_{t-1}, t+1)], \end{aligned} \tag{5$'$}$$

The first-order condition for an optimum are

$$\frac{\partial U_t}{\partial F_t} + \left(\frac{\partial U_t}{\partial H_t} + \kappa\frac{\partial V_{t+1}}{\partial H_t}\right)\cdot\frac{\partial H_t}{\partial F_t} = \lambda_t P_{F,t} \tag{7a$'$}$$

$$\left(\frac{\partial U_t}{\partial H_t} + \kappa\frac{\partial V_{t+1}}{\partial H_t}\right)\cdot\frac{\partial H_t}{\partial M_t} = \lambda_t P_{M,t} \tag{7c$'$}$$

$$\frac{\partial U_t}{\partial LP_t} + \left(\frac{\partial U_t}{\partial H_t} + \kappa \frac{\partial V_{t+1}}{\partial H_t} \right) \cdot \frac{\partial H_t}{\partial LP_t} = \lambda_t W_t \tag{7d$'$}$$

$$\frac{dS}{dFS_t} + \lambda_t P_{F,T} \leq 0, \ FS_t \geq 0,$$

$$FS_t \left(\frac{dS}{dFS_t} + \lambda_t P_{F,T} \right) = 0 \tag{7f$'$}$$

$$\frac{\partial V_{t+1}}{\partial H_t} = \frac{\partial U_{t+1}}{\partial H_{t+1}} \cdot \frac{\partial H_{t+1}}{\partial H_t} \tag{7g$'$}$$

$$\frac{\partial V_{t+1}}{\partial A_{t+1}} = \lambda_{t+1} = \frac{\lambda_t}{\kappa \left(1 + r_{t+1}\right)}, \tag{7h$'$}$$

and the set of demand equations now contains last periods health, H_{t-1}:

$$F_t^* = F(\lambda_t, P_{F,t}, P_{M,t}, W_t, H_{t-1}; Z_t, \phi, \varphi) \tag{8a$'$}$$
$$C_t^* = C(\lambda_t, P_{F,t}, P_{M,t}, W_t, H_{t-1}; Z_t, \phi, \varphi) \tag{8b$'$}$$
$$M_t^* = M(\lambda_t, P_{F,t}, P_{M,t}, W_t, H_{t-1}; Z_t, \phi, \varphi) \tag{8c$'$}$$
$$L_t^* = L(\lambda_t, P_{F,t}, P_{M,t}, W_t, H_{t-1}; Z_t, \phi, \varphi) \tag{8d$'$}$$
$$LP_t^* = LP(\lambda_t, P_{F,t}, P_{M,t}, W_t, H_{t-1}; Z_t, \phi, \varphi) \tag{8e$'$}$$
$$LO_t^* = LO(\lambda_t, P_{F,t}, P_{M,t}, W_t, H_{t-1}; Z_t, \phi, \varphi) \tag{8f$'$}$$
$$FS_t^* = FS(\lambda_t, P_{F,t}, P_{M,t}, W_t, H_{t-1}; Z_t, \phi, \varphi) \tag{8g$'$}$$
$$\begin{aligned} H_t^* &= H(F_t^*, LP_t^*, M_t^*, H_{t-1}; Z_t, \phi) \\ &= H(\lambda_t, P_{F,t}, P_{M,t}, W_t, H_{t-1}; Z_t, \phi, \varphi). \end{aligned} \tag{8h$'$}$$

Note, for example, Equation (3′)(3′) permits a negative shock to health in t – 1 to reduce current health status and thereby affect current production of good health. In addition, Equations (8a′)–(8h′) show that lagged health status enters current demand for food, other purchased goods, leisure, and health.

3 | THE DATA AND SAMPLE

Our panel data set is the composed of the females in the NLSY79. The complete NLSY79 consisted of a nationally representative sample of men and women who were born in the years 1957–64 (Rothstein, Carr, & Gooksey, 2019). Respondents were 14–22 years of age when first interviewed in 1979. The original female sample (in 1979) consisted of 6,283 individuals. The survey was conducted annually from 1979 to 1994 and has been conducted biennially since 1996 (Bureau of Labor Statistics, 2003). Each round collected detailed information on the respondents' health status, number of family members, schooling, labor market behaviors, income and expenditures, and so on. We extract female observations from six rounds taken at 4-year intervals, that is, 1986, 1990, 1994, 1998, 2002, and 2006, to create a balanced working sample. It is noteworthy that in 1986, all respondents were at least 21 years of age and passed their juvenescent phase. Hence, they had attained full height. Second, if we had all of the annual data 1986–1992, the time series would be too short to meaningfully test for autocorrelation. Third, we excluded those respondents in the military from our sample because their health status or BMI may be related to special training, and thus are less representative. There was attrition over time, and women were excluded who left the sample (Bureau of Labor Statistics, 2003). Other women were excluded because they had missing information. Our balanced panel of women consisted of sample of 1,638 women in each year, and with 6 years of data we have a total of 9,828 observation.

The NLSY79 collected data on sociodemographic attributes of women at the initiation of the panel, and starting in 1986, it collected data on households' participation in Food Stamp or SNAP program. For the U.S. Department of Labor, we obtained special permission to access geocode data for each household (and woman) giving their metropolitan statistical area with information on metropolitan area price data on food, drink, and medical services from the ACCRA. For individuals living outside of metropolitan areas, we developed special procedures to create prices for sample observations living outside metropolitan statistical areas (MSAs; see details in Supplemental Appendix: Data Issues.)[7]

The ACCRA price data were also used to construct local cost of living indexes for sample women, so the price of food, drink, and medical services and the woman's opportunity cost of time or wage are in real terms (see Supplemental Appendix: Data Issues for more details on the derivation of prices, and Table 1 for a list of variables used in the empirical analysis).

Summary statistics of our sample are presented in Supplemental Table A2. About 56.5% of women are White, 28.8% are Black, and 14.7% are of other races. The share of sample women who were married was 44% in 1986, when they were relatively young, but was substantially larger in 1990 at 55% and thereafter changed very little. The share of sample women that were obese in 1986 was only 4.5% and slowly but steadily the share rose to 26% in 2006. Women's average BMI was 22.6 in 1986, and it rose slowly and steadily to 27 in 2006. Seventy-nine percent of women had an urban residence in 1986, when they were young, but this share declined slowly and steadily to 68% in 2006. The share of women living in a MSA varies more than for the share urban, partly because Office of Management and Budget (OMB) periodically expanded the area

[7] For the time period covered in this study, the ACCRA data are one of the few data sets that exist on prices at the local level. However, the prices are for a limited set of goods and they are collected from urban and suburban establishments that had been visited more frequently by professional and managerial households (Council for Community and Economic Research, 2015).

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TABLE 1 Symbols and a brief variable definition

Variable	Definition
BMI	Body mass index, defined as weight/square of height (in kg/m^2)
D(Obese)	=1 if the individual was obese (BMI≥30); =0 otherwise
D(FSP)	=1 if the individual participated in SNAP; =0 otherwise
Wage	The individual's average hourly real wage rate
PR_FFruVeg	Price of fresh fruits and vegetables
PR_PFruVeg	Price of processed fruits and vegetables
PR_Meat	Price of meat and fish
PR_Dairy	Price of dairy food
PR_Alco	Price of alcoholic drinks
PR_Nalco	Price of non-alcoholic drinks
PR_FF	Price of fast food
PR_HC	Price of health care
Edu	The highest grade completed by the individual
Rotter Scale	The Rotter Internal-External Locus of Control Scale
Internal Scale	Reversed Rotter Internal-External Locus of Control Scale
Rosenberg Scale	The Rosenberg Self-Esteem Scale
Noncog Scale	Comprehensive index for non-cognitive abilities, combine Internal and Rotter Scales
Inc	Predicted household real non-labor income (in 1,000 dollars)
Age	Age of the individual
Married	=1 if the individual was married and the spouse was present; =0 otherwise
Kids	Number of children in the household
Urban	=1 if the individual lived in an urban area; =0 otherwise
MSA	=1 if the individual lived in a metropolitan statistical area; =0 otherwise
NC	=1 if the individual lived in north central or middle west; =0 otherwise
South	=1 in the individual lived in south; =0 otherwise
West	=1 if the individual lived in west; =0 otherwise
preg	=1 if the female respondent was pregnant; =0 otherwise

covered by the MSA definition.[8] This variation seems clearly to be unrelated to health status or SNAP participation of sample women.

The average real hourly wage rate for sample women is \$6 per hour in 1986, when they were young and increases to \$9.57 in 1990, and thereafter rose slowly to \$19.50 in 2006. The price-setting mechanism for U.S. dairy products is unusual relative to other food products (see Supplemental Appendix: Data Issues).

4 | THE ECONOMETRIC MODEL

The theoretical models developed in the previous section imply a set of demand equations for decisions at each year of age in a woman's finite-life, life cycle, including a woman's health status (BMI or being obese) and SNAP food purchases (*FSP*). However, considerable interest exists in the impact of SNAP program participation on women's health. Hence, we convert the woman's health demand equation into a structural equation by including an indicator for her SNAP participation. Otherwise, the economic model of life cycle decisions remains unchanged, including the equation for SNAP participation. Our econometric model consists of a structural equation for women's health status and equations for instrumenting SNAP participation and a woman's market wage.

Consider the following model of a woman's BMI or obesity:

$$\ln BMI_{it}[\text{or } Obese^*_{it}] = X_{1it}\mathrm{B} + \mu_{1it}.$$

However, $Obese^*_{it}$ is a latent variable and not observed, but what we observe is

$$D(Obese)_{it} = \begin{cases} 1 & \text{if } Obese^*_{it} > 0 \\ 0 & \text{otherwise} \end{cases},$$

[8] In 2003, OMB revised the 1990 standard from MSA and related areas. The main difference was to extend the coverage of this classification system (OMB, 2003).

where X_1 include an individual-specific fixed effect and her age and age squared, and μ_1 represents all other effects and has a zero mean. The probability of woman i in year t of her life cycle being obese can now be expressed as

$$\begin{aligned} p_{1it} &= \Pr(D(Obese)_i = 1)) = \Pr\,(Obese^*_{it} > 0) \\ &= \Pr(X_{1it}\beta + \mu_{1it} > 0) = \Pr(\mu_{1it} > -X_{1it}\beta) \\ &= \Pr(\mu_{1it} < X_{1it}\beta) = F(X_{1it}\beta), \end{aligned} \tag{11}$$

where $F(\cdot)$ is a cumulative distribution function for μ_{1i}, evaluated at $X_{1i}\beta$. We employ the linear probability version of this empirical model

$$D(Obese)_{it} = X_{1it}\beta + e_{1it}, \text{ where}$$

$$e_{1it} = \begin{cases} 1 - X_{1it}\beta & \text{with probability } X_{1it}\beta \\ -X_{1it}\beta & \text{with probability } (1 - X_{1it}\beta) \end{cases},$$

$$\text{with } E\left(e_{1it}\right) = 0, \tag{12}$$

so as to be able to rely on properties of linear models in our estimation (Greene, 2003; Maddala, 1984; Wooldridge, 2010).[9] X_{1it} includes the SNAP participation indicator for the ith woman and year t of life cycle, the price of her time (wage), the local prices of food, drink,[10] and health care, social demographic attributes, including her age and age squared and an individual fixed effect, a marital status indicator, number of kids in her household, and urban residence. Our model includes individual fixed effects but excludes variables such as women's education, which was largely completed by the youngest women in our sample who are 21 years of age.

A woman's opportunity cost of time is important to decisions on time and goods at each age. Purchasing raw food ingredients and preparing nutritious meals for one's self and family require a significant amount of time; some would say that these meals are time intensive. When a woman's opportunity cost of time increases, we might expect her to purchase labor-saving foods in the form of greater convenience, for example, by buying more highly processed foods for food-at-home (FAH), which may lower her health status (see Larson, Perry, Story, & Neumark-Sztainer, 2005; Okrent & Kumcu, 2016; Pollan, 2013; Warner, 2013; Zick, Stevens & Bryant 2011). However, as a woman's wage increases, her personal appearance may become more important to a good job rating. This would create a force leading to a high wage causing a lower BMI or probability of being obese (Cawley, 2004).

A household purchases food and drink to obtain nutrients (carbohydrates, fats, protein, vitamins, and minerals). An increase in the local price of a food and drink item, holding the marginal utility of wealth constant, is expected to reduce a household's current demand.[11] When the price increase is for dairy products, the reduced demand is expected to reduce BMI and probability of being obese. When the price increase is for fresh fruits and vegetable, an increase in BMI and probability of being obese is expected to occur. An increase in the price of processed fruits and vegetables,[12] which generally contain significant amounts of added sugar, is expected to reduce the demand for these foods, which may lower a woman's BMI and the probability of being obese. An increase in the price of meat and fish is expected to reduce a household's demand for these foods, which tend to be calorie dense, and this may lower women's BMI and the probability of being obese. Similarly, most fast foods are calorie dense, and an increase in their price is expected to reduce a woman's consumption of them, which may lower her BMI and probability of being obese. Although there has been debate about eliminating sweetened beverages, for example, soft drinks, from the list of SNAP eligible products, they remain on the list of permitted drinks (Barnhill, 2011). However, beer, wine, and hard liquor purchases are not eligible for SNAP benefits (Food and Nutrition Service, 2019). But, if a household has other income, it can spend it on excluded drinks, including nonalcoholic drinks without a nutrient facts label), and other excluded foods, for example, hot foods, so the net effect of excluding them may not be very large (Cuffey, Beatty, & Harnack, 2015). Dairy products can be purchased with SNAP benefits, and we expect an increase in the price of these products to reduce consumption and women's BMI and probability of being obese. A higher price of simple health care is expected to shift attention to lifestyle production of good health and reduce the probability that an individual is obese.

[9] Because the first-stage estimation of the IV-estimator is a linear model, the problem that arises with nonlinear functions (Terza et al., 2011) is not present in our econometric model.

[10] An alternative strategy for using the prices of food and drink would be to examine the effect of one price index covering the prices of FAH) and food-away-from-home (FAFH). One might also consider the cost of ERS's Thrifty Food Plan (Hoynes, Bronchetti, & Christensen, 2017). These are alternative approaches compared to how we proceed.

[11] The story becomes more convincing when we recognize that in our linear models explaining probability of being obese or ln (BMI) there is an equivalent representation where the dependent variable and the regressors are all expressed relative to their respective sample mean. Hence, an estimate of a regression coefficient is an estimate of the marginal impact of a regressor as it increases from its mean on the dependent variation from its mean (Greene, 2003). The sample mean of women's BMI is 25.0, and probability of being obese is 17%.

[12] In this study, processed fruits and vegetables include canned peaches, canned sweet peas, fresh orange juice, and frozen corn (see Appendix I and II). Canned peaches and sweet fruits normally included added sugar. Pure orange juice provides naturally occurring sugar–fructose in this case—that occurs naturally. However, some brands of orange juice may add extra sugar. Frozen corn does not generally contain added sugar. However, with all canned and frozen fruits and vegetables, the food label lists ingredients, for example, peaches, water, and sugar, and tells whether sugar has been added (see Cording, 2018).

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Fifth, a change in current urban (versus rural) residence and regional location may affect a woman's health status because of possible differences in the costs of health production.[13] In rural nonmetro areas, including the North Central, West, and South, space for physically active leisure is widely available and cheaper, and space and good soils are more likely to be available for growing a vegetable garden. However, urban women may have easier access to organized fitness activities and fitness centers and to medical care.

In Equations (11) and (12), we need instruments for the woman's *SNAP* participation and wage. To instrument *SNAP* participation, we use the prices of food, drink, and health care, age and age-squared, marital status, number of kids, location in an MSA, and current household income. Recall that in our finite-life life cycle model of household decision making, household wealth is allocated over the life cycle to meet conditions in Equation (7g) dealing with equalizing the marginal utility of wealth over time, and current income does not enter these demand Equations (8a)–(8h). We then can use it to help identify the reduced-form *SNAP* participation equation.[14]

We believe that an urban–rural residence is the best location variable for determining obesity, but we argue that being a resident of an MSA is more appropriate for *SNAP* participation. Although urban–rural residence versus MSA–non-MSA residence location indicators that have similar but not exactly the same coverage. An MSA is an entity defined by OMB for the purpose of reporting statistical data to federal agencies by firms and households, and, hence, it is different from the Census' urban–rural designation, which is a sociodemographic variable used in the Census of Population and Current Population Survey. For example, MSAs contain both rural and urban areas.[15] However, in extremely rural areas, an individual being in a non-MSA coincides with a non-MSA location. MSAs represent governmental administrative boundaries and tend to reduce the cost of government program participation.

We instrument the wage using an individual's age, age-squared, north versus south residence (U.S. Census Bureau definition), and an interaction between age and education and between age and noncognitive ability. Recall that the youngest woman in our sample is 21 years of age in 1986, and by this age a large share of them have completed their formal schooling. However, there may be a correlation between the amount of education and age, for example, women who were younger at the initiation of the NLSY in 1979 may have had a tendency to complete more years of schooling. By interacting a woman's age with her noncognitive ability, we permit the impact of the noncognitive scale to have different effects at younger than older ages. Noncognitive ability is a combined index of Rotter's (1966) scale for external versus internal control and Rosenberg's (1965) scale for self-esteem; see Supplemental Appendix: Data Issues).

5 | EMPIRICAL RESULTS: MODEL I

The econometric estimates of empirical Model I are reported in Table 2. To be able to draw upon properties of linear models, ln(*BMI*), *D*(*Obesity*), ln(*wage*) and *D*(*SNAP*) participation are all fitted by least squares so that the estimates of the parameters of the ln(*BMI*) and *D*(*Obesity*) equations are estimated consistently (Greene, 2003; Wooldridge, 2010).

The reduced-form *SNAP* participation equation reported in column (3) has some notable properties. First, variables *inc* and *MSA* have statistically significant coefficients. They also pass the over-identification test in the ln(*BMI*) and probability of being obese equations, that is, they are not jointly significantly different from zero. The test for weak instruments also suggests that these two variables are strong because the *F*-statistic for joint significance in the *SNAP* equation is larger than 10 (Stock and Yogo 2005). Second, a woman's number of children has a large positive impact on the probability of her being a *SNAP* participant, that is, a one child increase increases the probability of a woman being a SNAP participant by 6 percentage points. In addition, a higher price of fast food significantly increases a woman's probability of being on *SNAP*, and a woman who lives in an *MSA* is 3.3 percentage points more likely to be a *SNAP* participant than those in non-MSA areas. Third, the probability of a woman being on SNAP is highest at an early age, and as she ages, her probability of being a SNAP participant declines as she becomes older until she reaching 56 years of age, when probability of participation in the SNAP declines as she further ages. Third, the equation has good explanatory power, given that the dependent variable is dichotomous (1-0) type, and we reject the null hypothesis that this equation has no explanatory power at better than the 1% significance level. The sample value of the *F*-statistic for this test is 42.7, and the critical value with 15 and infinite degrees of freedom at the 1% significance level is only 2.06.

Given that the wage equation (as well as other equations) contain individual fixed effects, the empirical wage equation may seem a bit sparse in regressors (see Table 3, column (4)).

[13] The Census Bureau defines an urban residence as one located in a place of 2,500 or more people. In contrast, OMB defines an MSA as a geographic entity for use by federal statistical agencies, including the Bureau of Economic Analysis but not the Census, for use in collecting, tabulating, and publishing federal statistics. Counties included in MSAs contain both urban and rural areas and populations (CBER, 2018). The urban–rural designation seems most appropriate for explaining BMI and obesity.

[14] It is noteworthy that a woman's average household income was only $5,900 in 1986, rose to $15,000 in 1990 and 1994, then jumped to $26,000 in 1998, and to $33,700 in 2002, and $38,700 in 2006 (Suppl Appendix Table A1).

[15] Reporting of SNAP participation and payments is most closely associated with the MSA designation (see footnote 7 for the key differences between MSA and urban–rural designations). However, other regional indicators are excluded from this equation.

TABLE 2 IV estimation for health outcomes of women in a Frisch model; ordinary least squares (OLS) estimates of first-stage equations; all with individual fixed-effects in a balanced panel, 1986–2006 (sample size of 9,828 = 6 × 1,638)

	Instrumental variables (IV) estimates		First Stage estimates	
	lnBMI	D(Obese)	D(FSP)	lnWage
Variable	**(1)**	**(2)**	**(3)**	**(4)**
D(FSP)	−0.1567**	−0.5633**		
	(−2.14)	(−2.42)		
lnWage	−0.0312	−0.3485**		
	(−0.72)	(−2.54)		
PR_FFruVeg	0.0283	0.1107	0.1090*	
	(1.24)	(1.53)	(1.77)	
PR_PFruVeg	0.0381	0.1119	−0.0401	
	(1.19)	(1.11)	(−0.43)	
PR_Meat	−0.0304	−0.1084	0.0699	
	(−0.92)	(−1.03)	(0.73)	
PR_Dairy	−0.0593**	−0.3078***	−0.1591**	
	(−1.97)	(−3.23)	(−1.97)	
PR_Alco	0.0644**	0.0626	−0.0243	
	(2.38)	(0.73)	(−0.32)	
PR_NAlco	0.0562**	0.2056**	0.0834	
	(2.06)	(2.37)	(1.10)	
PR_FF	0.0913***	0.1395	0.1993***	
	(3.29)	(1.58)	(2.88)	
PR_HC	−0.0436*	0.0095	0.0663	
	(−1.85)	(0.13)	(1.05)	
Age	0.0190**	0.0706***	−0.0113***	0.1535***
	(2.52)	(2.96)	(−2.43)	(12.24)
Age^2	−0.0002***	−0.0006***	0.0001*	−0.0014***
	(−2.79)	(−2.93)	(1.52)	(−9.74)
Married	0.0099*	−0.0140	0.0604*	
	(1.68)	(−0.74)	(1.90)	
Kids	0.0082**	0.0270**	0.0614***	
	(2.00)	(2.06)	(15.58)	
Preg	0.0652***	0.0291*		
	(13.96)	(1.96)		
Urban	−0.0059*	0.0056		
	(−1.98)	(0.60)		
NC	0.0259**	−0.0298		
	(2.11)	(−0.76)		
South	0.0164	−0.0601*		−0.0574
	(1.55)	(−1.79)		(−1.09)
West	0.0209*	−0.0130		
	(1.66)	(−0.33)		
*Age**Edu*				0.0000
				(0.66)
*Age**Noncog Scale*				0.0018***
				(2.73)

(Continues)

TABLE 2 (Continued)

	Instrumental variables (IV) estimates		First Stage estimates	
	lnBMI	D(Obese)	D(FSP)	lnWage
Variable	**(1)**	**(2)**	**(3)**	**(4)**
MSA			0.0326***	
			(3.96)	
Inc			−0.0047***	
			(−4.29)	
Constant	2.6821***	−1.0361***	0.1179*	−2.4590***
	(26.09)	(−3.18)	(1.76)	(−14.77)
Test for weak instruments				
			11.86	3.94
Test for overidentification in SNAP equation				
Sargan statistics	0.3838	2.2082		
P-value	.5356	.1373		
R^2	0.402	0.105	0.061	0.531

Notes. *z*-statistics are in parentheses.
*** represents statistical significant level in 1%, ** represents statistical significant level in 5%, and * represents statistical significant level in 10%.

However, the wage equation is strongly concave in a woman's age, and the maximum impact occurs at 54.9 years. The age-education effect is not significantly different from zero, but the age-noncognitive scale has a positive coefficient that is significantly different from zero at the 1% level.

Estimates of the structural equation of Model I for women's health status is of prime interest in this paper, columns (1) and (2) (Table 3). Across the estimated ln(*BMI*) and probability of being obese equations, the signs of the estimated coefficients for a given regressor are generally the same, but the significance levels are usually different. Not surprising are the strong impacts of a woman's age on her BMI and probability of being obese. Starting at a young age, our results show that her BMI increases with her age up to 47.5 years and probability of being obese up to 59 years, and thereafter declines.

A woman who participates in SNAP has a lower ln(*BMI*) and probability of being obese than other women. Specifically, if a woman participates in SNAP, she has a lower BMI by 15.7% and a lower probability of being obese by 56.3 percentage points. These magnitudes are large and significantly different from zero at the 1% level. Moreover, these negative and significant effects of SNAP participation on BMI and probability of being obese are much different than the positive effects reported by Chen et al. (2005) and Gibson (2003, 2004) in cross-sectional data, and by Meyerhoefer and Pylypchuk (2008) and Baum (2011) in short panels.

We turn next to price effects on BMI and being obese. Women who have a higher opportunity cost of time, as reflected in their predicted wage, are less likely to be obese (significant at the 1% level) and negative but not significant her BMI equation. A woman's BMI and probability of being obese is not significantly affected by the local relative price of fresh fruits and vegetables, processed fruits and vegetables, or price of meat (at least as we have measured them). However, an increase in the price of dairy products reduces significantly a woman's BMI and probability of being obese.

An increase in the local prices of alcoholic and nonalcoholic drinks (excluding water) increases significantly women's BMI, but only a higher price of nonalcoholic drinks increases her probability of being obese.[16] These results suggest that higher beverage prices do not improve a woman's weight situation.[17] How can this be? Americans find that consuming drinks and salty snacks are complementary, but increasing the price of drinks can increase total calories consumed if the increase in snacks contains more calories than the reduction in calories from higher priced drinks (Bleich & Wolfson, 2015).[18] Since the probability of being obese is not increased for an increase in the price of alcoholic drinks, this suggests that this substitution effect is operating primarily for nonobese women.

Other things equal, an increase in the price of fast food increases a woman's BMI (significant at the 5% level) and her probability of being obese (significant at the 12% level). Since the demand for fast food should decrease with an increase in the price, thereby reducing calories, the increase in BMI and

[16] Pass-through taxes are included in the ACCRA data on prices of alcohol and other purchased goods (Forbes, 2019). However, state and local excise taxes that retailers apply at the point of sale to consumers are not included in any of the ACCRA price data (The Council for Community and Economic Research, 2019).

[17] Todd and Ver Ploeg (2014) conclude that taxing sugar-sweetened beverages is unlikely to reduce consumption.

[18] In the 1988-94 and 1999–2000 NHANES, salty snacks accounted for 2.5% of total calories consumed by the U.S. population. Regular soft drinks and beer accounted for 9.5% (see Block, 2004).

TABLE 3 Arellano-bond difference general method of moments (GMM) estimations for female balanced sample (sample size of 6,552 = 4*1,638)

Variable	*lnBMI* (1)	*D(Obese)* (2)
$\ln(BMI_{t-1})$ *or* $P(Obese_{t-1})$	−0.3716***	−0.1987***
	(−31.49)	(−7.51)
D(FSP)	−0.0112**	−0.0376**
	(−2.35)	(−2.35)
lnWage	0.4450***	−0.1274
	(2.99)	(−0.26)
PR_FFruVeg	−0.0076	−0.0135
	(−0.33)	(−0.17)
PR_PFruVeg	0.0712**	0.2197**
	(2.15)	(1.99)
PR_Meat	−0.0185	0.0785
	(−0.48)	(0.61)
PR_Dairy	−0.0578*	−0.3368***
	(−1.85)	(−3.23)
PR_Alco	0.0390	0.0705
	(1.25)	(0.68)
PR_NAlco	0.0149	0.0367
	(0.54)	(0.40)
PR_FF	0.1469***	0.1374
	(3.11)	(0.87)
PR_HC	0.0060	−0.0187
	(0.23)	(−0.21)
Age	−0.0543**	0.0454
	(−2.08)	(0.52)
Age^2	0.0004*	−0.0003
	(1.95)	(−0.51)
Married	0.0248***	0.0304***
	(7.54)	(2.78)
Kids	0.0006	−0.0003
	(0.38)	(−0.05)
Preg	0.0367***	0.0011
	(7.04)	(0.06)
Urban	−0.0022	0.0007
	(−0.72)	(0.07)
NC	0.0226	−0.0119
	(1.45)	(−0.23)
South	0.0445***	0.0112
	(2.72)	(0.21)
West	0.0116	0.0326
	(0.74)	(0.62)
Arellano–Bond test for AR(1) in first differences[a]		
P-value	.000	.000
Sargan test of overidentification restrictions		
P-value	.000	.000

Notes. *z*-statistics are in parentheses.

[a]The Arellano–Bond test for AR(1) in first differences is to test the autocorrelation over a 4-year rather than a 1-year period.

*** represents statistical significant level in 1%, ** represents statistical significant level in 5%, and * represents statistical significant level in 10%.

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probability of being obese can only occur if they substitute toward less healthy food and/or less physical activity.[19]

An increase in the price of simple medical services reduces women's BMI (significant at 10% level), but not the probability of being obese. Hence, there is weak evidence that BMI responds to the price of over the counter medicines.

6 | EMPIRICAL RESULTS: MODEL II

The multiyear, finite-life, life cycle decision making of a woman can include updating at least some decisions in each year, and we emphasize health status. A woman's health status in the previous year, may affect her ability to conduct some activities, for example, plan and produce meals, engage in physically active leisure, and to produce good health in the current period. Also, her current health status is a result of an especially complex process, including genetic endowment at birth, long-term habits, past health shocks, and accumulated past health investments. Therefore, a rational person might take advantage of the most recent information in current decisions.

For empirical Model II of ln ln(*BMI*) and probability of being obese, we adopt the Arellano-Bond difference general method of moments (GMM) estimator (Arellano & Bond, 1991).[20] This method uses first-differences to eliminate individual fixed effects from the estimated equations, and then uses GMM estimation by instrumenting the first-differenced lagged dependent variable for health status (BMI or probability of being obese) by its past level. In applying this method, one observation per woman is lost in differencing and another observation is lost due to using lagged health status to instrument for the change in health status. Specifically, for observations in 1994, the dependent variable becomes the change of a woman's health status between 1990 and 1994, and lagged health status becomes the change of health status between 1986 and 1990, but the health status in 1986 is then used as an instrument for it. Therefore, the size of our sample is reduced substantially leaving only observations from 1994, 1998, 2002, and 2006, or four observations per woman and a total of 6,552 observations.

The estimate of women's $\ln(BMI_t)$ and $P(Obese_t)$ equations are reported in Table 3, column (1) and (2), respectively. New to these results is the estimated effects of lagged health status on current health status. In particular, the point estimate of the impact of an increase in $\ln(BMI_{t-1})$ on $\ln(BMI_t)$ is an elasticity of –0.37. Moreover, the asymptotic z-value for a test of no effect is –31, significant at better than 0.0001 probability. In addition, the point estimate of the impact of an increase in $D(Obese_{t-1})$ by 10 percentage points on $D(Obese_t)$ is to reduce it by 0.2 percentage points. Moreover, the asymptotic z-value for a test of no effect is –7.5, significant at better than 0.001 probability. Hence, these results provide strong evidence for updating current health decisions based on last periods outcomes.

An increase in a woman's wage now increases her ln(*BMI*) significantly (elasticity of 0.45), but has no significant effect on her probability of being obese.

Turning to food, drink, and health prices, we note some differences from those of Model I. A higher price of processed fruits and vegetables now has a significant positive effect on both measures of health. The price of alcoholic and nonalcoholic drinks is not significantly different from zero. The price of health care now has no significant effect on ln(*BMI*). In addition, it is noteworthy that the price of dairy products has approximately the same size of effect on ln(*BMI*) in empirical Model II as Model I. A similar result holds for the impact of the price of dairy products on the probability of a woman being obese in empirical Model II as in Model I.[21]

7 | CONCLUSION

In this paper, we have developed multiyear, finite-life, life cycle models of household decisions on food, leisure, and health (BMI and probability of being obese). The econometric versions of these models treats SNAP participation as endogenous in women's health outcome equations. The study is unusual in that it used panel data. These women were taken from the NLSY 1979 Cohort, and we used data at 4-year intervals over the 20-year period starting in 1986, when SNAP program participation first became available. The effects of SNAP participation on a woman's weight and tendency to be obese are important public policy issues related to needy households—those who meet primarily an income standard.

In our empirical model without updating for health status, we find that when a woman participates in SNAP, it reduces her BMI by 16% and probability of being obese by 56 percentage points. However, when we permit updating due to prior health status, the marginal effect of her participating in SNAP

[19] However, people who cook at home more often, rather than eating out, tend to have healthier overall diets without higher food expenses. In addition, they perform significantly better on the HEI and were less likely to be obese (Tiwari et al., 2017)

[20] The estimator is especially designed for situations where (i) there is "small T, but large N" panels; (ii) the dependent variable depends on its past realizations; (iii) regressors are not strictly exogenous; (iv) fixed-individual effects are included; and (v) where autocorrelation (and heteroscedasticity) within individuals may exist but not across them.

[21] Although Table 3 reports some evidence of first-order autocorrelation in the residuals, the *T* is too small to do anything about it.

is to reduce her BMI by –1.1% and probability of being obese by 3.8 percentage points. In contrast to past studies, we find that SNAP participation reduces significantly a women's BMI and probability of being obese.

The price of dairy products has consistent effects on women's health status in empirical models without and with health status updating. An increase in the price of milk reduces significantly women's BMI and probability of being obese. In particular, the size of these effects is approximately the same in both models. The prices of other foods and drink do not have similar effects across the two empirical models (with or without health status updating). In the empirical models with updating, an increase in a woman's lagged BMI 10% reduces her current BMI by 3.7% and the probability of being obese by 2.0 percentage points. These results suggest that inter-year health status adjustments are stabilizing. Several years ago, the USDA's initiated SNAP-ED, which attempts to help SNAP participants make healthier food choices by providing information on how to prepare a diverse set of foods or meals (National Institute of Food and Agriculture, 2018).

ACKNOWLEDGMENTS

We thank two anonymous reviews, Peter Orazem, Joe Herriges, Helen Jensen, Jonathan McFadden, Ruth Litchfield, and Abe Tegene for helpful suggestions. Deb Gruca provided helpful editorial assistance. We thank the U.S. Department of Labor for making the NLSY79 data set available with geocode information. We thank the USDA-ERS for funding under a cooperative agreement and to the Iowa Agricultural Experiment Station for long-term financial assistance.

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SUPPORTING INFORMATION

Additional supporting information may be found online in the Supporting Information section at the end of the article.

How to cite this article: Huang Y, Huffman WE. Life cycle models of women's body mass index and probability of being obese: Evidence from panel data. *Agricultural Economics*. 2019;50:509–524. https://doi.org/10.1111/agec.12506