The Monthly Food Stamp Cycle: Shopping Frequency and Food Intake Decisions in an Endogenous Switching Regression Framework

Parke E. Wilde and Christine K. Ranney

Mean food spending by food stamp households peaks sharply in the first three days after benefits are received. For those who conduct major grocery shopping trips only once per month (42% of all food stamp households), mean food energy intake drops significantly by the fourth week of the month. For the remaining households, intake remains steady over the course of the month. These patterns motivate an empirical model that simultaneously accounts for the shopping frequency and food intake decisions over time. Results have implications for policies that may affect the frequency of grocery shopping by food stamp households.

Key words: food intake, food stamps, shopping frequency, switching regression.

This article makes two contributions to the study of food demand by U.S. food stamp recipients. First, it employs nationally representative data to describe and measure monthly cycles in food expenditure and food intake. Second, because the food intake cycle is found to depend on the frequency of major grocery trips, the article develops and estimates an econometric model of consumers' simultaneous shopping frequency and food intake decisions in two halves of the food stamp month. The econometric results suggest implications for policies that affect the frequency of grocery shopping.

Understanding the monthly food stamp cycle is important for policy makers, who are concerned about periodic or episodic hunger among low-income Americans (Food and Consumer Service 1994). It is also important for applied economists, because ignoring this type of cycle can induce inefficiency in food demand estimates using survey data where food expenditure or food intake information is collected for short periods (Fraker). For econometric models with limited dependent variables, which account for the "kink" in the budget constraints of food stamp recipients (Moffitt 1989, Wilde and Ranney), ignoring the food stamp cycle may produce biased estimates as well.

The need for further research on the food stamp cycle has been identified previously. In his 1990 review of the literature on the Food Stamp Program, Fraker observed, "Despite the fact that it may enhance our understanding of why econometric studies show that food stamps have a much larger effect on food use than does cash income, research on the existence and nature of this cycle has been scarce."

Literature Review

The food stamp cycle has not previously been measured using nationally representative data, and it has received little attention in the peer-reviewed economic literature. Here we focus first on how writers in other disciplines have addressed this issue before considering what economic research has been done.

Journalists and researchers in other disciplines have described the food stamp cycle using anecdotal evidence and small surveys in

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particular localities. Lelyveld wrote in the *New York Times Magazine,* "Most food-stamp families live on a nutritional cycle that starts off reasonably well, then deteriorates as the month wears on, becoming marginal if not desperate in the final week or ten days, depending how frugal they were earlier." Temporal patterns in food use have been described with similar concern by sociologists (Rank and Hirschl) and antihunger advocates (Food Research and Action Center). Emmons found that 76 low-income families in Cleveland bought most of their food in the first two weeks, although actual intake of most foods remained relatively steady through the last week of the month. Based on two samples from upstate New York and New York City, Thompson et al. reported that the mean number of meals served weekly in soup kitchens followed a sharp sawtooth pattern over the year, with a peak at the end of almost every month.

Previous work has described an association between participation in the Food Stamp Program and infrequent grocery shopping (Bradbard et al., Fraker). The only previous econometric model of this phenomenon that we found reported that food stamp participation substantially reduced the probability of shopping once a week or more frequently (Blaylock).

The economic literature provides a large body of previous results on the effects of the U.S. Food Stamp Program. Nonexperimental studies (reviewed in Fraker) and experimental studies (reviewed in Fraker, Martini, and Ohls) generally find that food stamps have a strong positive effect on food expenditure, and that this effect is stronger than the corresponding effect of cash income. Results have been more ambiguous in studies of actual food energy intake, which is the dependent variable in this article's econometric model. Fraker reported two "notable patterns" in the estimated effects of food stamps on nutrient intake: "the scarcity of significant estimates and the presence of a substantial proportion (one-fourth) of negative estimates." One recently published study concluded, perhaps counterintuitively, that after controlling for self-selection into the program, increased resources from food stamps and cash income appear to be associated with reduced nutrient intake (Butler and Raymond).

An early economic analysis of the Food Stamp Program in rural areas of central Pennsylvania gave attention to the timing of receipt of food stamp benefits and cash income into the household (Madden and Yoder). In one county, program participation was associated with improved nutrition, but this beneficial effect appeared only for households interviewed within two weeks after the family purchased the stamps.[1] Also, the beneficial effect was perceptible only when more than two weeks had elapsed since the family had received its major income for the month. A more recent economic analysis of a demonstration program in Washington included a variable for "the number of days between receipt of food benefits and the [survey] period" as a regressor in a study of food spending (McCracken, McCracken, and Shi). The estimated parameter on this time-of-month variable took different signs in equations for different goods.

Data Sources

The analysis here uses expenditure data from the *Consumer Expenditure Diary Survey* (CEX) for 1988–92 (U.S. Department of Labor) and intake data from the *Continuing Survey of Food Intake by Individuals* (CSFII) for 1989–91 (U.S. Department of Agriculture). The CEX reports each household's daily expenditures over one or two weeks. The CSFII reports each individual's daily food intake over three days. The descriptive results below employ these individual food intake data from the CSFII. However, these data are aggregated to the household level for the econometric analysis, because all income variables and many demographic variables are only known at the household level. The main dependent variable in the econometric analysis is household food energy intake as a proportion of the Recommended Dietary Allowance (RDA) for food energy. This dependent variable is calculated as the sum of all members' food energy intake divided by the sum of all members' reference food energy intake levels in the RDA, where each member's reference level is based on that member's age, sex, and pregnancy/lactating status.

Both surveys report the date on which food stamps were most recently received and the dates to which food expenditure or intake data refer, so the number of days since food

[1] At the time of the study by Madden and Yoder, program participants had to purchase their food stamp coupons for a portion of the face value.

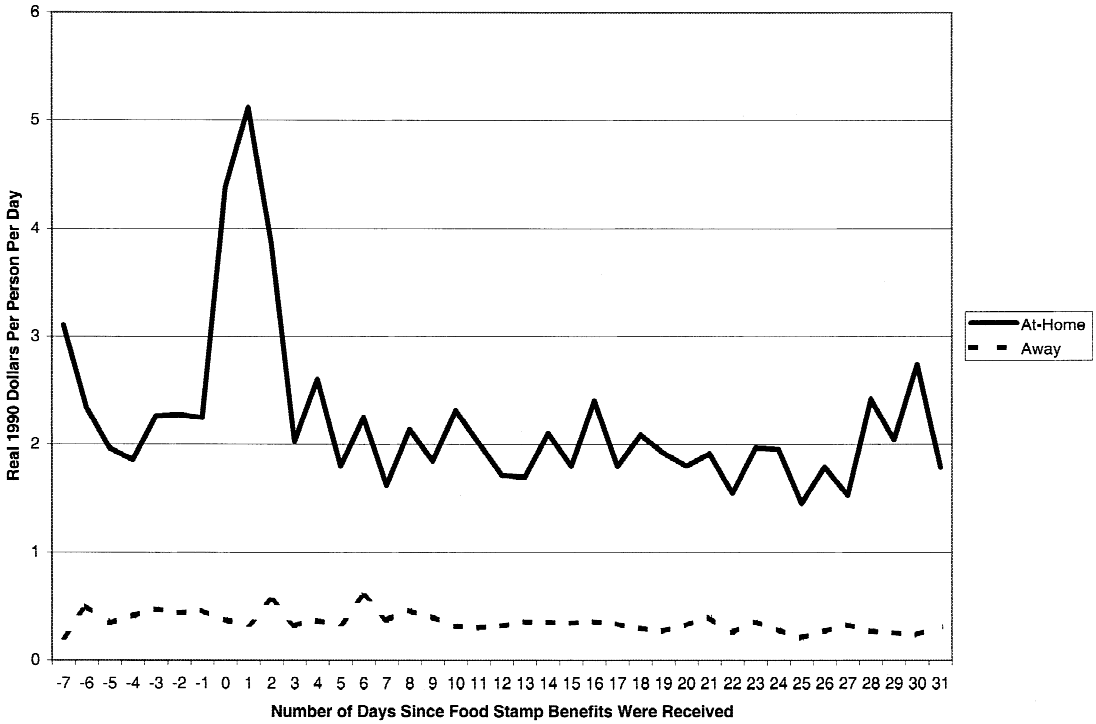

Figure 1. Food expenditure by consumer units, at-home and away-from-home
source: *Diary Consumer Expenditure Survey,* U.S. Department of Labor, Bureau of Labor Statistics

stamps were received can be calculated by subtraction. Therefore, although the data are cross-sectional, we can measure patterns in mean expenditure and intake over the food stamp month.

The number of observations from the CEX is large (2,875 food stamp consumer unit observations on 12,308 days with complete information). These expenditure data allow adequately precise comparisons of mean food expenditure on each day of the food stamp month. The number of food intake observations from the CSFII is smaller (the descriptive results use observations for 1,516 individuals and the econometric estimation uses observations for 617 food stamp households with complete information). The food intake sample sizes place limits on how finely we may subdivide the sample. The descriptive results below report food intake for each of the four weeks of the month, and the econometric work divides the month into two halves.

The descriptive results use the sampling weights provided with the public data sets, but these weights are not used in the econometric estimation. The sample weights were constructed based on fourteen demographic characteristics, not including food intake (the dependent variable in the econometric model below). The econometric analysis deals with the effects of demographic characteristics explicitly in the model, rather than through weighting. The CEX and CSFII data sets are publicly available from the U.S. Department of Labor and the U.S. Department of Agriculture, respectively.

Monthly Patterns in Mean Food Expenditure and Food Intake

The monthly pattern in mean food expenditure is striking (figure 1).[2] Mean daily expenditure per person on food at home peaks sharply in the first three days of the food stamp month and flattens out at a much lower level for the remainder. Foods that are pur-

[2] Because the CEX includes up to two weeks of daily food expenditure data, it is possible in figure 1 to have a date of most recent food stamp receipt that occurs after the date to which a particular food expenditure refers, leading to a negative value for the number of days since food stamps were received. Furthermore, mean food expenditure measured for day –1 (the day before benefits are received) and for day 30 or 31 may not match as perfectly as one might expect for two reasons: sampling variation and the possibility that some households recorded at day 30 or 31 could be in the process of leaving the Food Stamp Program.

chased proportionately most heavily at the start of the month include some that are easily stored for consumption throughout the month, such as grains or canned vegetables, and some foods that are relatively perishable and probably represent some degree of splurging, such as seafood and miscellaneous dairy.

The monthly pattern in food intake is more moderate, and it depends on how frequently the household conducts major grocery shopping trips (figure 2). Households that conduct a major grocery shopping trip more frequently than once per month are defined as "frequent" shoppers. Households that conduct such trips once per month or less frequently are defined as "infrequent" shoppers. For frequent shoppers, mean food energy intake remains steady during the four weeks of the food stamp month. For infrequent shoppers, mean food energy intake falls from 83.0% of the RDA in the first week to 73.4% of the RDA in the fourth week. A one-tailed *t*-test finds that the difference between food energy intake in the first week and the fourth week is statistically significant at the 0.05 level.

Even in the first three weeks, caloric intake appears low relative to the RDA, but this could perhaps reflect the difficulty of collecting complete intake data in a survey, rather than general undernutrition (Cleveland et al.; Rose, Habicht, and Devaney). Mean food energy intake appears just as low (78% of the RDA) for CSFII respondents who are not poor (Tippett et al.), probably due to underreporting of intake. In this article, we necessarily assume that any underreporting, if it does occur, is independent of the variables under study.

The food intake pattern for infrequent shoppers is notable, because food stamp recipients are more likely than low-income nonrecipients to be infrequent shoppers. Using the CSFII data, 42% of food stamp households were classified as infrequent shoppers. Only 16% of a comparison group of low-income nonrecipients were classified as infrequent shoppers. This comparison is imperfect, because even low-income nonrecipients may have higher average incomes than food stamp recipients, but the large difference in shopping patterns is suggestive. The main descriptive result, which motivates the analytic work

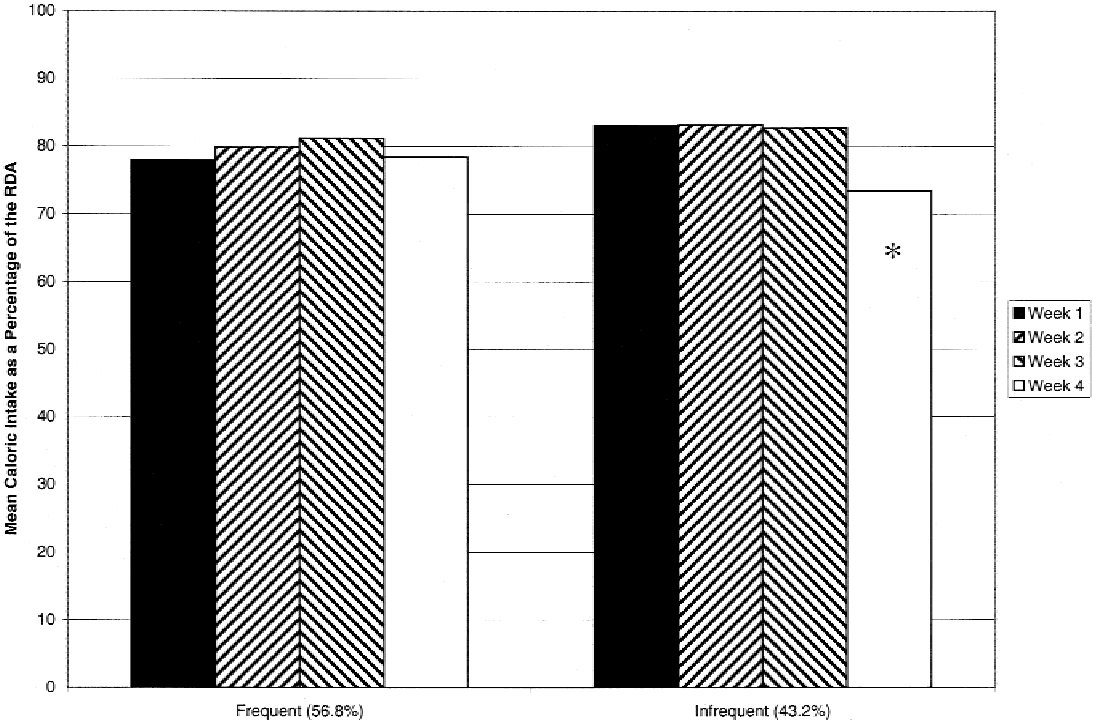

Figure 2. Food energy intake by individuals, according to shopping frequency
* signifies Week 4 intake is significantly less than Week 1 intake (one-tailed test, $\alpha = 0.05$)
source: *Continuing Survey of Food Intake by Individuals,* U.S. Department of Agriculture

to follow, is that frequent shoppers appear to avoid monthly cycles in food energy intake through successful food purchase and storage behaviors, but infrequent shoppers experience a significant drop in food energy intake at the end of the food stamp month.

A Theory of Shopping Frequency and Food Intake

The direction of causation for this relationship between food shopping and food intake is not obvious. The quotation from Lelyveld given earlier suggests that some households may experience low food intake at the end of the month because they were not "frugal" enough to save their food stamp resources for a longer period. Alternatively, we suggest that households facing transportation difficulties, time constraints, or stigma may choose to conduct a major grocery trip with food stamps only once monthly, and they may have trouble storing food for consumption four weeks later as a consequence.

The theory developed here supposes that consumers weigh the disadvantages of frequent major grocery trips (loss of leisure time, stigma, and so on) against the advantages (less food spoilage, less need for smaller trips to closer, higher-priced stores toward the end of the month). This theory supports a tractable econometric model: an endogenous switching regression model where the consumer simultaneously chooses a shopping frequency regime and food intake levels in each half of the month.

Suppose the consumer has well-defined (complete, transitive, and continuous) preferences over food (F) and other goods (X) in two halves of the food stamp month ($t = 1, 2$). These preferences depend in part on a vector of individual-specific variables (θ), including demographic characteristics and an idiosyncratic household-specific variable, which is nonstochastic from the point of view of the individual but which is a random disturbance from the point of view of the analyst. The consumer's preferences over goods in the two periods may be described by the monotonically increasing and quasi-concave utility function U.

The consumer chooses between two shopping regimes: less frequent major grocery trips ($d = 0$) or more frequent major grocery trips ($d = 1$). More frequent shopping involves a loss of leisure time and perhaps a greater sensation of stigma from using food stamps in the checkout line. We assume preferences are strongly separable between goods and shopping regimes, so they may be described by the utility function U^*:

$$(1) \qquad U^*(F_1, X_1, F_2, X_2, d; \boldsymbol{\theta}, \boldsymbol{\theta}^*) = U(F_1, X_1, F_2, X_2; \boldsymbol{\theta}) + \phi(\boldsymbol{\theta}^*)d,$$

where ϕ reflects the additional inherent utility (if positive) or disutility (if negative) of shopping frequently, $\boldsymbol{\theta}$ is the vector of characteristics that affect preferences over food and nonfood, defined above, and $\boldsymbol{\theta}^*$ is a vector of characteristics that affect preferences over shopping regime. The separability assumption corresponds to the one used by Moffitt (1983) to describe "flat" welfare stigma. Here, we assume a "flat" utility or disutility from shopping more frequently.

The costs of food perishability are described using the concept of the "effective" price of food, the cost per unit of food consumed rather than per unit of food purchased. For a household that shops infrequently, the effective price of a unit of food consumed in period 2 is higher if some proportion of food spoils in storage between the two periods. Or, if the same household chooses to avoid spoilage by purchasing some foods in more expensive local stores later in the month (purchases that do not qualify as a "major" grocery shopping trip), then the effective price of food in period 2 is again higher. Because food intake is our substantive interest, we can afford to be agnostic about the precise source of the higher effective food price for infrequent shoppers, so long as this price is correctly defined in terms of food intake.

For a household that shops frequently, we assume that the effective food price is constant for the two periods. Two empirical observations from the preceding section support this assumption: 1. the spike in mean food expenditure in the first three days of the food stamp month is pronounced for all household types studied, so it is reasonable to assign the first "major" grocery trip to this period; and 2. households with more than one major grocery trip per month experience no drop in mean food intake at the end of the month for any food group, so it is reasonable to treat their effective price of food as constant over time.

If p_X is the price of nonfood, p_F is the nominal "supermarket" price of food, and q_F is the potentially higher effective price of food in period 2, the consumer's problem may be written

$$(2)\quad \max_{F_1,X_1,F_2,X_2,d} \quad U^*(F_1, X_1, F_2, X_2, d; \boldsymbol{\theta}, \boldsymbol{\theta}^*),$$

$$\text{s.t.}$$

$$\text{(Regime 0)}\quad p_F F_1 + p_X X_1 + q_F F_2 + p_X X_2 = S + C \quad \text{if } d = 0,$$

$$\text{(Regime 1)}\quad p_F F_1 + p_X X_1 + p_F F_2 + p_X X_2 = S + C \quad \text{if } d = 1,$$

where total income on the right-hand side of the budget constraints equals monthly cash income (C) plus food stamp benefits (S). It should be noted that this model describes the constraints faced by inframarginal recipients, who contribute some of their own cash income to their food budget. For inframarginal recipients, the additional restriction that food stamps may only be spent on food is a nonbinding constraint. Previous empirical research in the United States has repeatedly found that food stamps have a greater marginal effect on food demand than cash income does, even for the large majority of recipients who are inframarginal (Fraker, Levedahl, Wilde and Ranney). Thus, in the empirical work below, we test a specification that permits food stamps and cash income to have distinct effects on food intake, even though these distinct effects are not implied in theory.

Because the cross-sectional CSFII data do not report prices, the empirical work focuses on "Engel" relationships, describing the impact of household resources on food intake. Although we could write the food demand functions that solve equation (2) as functions of all prices and income, it is more straightforward here to describe food demand in period t conditional on the two regimes as distinct functions of income. In this manner, the distinct effective food prices for frequent and infrequent shoppers are absorbed into the notation for the functions themselves:

$$(3)\quad F_t = F_t^0(S, C; \boldsymbol{\theta}) \quad \text{if } d = 0, \quad \text{and}$$

$$F_t = F_t^1(S, C; \boldsymbol{\theta}) \quad \text{if } d = 1.$$

If we rule out Giffen goods, the negative own-price effect of a higher effective food price ($q_F > p_F$) implies that the second-period conditional food intake function will be lower for regime 0 (infrequent shoppers) than for regime 1 (frequent shoppers). However, we can make no such unambiguous statement for the first period. The substitution effect of the higher price q_F would tend to raise first-period food intake in regime 0, while the income effect would have the opposite effect.

The unconditional food intake function for period t, which is denoted $F_t(S, C; \boldsymbol{\theta}, \boldsymbol{\theta}^*)$, will equal one of the two conditional food intake functions for the two shopping regimes, depending on which shopping regime is preferred. Let $X_t^d(S, C; \boldsymbol{\theta})$ be the conditional Engel function for the nonfood good that corresponds to $F_t^d(S, C; \boldsymbol{\theta})$ for the food good. The conditional indirect utility functions may be written

$$(4)\quad V^0(S, C; \boldsymbol{\theta}) = U(F_1^0, X_1^0, F_2^0, X_2^0; \boldsymbol{\theta}), \quad \text{and}$$

$$V^1(S, C; \boldsymbol{\theta}) = U(F_1^1, X_1^1, F_2^1, X_2^1; \boldsymbol{\theta}),$$

where we have suppressed notation indicating that demand for each good is a function of S, C, and θ.

The consumer chooses to shop frequently if the difference in these indirect utilities is enough to compensate for the disutility, if any, of shopping more frequently:

$$(5)\quad d(S, C; \boldsymbol{\theta}, \boldsymbol{\theta}^*) = 1 \quad \text{if } V^*(S, C; \boldsymbol{\theta}, \boldsymbol{\theta}^*) = V^1(S, C; \boldsymbol{\theta}) - V^0(S, C; \boldsymbol{\theta}) + \phi(\boldsymbol{\theta}^*) \geq 0, \quad \text{and}$$

$$d(S, C; \boldsymbol{\theta}, \boldsymbol{\theta}^*) = 0 \quad \text{otherwise.}$$

Thus, unconditional food intake is

$$(6)\quad F_t(S, C; \boldsymbol{\theta}, \boldsymbol{\theta}^*) = [1 - d(S, C; \boldsymbol{\theta}, \boldsymbol{\theta}^*)] F_t^0(S, C; \boldsymbol{\theta}) + [d(S, C; \boldsymbol{\theta}, \boldsymbol{\theta}^*)] F_t^1(S, C; \boldsymbol{\theta}).$$

Econometric Model

We begin with a specification for the food intake functions in equation (3) that permits nonlinear (quadratic) Engel curves and distinct marginal effects for food stamp benefits and cash income:

$$(7)\quad F_t^d = \beta_t^{0d} + \beta_t^{1d} S + \beta_t^{2d} S^2 + \beta_t^{3d} C + \beta_t^{4d} C^2 + \boldsymbol{\beta}^{5d\prime} \mathbf{Z}^f + \varepsilon^d,$$

where t is the half of the month ($t = 1, 2$), d is the shopping regime ($d = 0, 1$), $\mathbf{Z}^f$ is a vector of the nonstochastic elements of θ, the disturbance ε^d is the stochastic element of θ, and the β's are parameters to be estimated by maximum likelihood. For notational convenience, we suppress a subscript i indicating that each independent variable and disturbance may differ across households.

Similarly, the functional form for V^*, defined in equation (5), includes separate linear

and quadratic terms for food stamp benefits and cash income:

$$(8)\qquad V^* = \gamma^0 + \gamma^1 S + \gamma^2 S^2 + \gamma^3 C + \gamma^4 C^2 + \boldsymbol{\gamma}^{5\prime}\mathbf{Z}^f + \boldsymbol{\gamma}^{6\prime}\mathbf{Z}^r + \varepsilon^r,$$

where $\mathbf{Z}^r$ is a vector of nonstochastic elements of θ^* that do not also appear in θ, the disturbance ε^r is a function of the stochastic elements of both θ and θ^*, and the γ's are parameters to be estimated by maximum likelihood.

We also consider a more parsimonious special case. Using asymptotically equivalent Wald and Likelihood Ratio statistics, we consider the joint hypothesis that the parameters on the quadratic terms in equations (7) and (8) are zero and that food stamp benefits and cash income have the same marginal effect on the dependent variables. Based on these hypothesis tests, this special case is chosen as our preferred specification.

The independent variables in $\mathbf{Z}^f$, which affect both the shopping regime choice and the conditional food intake functions, were chosen on the grounds of their usefulness in previous food stamp research and their availability in the data set. They include household size in adult male equivalents (AME) and binary variables for cash welfare receipt, female headship, participation in the Women, Infants, and Children (WIC) Program, urban residence, and residence in the Southern states. The vector $\mathbf{Z}^r$ includes independent variables that affect the shopping regime choice, while having no effect on food intake conditional on the shopping regime choice. This vector, which appears in equation (8) but not in equation (7), is required to avoid nonlinear identification that relies entirely on the normality assumption in the specification of the stochastic terms. The only variable in the CSFII that could be assigned to $\mathbf{Z}^r$ a priori is the distance to the grocery store where major grocery shopping trips occur. All variable names and mean values appear in table 1.

Endogenous switching regression models are known to yield inconsistent estimates in the presence of misspecifications of the error structure, such as heteroskedasticity. In this model, one may suspect heteroskedasticity with respect to family size, because even with homoskedastic errors in individual food intake the variance of household mean food intake would decline with the number of household members. A lively and current field of research has developed around semi-nonparametric methods for relaxing the distributional assumptions required in limited dependent variable models (e.g., Lee). Here, however, we use a well-known parametric functional form for multiplicative heteroskedasticity:

$$(9)\qquad \varepsilon_i^d = \varepsilon^{*d}_i \exp(\delta^d W_i),$$

where ε^{*d}_i is an "underlying" homoskedastic disturbance, W is household size in AME, and δ^d must be estimated. The "underlying" homoskedastic variance-covariance structure is jointly normal by assumption:

Table 1. Mean Values and Definitions of Model Variables

Name	Definition	Mean
Dependent		
Food intake	Mean HH caloric intake as % of RDA	74.590
Frequent	Dum: regime 1 (shops frequently)	0.579
Independent		
Total income	Monthly FS benefits plus cash ($100s per AME)	5.915
Vector $\mathbf{Z}^f$		
HH size	HH size in adult male equivalents (AME)	1.697
Welfare	Dum: AFDC receipt	0.506
Female head	Dum: unmarried female head	0.645
WIC	Dum: WIC receipt	0.207
Urban	Dum: residence in central city	0.462
South	Dum: residence in South Atlantic, East South Central, or West South Central States	0.444
Vector $\mathbf{Z}^r$		
Distance	Distance to grocery store in miles	3.984

Source: *Continuing Survey of Food Intake by Individuals,* U.S. Department of Agriculture.

$$(10)\quad \begin{bmatrix} \varepsilon^{*0}_i \\ \varepsilon^{*1}_i \\ \varepsilon^{r}_i \end{bmatrix} \sim N(0, \boldsymbol{\Sigma}),$$

$$\text{where } \Sigma = \begin{bmatrix} \sigma_{00} & \sigma_{01} & \sigma_{0r} \\ & \sigma_{11} & \sigma_{1r} \\ & & 1 \end{bmatrix}.$$

Note that even if the stochastic elements of θ and θ^* are statistically independent, the disturbance ε^r may be correlated with ε^0 and ε^1, because the three disturbances share a dependence on the stochastic element of θ. This type of cross-equation correlation is reflected in the elements σ_{0r} and σ_{1r} of the matrix $\boldsymbol{\Sigma}$.

Econometric Results

This section presents results for the final specification discussed above, which has identical food stamp and cash income effects and no quadratic terms. A corresponding table for the more general specification, with quadratic terms and distinct food stamp and cash effects, is available from the authors upon request. The Wald test statistic for the restrictions on the general model is 19.91 (15 d.f., p-value = 0.18). The likelihood ratio test statistic for the same set of restrictions is 20.10 (15 d.f., p-value = 0.17). Thus, the restrictions are not rejected at conventional significance levels.

Food Intake

Parameter estimates for food energy intake under the two shopping regimes appear in the top section of table 2. There are four parameters for the effects of total monthly income (food stamp benefits plus cash income). Each parameter represents the marginal effect of total income on a latent food intake variable for a particular shopping regime in a particular half of the month. These parameters may in principle differ from the marginal effect of total income on expected food intake for participants who are actually observed in the two shopping regimes, because the latter marginal effect requires an adjustment for self-selection into shopping regimes. As we report below, however, the estimated covariances that would indicate such self-selection are not statistically significant.

For the frequent shopping regime (regime 1), the marginal effects of total income on latent food intake in the two periods are positive but very near zero and not statistically significant. The p-values for one-tailed z-tests of the null hypotheses that the true parameters are zero are 0.46 for the first half of the month and 0.20 for the second half. Thus, food energy intake does not appear to increase with additional total income under the frequent shopping regime.

For the infrequent shopping regime (regime 0), the estimated marginal effects of total income on latent food energy intake in the two periods are positive and larger than the comparable parameters under regime 1, although they still fail to register as statistically significant at conventional levels. The p-values for one-tailed z-tests of the null hypotheses that the true parameters are zero are 0.13 for the first half of the month and 0.11 for the second half. Thus, we cannot rule out sampling variation as an explanation for this observed effect.

The four Engel curves corresponding to these results are illustrated in figure 3, where total income varies from approximately the 10th percentile to the 90th percentile of the low-income sample and other variables are held constant at their mean values. The frequent shopping regime has the highest levels of predicted latent food energy intake at all levels of total income. The infrequent shopping regime has lower predicted latent food energy intake in both halves of the month. The fall in food intake from the first half of the month to the second is greater under the infrequent shopping regime than under the frequent shopping regime.

Turning to the remaining parameters in the top section of table 2, the estimated parameter for household size in adult male equivalents is positive and significant for regime 0 and positive and insignificant for regime 1. Because the dependent variable, food energy intake, is measured on a per AME basis, a positive household size parameter can be interpreted as scale advantages for larger households in producing food intake.

Female headship and residence in the South generally have small and insignificant effects on the latent food intake variable under each regime. This result is interesting, because these variables have strong effects on the shopping frequency decision, discussed below. Female headship and residence in the South appear to influence food intake by significantly reducing the probability of shopping frequently, not by affecting the food in-

Table 2. Endogenous Switching Regression Model of Food Energy Intake

	Regime 0 (R0)		Regime 1 (R1)	
	Estimates	Std. Err.	Estimates	Std. Err.
Dum: 1st half month	56.437	14.667	77.658	5.940
Dum: 2nd half month	52.144	14.867	73.830	6.072
Total income* 1st half	0.890	0.785	0.041	0.429
Total income* 2nd half	0.580	0.464	0.317	0.378
Household size	4.797**	1.488	0.364	1.229
Dum: welfare	1.063	3.583	6.281**	2.913
Dum: female head	2.591	3.781	–0.227	2.895
Dum: WIC	8.420**	3.584	6.573**	3.282
Dum: urban	0.761	3.043	–5.474**	2.550
Dum: South	1.207	3.375	–3.100	2.854
Switching Function				
	Estimates	Std. Err.		
Intercept	0.691	0.217		
Total income	0.010	0.013		
Household size	0.018	0.059		
Dum: welfare	–0.241**	0.119		
Dum: female head	–0.235**	0.118		
Dum: WIC	–0.134	0.134		
Dum: urban	–0.156*	0.109		
Dum: South	–0.252**	0.110		
Distance	–0.023**	0.008		
Distributional Parameters				
	Estimates	Std. Err.		
Standard deviation (R0)	33.275**	2.690		
Standard deviation (R1)	27.268**	1.868		
Covariance (R0)	–3.404	11.549		
Covariance (R1)	–5.030	6.112		
Het. with HH size (R0)	–0.192**	0.043		
Het. with HH size (R1)	–0.090**	0.032		

Source: *Continuing Survey of Food Intake by Individuals,* U.S. Department of Agriculture.
Note: * indicates significant at $\alpha = 0.10$, one-tailed test. ** indicates significant at $\alpha = 0.05$.

take functions for each regime directly. By contrast, participation in the WIC program appears to affect food intake directly. The WIC parameter is large and positive under both shopping regimes.

Shopping Frequency

The parameter estimates for the switching equation appear in the middle section of table 2. Cash welfare participation, female headship, urban residence, residence in the South, and increased distance to "major" grocery store each significantly reduces the probability of shopping frequently. By contrast, although parameter estimates for total income and household size are positive, as one might expect, they are not significantly different from zero.

Distributional Parameters

The cross-equation covariances are small and not significantly different from zero (table 2, bottom section). Thus, although one could not have known so a priori, endogenous self-selection into the two shopping regimes did not prove an important consideration in the empirical estimation.

The estimated standard deviations of the "underlying" homoskedastic disturbances are 33.28 for regime 0 and 27.27 for regime 1. The heteroskedasticity parameters for household size are negative and statistically significant, indicating that the standard deviation falls with household size as expected. From these parameters and the household size variable, an estimated standard deviation may be computed for each household in the sample. The means of these estimated standard de-

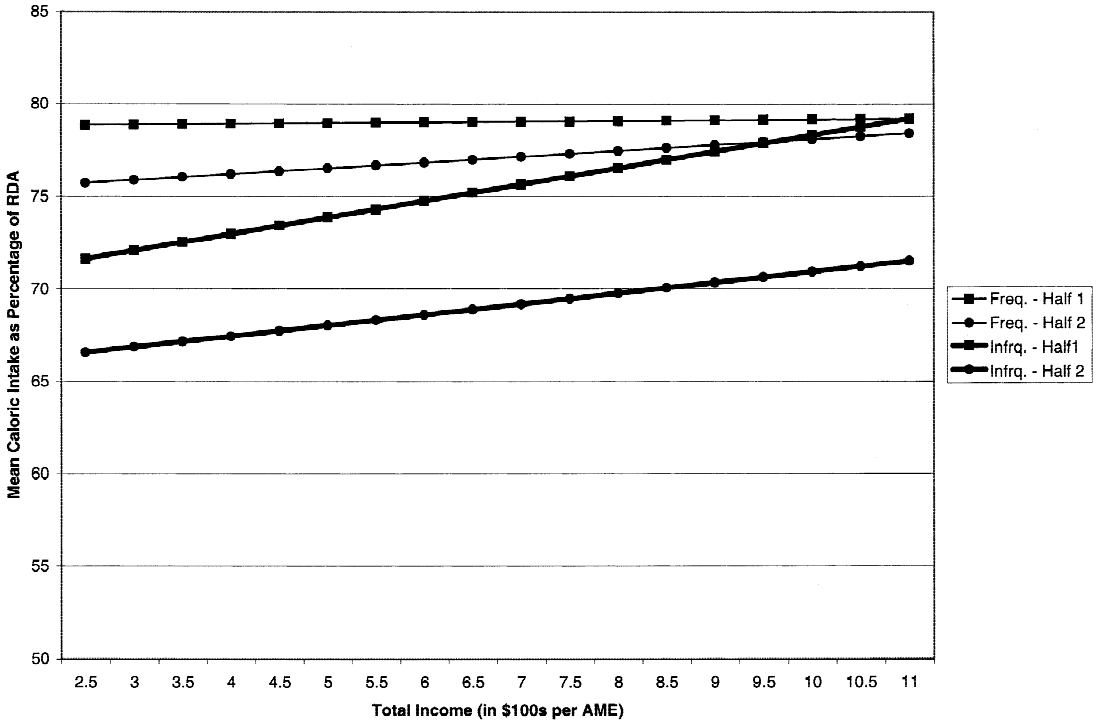

Figure 3. Expected latent food energy intake for each time period and shopping regime
source: *Continuing Survey of Food Intake by Individuals,* U.S. Department of Agriculture

viations are 24.5 for regime 0 and 23.5 for regime 1.

Simulated Changes in Independent Variables

To illustrate the main results, we calculate the expected probability of shopping frequently and the expected value of food energy intake in the two halves of the month, at different levels of the independent variables (table 3). These illustrations show the main effects of the independent variables, after taking into account their influence on both the shopping regime choice and the food energy intake level conditional on that choice.

The entries to table 3 are computed as follows. For each independent variable, a "low" value and a "high" value are considered. For continuous variables, these values are the first and third quartiles, respectively. For the dichotomous variables, these values are zero and unity, respectively. In each illustration, all variables other than the variable under study are left unchanged in the data set. Parameters from table 2 and variables from the survey data determine the expected value of food intake in the two halves of the month for each household, conditional on observing that household in the two shopping regimes. These expected values include an inverse Mill's ratio term to account for self-selection into shopping regimes (although, once again, that effect is not statistically significant). Weighting the conditional expected food energy intake levels for the two regimes by each household's estimated probability of choosing the regimes, one gets the expected food energy intake in the two halves of the month. The means for the whole sample are then reported in table 3.

Consistent with the parameter estimates above, the effect of total income on expected food energy intake is small in real terms as well as statistical terms. When total income increases from the first quartile ($307 per AME) to the third quartile ($704 per AME) of the low-income sample, expected food energy intake as a percentage of the RDA increases by only 2.2 percentage points in the first half of the month. Food energy intake in the second half of the month shows a still smaller increase, even though it starts from a lower base. The effect of the increase in total income on the probability of being a frequent shopper is also negligible.

Table 3. Expected Food Energy Intake and Probability of Shopping Frequently

Single-Variable Comparisons	Expected Food Energy Intake		Probability of Shopping Frequently
	First Half	Second Half	
Low income ($307 per AME)	74.96	70.69	56.8%
High income ($704 per AME)	77.14	72.58	58.3%
Low HH size (0.76 AME)	74.02	69.48	57.2%
High HH size (2.31 AME)	78.38	73.80	58.2%
No cash welfare	75.28	70.57	62.5%
Cash welfare	77.94	73.58	53.3%
No female head	75.98	71.21	63.6%
Female head	76.89	72.46	54.7%
No WIC	75.11	70.52	58.9%
WIC	82.36	77.97	53.8%
Not urban	77.62	72.96	60.6%
Urban	75.34	70.91	54.7%
Not South	77.13	72.42	62.0%
South	75.85	71.51	52.5%
Low distance to store (0.5 miles)	76.79	72.13	60.8%
High distance to store (4.0 miles)	76.60	72.06	57.8%

Source: *Continuing Survey of Food Intake by Individuals,* U.S. Department of Agriculture.

Of the other independent variables, household size and WIC have the largest effects on expected food energy intake. Female headship, residence in the South, and distance to the major grocery store (which does not enter directly into the food intake equations) have the smallest effects on expected food energy intake.

The geographic and demographic variables have a substantial impact on the probability of shopping frequently. The effects of individual variables on this probability range from 3 percentage points (for distance) to nearly 10 percentage points (for residence in the South). In combination, the independent variables can have a yet stronger effect. For example, the expected probability of shopping frequently for a household with no cash welfare, no female head, and no WIC is 69% (not shown in table 3). The corresponding probability for a household with cash welfare, a female head, and WIC receipt is 46%.

Discussion

The descriptive analysis of nationally representative data on food expenditure and food intake yields three conclusions:

- There is a sharp spike in mean food expenditure in the first three days of the food stamp month, counting from the day benefits are received.
- For households that shop frequently (conducting a major grocery trip more than once per month), food energy intake is nevertheless quite smooth over the food stamp month.
- For households that shop infrequently, by contrast, food energy intake dips significantly between the first and fourth weeks of the food stamp month.

These results motivate an econometric model that simultaneously accounts for the shopping frequency decision and the food intake decision in the two halves of the month. Key results are the following:

- For households that shop frequently, total income (food stamp benefits plus cash income) has no measurable marginal effect on food energy intake in either half of the month.
- For households that shop infrequently, the corresponding marginal effects are estimated to be somewhat larger, but still not statistically significant.
- Total income has no measurable effect on the probability of shopping frequently.
- Latent food energy intake is estimated to be higher for frequent shoppers (in either half of the month) and lower for infrequent

shoppers (especially in the second half of the month).

- Other demographic and geographic variables have stronger effects than total income on both food energy intake and the probability of shopping frequently. In particular, participation in the WIC program has a strong positive effect on food energy intake. Receiving cash welfare, female headship, urban residence, residence in the South, and distance to the store each reduce the probability of being a frequent shopper.

Our econometric model allows unobserved factors that influence the shopping frequency decision also to influence food energy intake decisions. However, these cross-equation effects do not prove to be statistically significant. Future empirical work in this area will have to weigh the advantage of explicitly considering endogenous shopping regime choice against the opportunity cost in terms of other considerations that could be addressed instead.

The Engel functions employed in our final model incorporate parameter restrictions that might not be favored a priori. The estimation is based initially on a specification that permits nonlinear (quadratic) Engel functions and distinct effects of food stamp benefits and cash income. The final model, with linear Engel functions and identical marginal effects for both types of household resource, is tested as a special case and not rejected. Given the complexity already introduced into the model by the switching regression structure, this simpler specification for the Engel functions appears most appropriate for this paper, but it runs contrary to two strains in the economic literature. First, concave Engel functions have a long history of successful use in theoretical and empirical work. Second, much recent empirical work on the Food Stamp Program has found that food stamp benefits and cash income have distinct effects on food spending.

The most important difference between the model used here and these two strains in the literature is that our dependent variable is food energy intake rather than food expenditure. Even if food spending has been found in past work to increase with food stamp benefits, some of the increase goes toward food characteristics other than food energy. Within a certain range of food stamp or cash income levels, it is not surprising that we find estimated Engel functions for food energy intake that are nearly horizontal, at least as far as we can distinguish formally with statistical tests of limited power. Given this finding, the two restrictions imposed in our final model are also reasonable in this research context: that the Engel functions are linear and that their slopes are not different between food stamp benefits and cash income. A limitation of our final model is that these restrictions would not be reasonable in the context of out-of-sample changes in income and food stamp benefits. Such larger, distinctly nonmarginal, changes in food stamp benefits are faced by legal immigrants who become disqualified from the Food Stamp Program and by able-bodied adults without dependents who reach time limits for program participation.

If key marginal income effects seem smaller in this article than in previous research on food spending, why choose food energy intake as the main dependent variable under study? After all, the monthly cycle in food spending is relatively larger, and it does not require consideration of particular subgroups (such as infrequent shoppers) or econometric control of other household characteristics to observe the main effect. An overall measure of food intake is interesting, we argue, because a large portion of food purchased at the start of the food stamp month clearly is stored for later use. If this storage strategy were completely effective at smoothing food intake, the cycle in food spending would have little importance as a policy concern. Instead, however, the sharp cycle in food spending leaves some households with less food intake late in the month, as we find in both the descriptive and econometric results.

This research focuses attention on how policies that affect shopping frequency could in turn affect the monthly cycle in food intake for food stamp recipients. For example, municipalities often express concern about attracting or retaining supermarkets in low-income urban areas. In terms of our econometric model, such policies affect the distance households must travel to the store where they conduct their major grocery shopping. The econometric results suggest that increased distance to the grocery store is significantly associated with lower probability of choosing the frequent shopping regime, which has a less severe monthly cycle in food intake. However, the magnitude of this effect in our estimates is not large enough to be an important policy consideration.

A policy with potentially greater impact is the recent introduction of Electronic Benefit Transfer (EBT) systems, using plastic cards akin to automatic teller cards, in place of traditional food stamp coupons. Thirty-five states and the District of Columbia use EBT systems, and twenty-seven of these systems are implemented statewide. From the point of view of traditional consumer demand theory, this change might seem minor in the sense that it affects neither total household resources nor the legal requirement that food stamp benefits are spent on food. In the framework of this article, however, certain features of EBT seem more important. For example, if EBT reduces the stigma associated with using food stamps, reduces recipients' fear of theft, or improves their ability to budget over the month, one might anticipate an increase in the propensity to choose the frequent shopping regime. Moreover, because the routine updating of benefits is implemented electronically under EBT, the new technology would make it less expensive to deliver benefits in smaller portions more frequently than once per month. Though research would be required to demonstrate so, we would foresee a sharp increase in the proportion of frequent shoppers under such a policy.

The potential advantages of updating food stamp benefits more than once per month would have to be weighed against the restrictions it might place on household budgeting and preferences. Perhaps surprisingly, this change was recommended by some food stamp recipients themselves in focus group discussions conducted as part of a food stamp cash-out experiment in San Diego (Ohls et al.). The merits and demerits of such a proposal would be a worthwhile topic of future research as post-EBT data sources become available. For now, the contribution of this article is to suggest that policy instruments other than the food stamp benefit schedule are available to influence shopping frequency and, as a consequence, to affect the monthly cycle in food intake.

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References

Blaylock, J.R. "An Economic Model of Grocery Shopping Frequency." *Appl. Econ.* 21(June 1989):843–52.

Bradbard, S., E.F. Michaels, K. Fleming, and M. Campbell. *Understanding the Food Choices of Low Income Families.* Alexandria VA: U.S. Department of Agriculture, Food and Consumer Service, May 1997.

Butler, J.S., and J.E. Raymond. "The Effect of the Food Stamp Program on Nutrient Intake." *Econ. Inquiry* 34(October 1996):781–98.

Cleveland, L.E., A.J. Cook, J.W. Wilson, J.E. Friday, J.W. Ho, and P.S. Chahil. *Pyramid Servings Data: Results from USDA's 1994 Continuing Survey of Food Intakes by Individuals.* Riverdale MD: U.S. Department of Agriculture, Food Surveys Research Group, 1997.

Emmons, L. "Food Procurement and the Nutritional Adequacy of Diets in Low-Income Families." *J. Amer. Dietetic Assoc.* 86(December 1986):1684–93.

Food and Consumer Service. *Conference on Food Security Measurement and Research.* Washington DC: U.S. Department of Agriculture, 1994.

Food and Consumer Service. *Nutrition Program Facts: Electronic Benefit Transfer.* Alexandria VA: U.S. Department of Agriculture, September 1997.

Food Research and Action Center. *Community Childhood Hunger Identification Project: A Survey of Childhood Hunger in the United States.* Washington DC: 1995.

Fraker, T. *The Effects of Food Stamps on Food Consumption: A Review of the Literature.* Washington DC: Mathematica Policy Research, Inc., October 1990.

Fraker, T.M., A.P. Martini, and J.C. Ohls. "The Effect of Food Stamp Cashout on Food Expenditures: An Assessment of the Findings from Four Demonstrations." *J. Human Resour.* 30(Fall 1995):633–49.

Lee, M.J. *Methods of Moments and Semiparametric Econometrics for Limited Dependent Variable Models.* New York: Springer, 1996.

Lelyveld, J. "Hunger in America: the Safety Net Has Shrunk But It's Still In Place." *New York Times Magazine,* 16 June 1985, pp. 000–000.

Levedahl, W. "A Theoretical and Empirical Evaluation of the Functional Forms Used to Estimate the Food Expenditure Equation of Food Stamp Recipients." *Amer. J. Agr. Econ.* 77(November 1995):960–8.

McCracken, C.A., V.A. McCracken, and H. Shi. "The Effects of A Food Stamp Program Cashout on Household Food Allocation Decisions and Nutrient Demand Responses." Paper presented at AAEA annual meeting, Indianapolis IN, August 1995.

Madden, J.P., and M.D. Yoder. "Program Evaluation: Food Stamps and Commodity Distribution in Rural Areas of Central Pennsylvania." Dept. Agr. Econ. Bull. No. 780, Pennsylvania State University, June 1972.

Moffitt, R. "An Economic Model of Welfare Stigma." *Amer. Econ. Rev.* 73(December 1983):1023–35.

Moffitt, R. "Estimating the Value of an In-Kind Transfer: the Case of Food Stamps." *Econometrica* 57(March 1989):385–409.

Ohls, J.C., T.M. Fraker, A.P. Martini, and M. Ponza. *The Effects of Cash-Out on Food Use by Food Stamp Program Participants in San Diego.* Princeton NJ: Mathematica Policy Research, Inc., 1992.

Rank, M.R., and T.A. Hirschl. "The Food Stamp Program and Hunger: Constructing Three Different Claims." *Eating Agendas.* J. Sobal and D. Maurer, eds., pp. 241–58. New York: Aldine de Gruyter, 1995.

Rose, D., J.-P. Habicht, and B. Devaney. "Household Participation in the Food Stamp and WIC Programs Increases the Nutrient Intakes of Preschool Children." *J. Nutr.* 128(March 1997):548–55.

Thompson, F.E., D.L. Taren, E. Andersen, G. Casella, J.K.J. Lambert, C.C. Campbell, J.E.A. Frongillo, and D. Spicer. "Within Month Variability in Use of Soup Kitchens in New York State." *Amer. J. Public Health* 78(October 1988):1298–1301.

Tippett, K.S., S.J. Mickle, J.D. Goldman, K.E. Sykes, D.A. Cook, R.S. Sebastian, J.W. Wilson, and J. Smith. *Food and Nutrient Intakes by Individuals in the United States, 1 Day, 1989–91.* Washington DC: U.S. Department of Agriculture, Agricultural Research Service, 1995.

U.S. Department of Agriculture. *Continuing Survey of Food Intake by Individuals.* Washington DC: 1991.

U.S. Department of Labor, Bureau of Labor Statistics. *Consumer Expenditure Survey.* Washington DC: 1992.

Wilde, P., and C. Ranney. "The Distinct Impact of Food Stamps on Food Spending." *J. Agr. Resour. Econ.* 21(July 1996):174–85.