UMI Number: 9831227

THE MONTHLY FOOD STAMP CYCLE: SHOPPING FREQUENCY AND FOOD INTAKE DECISIONS IN AN ENDOGENOUS SWITCHING REGRESSION FRAMEWORK

A Dissertation
Presented to the Faculty of the Graduate School
of Cornell University
in Partial Fulfillment of the Requirements for the Degree of
Doctor of Philosophy

by

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May 1998

BIOGRAPHICAL SKETCH

Parke Wilde was born in Washington, D.C. and attended D.C. public schools through tenth grade. During his childhood, he lived overseas with his family at different times in Barbados, Paraguay, and Nicaragua. After graduating from Liberty High School in Bethlehem, PA, he spent a year in Indonesia on the Rotary exchange program. He graduated with honors from Swarthmore College in 1990, with a major in Political Science and a minor in Economics. His master's thesis in agricultural economics at Cornell received the Outstanding Master's Thesis award from the Northeastern Agricultural and Resource Economics Association (NAREA).

Parke's career has focused on research and writing about the politics and economics of food consumption. From 1990 to 1992, he edited *Nutrition Week*, the publication of the Community Nutrition Institute in Washington, DC. He also worked as a freelance journalist, writing articles for *Vegetarian Times* and a bi-monthly column for *Food Management*. His current research at Cornell investigates the economics of U.S. food and nutrition programs.

Whenever I tried to become wise and learn what goes on in the world,

I realized that you could stay awake night and day

and never be able to understand what God is doing.

Ecclesiastes 8:16-17

ACKNOWLEDGMENTS

The topic of this dissertation was suggested in earlier writings by and conversations with Tom Fraker at Mathematica Policy Research, Inc., and Steve Carlson at the Food and Nutrition Service. Many professors at Cornell have been helpful in diverse ways: Professors Christine Olson and Jean-Pierre Habicht in the Division of Nutrition Science; George Jakubson in Labor Economics; Elizabeth Peters in Policy Analysis and Management. Other graduate students have heard me out and offered great suggestions: Rob Olsen, Cara H. Olsen, Robert Ethier, Daniel Rondeau, and John Bernard, in particular, did not appear to fall asleep. Paul McNamara, a research associate in my department at Cornell, has been most generous with advice and wise counsel. Mary Hama at the Agricultural Research Service and Geoffrey Paulin at the Bureau of Labor Statistics shared their expertise on the two main data sources. I received too many excellent comments to list from those who heard earlier papers given for the American Agricultural Economics Association, the Economic Research Service, and the National Research Council's Board on Children, Youth, and Families.

Nobody could hope for a better dissertation committee. W. Keith Bryant is a great scholar in the economics of the household and family. Tim Mount is a premier econometrician. They both wielded their powers on the committee forcefully enough to call forth great improvements in this dissertation, but they kindly stopped short of demanding that it satisfy all the possibilities they saw in this work.

The committee's chair, Christine Ranney, has been a mentor to me. No one has greater expertise in the theory and methods used here to study the Food Stamp Program, and even more importantly, no one has more common sense, principle and determination to apply these tools to real policy issues. She worked hard in guiding this dissertation. I have learned from what she has taught me and from her example.

This dissertation was made possible financially by the generous support of Professor Ranney and the Department of Agricultural, Resource, and Managerial Economics at Cornell. One year of research funding was generously provided by the Food and Nutrition Service and the Institute for Research on Poverty, through their joint Small Grants Program. All errors and opinions are my own.

Sarah Huber, the love of my life, gets no thanks in these acknowledgments. While her support and friendship have admittedly been some comfort during this period of study, her wisdom and perspective have been detrimental to my work schedule. Our travels by bicycle have delayed completion of this project by days and weeks. I strongly suspect she is guilty of believing the most ridiculous heresy: that there is more to life than a dissertation.

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CHAPTER ONE

INTRODUCTION

At the start of the food stamp month, right after benefits arrive, most families that receive food stamps go grocery shopping. For forty percent of recipient households, this trip is the only major grocery-shopping trip of the month. In the first couple days of the month, food stamp families stuff their cupboards and their refrigerator with a large proportion of their whole month's supply of food. While many people at all income levels shop soon after resources arrive in the household, the degree to which food stamp recipients concentrate their food purchases in the first few days of the food stamp month distinguishes them even from other low-income Americans.

For many families, the food from this large grocery trip and from a few smaller food purchases is stored for relatively even consumption through the food stamp month. For this reason, the monthly cycle in food intake described in this dissertation has a much smaller amplitude than the cycle in food expenditure. Still, by the end of the month, some households show symptoms of food shortages. Mean intake of some foods such as fruits and dairy products drops significantly by the fourth week of the month. For households that conduct a major grocery trip only once monthly, even mean caloric intake from all food drops significantly by the fourth week. This drop in food intake may reflect substantial economic stress in food stamp households at the end of the month.

This dissertation asks several questions about the monthly cycles in food spending and food intake by food stamp recipients. How big are they? Why do they exist? What is their link to consumer choices about shopping frequency? How are they affected by changes in food stamp benefit levels? And how are they affected by other policy changes?

Chapter two reviews literature from economics and other disciplines that bears on the food stamp cycle. There has been little research on the food stamp cycle itself, but periodic food shortages and even a process of running out of food over the course of a month have implicitly been central to a large body of research on hunger and food insecurity in the United States. This chapter also considers the nutritional implications of a cycle in food intake, including the consequences of periodic food shortages for symptoms of undernutrition and also, paradoxically, a possible link with obesity.

Chapter three contains the main descriptive results about the cycles in food spending and food intake, based on two nationally representative surveys: the Consumer Expenditure Survey (CEX), and the Continuing Survey of Food Intake by Individuals (CSFII). There is a sharp peak in mean food expenditure in the first days of the food stamp month. There is a smoother pattern in mean intake of all foods, but some foods and some food stamp recipients display a significant drop in intake at the end of the food stamp month. This chapter considers in particular the differences between cash welfare (AFDC) recipients and nonrecipients, female-headed households and households with a male present, adults and children, and frequent and infrequent grocery shoppers. It also compares monthly spending and intake patterns for foods in the six main food groups of the U.S. Department of Agriculture's "Food Guide Pyramid." The univariate analysis in this chapter has shortcomings, which are addressed later in the dissertation, but these simple comparisons generate substantial new information about the nature of the food stamp cycle.

The remainder of the dissertation develops an economic model of consumer choice over time and estimates a corresponding econometric model. It explains how various economic factors simultaneously influence food intake and food shopping decisions. Chapter four reviews the applied economic literature on the Food Stamp Program, focusing on endogenous switching regression models of a type that will prove useful later. The chapter concludes that this family of models holds promise for aiding our understanding of the Food Stamp Program, but that accounting for the two most-studied endogenous regime choices (participate in the program or not, choose an inframarginal food bundle or not) have not made a great difference in the actual results.

Chapter five develops an economic theory of food intake choices in two time periods and under two shopping regimes. The model imagines that consumers weigh the advantages of frequent major grocery shopping trips (which lead to lower costs associated with food spoilage) against the disadvantages (loss of leisure time and increased stigma in the checkout line). Infrequent shoppers may then have reason to consume less food late in the food stamp month. This chapter builds an econometric model, based on the theoretical framework, which accounts for both the endogeneity of the shopping regime choice and also the potentially heteroskedastic error terms. Chapter six contains results and discussion for this econometric model.

Chapter seven employs the econometric results to conduct simulations that indicate the effects of different policy options. Some of these policy options, such as different levels of food stamp benefits, have been studied previously in the economic literature. Others, such as policies that might encourage households to conduct major grocery shopping trips most frequently, are more distinctive contributions of the approach developed in this dissertation. Chapter eight summarizes the dissertation and its policy implications, and it makes suggestions for future research.

Hopefully, this work will be useful for applied economists, whose models of the Food Stamp Program currently ignore differences in food demand at different times of month. This work should also be useful for policy-makers, who have in the past expressed concern and awareness about the food stamp cycle, but who to date have had no economic research on the matter and no measurements of this cycle based on nationally representative data.

Economists who study food insecurity and the Food Stamp Program have called for further research on the food stamp cycle. At the 1994 conference on food security measurement and research, Steve Carlson, director of the Office of Analysis and Evaluation for the Food and Consumer Service, recommended: "We need to work harder to figure out how we can identify, measure, and assess the consequences of a recurrent or cyclical pattern of hunger, for example, at the end of each month" (Food and Consumer Service 1994). In his 1990 literature review, Thomas Fraker discussed the state of current research on the monthly cycle: "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" (Fraker 1990). This dissertation is a response to these calls.

CHAPTER TWO:
LITERATURE REVIEW, PART I

2.1 Introduction

The literature review for this dissertation has two parts. This chapter reviews research from various disciplines that illuminates the food stamp cycle and its consequences for welfare and nutrition. Later, to provide background for our econometric model, chapter four will more specifically discuss applied economic research that studies food demand by food stamp recipients using a switching regression framework.

This chapter is organized as follows. Section 2.2 describes what has been written about the food stamp cycle itself, mainly in the nutrition and public health literatures. Section 2.3 discusses large hunger and food insecurity surveys, which shed light on the food stamp cycle indirectly. Section 2.4 considers the literature on an issue that will later prove central to understanding the monthly cycle in food intake: the peculiar infrequency in grocery shopping by food stamp recipients. Section 2.5 turns to possible consequences of the food stamp cycle.

2.2 The Food Stamp Cycle: Well-Known But Little-Studied

Monthly cycles in food spending and food consumption have not previously been measured using nationally representative data, but their broad outlines have been well known for years among journalists and researchers covering the Food Stamp Program. In the press, these cycles have been described with some alarm. "Inevitably," Joseph Lelyveld wrote in the New York Times Magazine 12 years ago (Lelyveld 1985), "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 10 days, depending on how frugal they were earlier."

Sociologists Mark Rank and Thomas Hirschl more recently reported the recipients' perspective on the Food Stamp Program:

> The recipients' economic struggles become even more difficult toward the end of each month.... For example, many recipients find that their food stamps routinely run out by the end of the third week. Even with the budgeting and stretching of resources that recipients try to do, there is simply not enough left at the end of each month (Rank and Hirschl 1995).

The Community Childhood Hunger Identification Project (CCHIP) report from the Food Research and Action Center described the same pattern:

> For many low-income families, hunger is cyclical. A lack of resources limits their ability to provide enough food at certain times each month -- for example, at the end of the month when the next pay check is due or when food stamps run out -- or during certain months of the year -- for example, during months when children do not get meals from school food programs (Food Research and Action Center 1995).

Journalistic and sociological writings on the food stamp cycle rely heavily on reports from individual recipients. Some economic analyses have used focus group interviews in the early stages. The hazards of these approaches are well-known, but one advantage is that these reports provide colorful and detailed commentary from recipients themselves, which is helpful in generating hypotheses for further research:

> The first part of the month I always cook us a good meal. Something we don't get and something we like. Fish usually. I just say at that point, 'I don't care what happens, I'm going to take care of myself.' -- *Single mother with three children in Houston, Texas* (Lelyveld 1985).

> Toward the end of the month, we just live on toast and stuff. Toast and eggs or something like that. I'm supposed to eat green vegetables. I'm

> supposed to be on a special diet because I'm a diabetic. But there's a lotta things that I'm supposed to eat that I can't afford. Because the fruit and vegetables are terribly high in the store. It's ridiculous! -- *Married woman in her mid-30s with six children* (Rank and Hirschl 1995).
>
> It's like you pay your bills and you buy your food and you just stretch it until the first [of the month]. That's all you do. -- *Focus group participant in San Diego, California* (Ponza and Cohen 1990).
>
> When it gets close to the end of the month, the food starts running out. It runs out when I'm getting checks and it runs out when I'm getting food stamps. At the end of the month, you compare your food and you're getting down to the end. Like right now. -- *Focus group participant in Fayette, Alabama* (Mazur and Ciemnescki 1991).
>
> Give it to us in two installments. At the end of the month I'm dying [for money]. If you got it on the 1st and the 15th, or whatever, it would be so much better. Checks or coupons, it doesn't matter, either way, but it does not last a month. The second part of the month is always a struggle. -- *Focus group participant in San Diego, California* (Fraker et al. 1992).

There is a small amount of more quantitative empirical research on the food stamp cycle, mainly in the nutrition and public health literatures. Emmons (1986) studied 76 low-income families in Cleveland, who were interviewed each week for one month. The first interview took place immediately after food stamps and public assistance were received. Although families bought most of their food in the first two weeks, actual food intake remained relatively steady through the last week of the month. Intakes of high-protein foods, fruit, and vegetables exhibited statistically significant drops from Week 1 to Week 4, while dried legumes showed an increase. "In spite of the decreased number of servings of food in some groups over the month," the study concluded, "the general pattern of food buying and food procurement suggested that heads of household did considerable planning so that food consumption remained as steady as it did."

A demonstration electronic benefit transfer program in Reading, PA, also found that food stamp benefits were spent early in the month, although it did not measure food intake. In this demonstration, recipients spent "an average of 19 percent of their monthly benefit on the day of issuance, 70 percent within the first week, and 89 percent within two weeks" (Fraker 1990). Such a monthly cycle in food spending among food stamp recipients has been linked to a monthly cycle in the use of emergency food relief sites. Thompson, Taren et al. (1988) found in two samples from New York City and Upstate New York that the mean number of meals served weekly in soup kitchens followed a sharp saw-tooth pattern over the year, with a peak at the end of almost every month.

This literature review unearthed only one study that considered time-of-month in a regression analysis of the impact of the Food Stamp Program. In their analysis of data from a food stamp cashout demonstration in Washington State, reported in a selected paper for the summer meetings of the American Agricultural Economics Association, McCracken et al. (1995) included the "number of days since receipt of food benefits" in a vector of demographic variables in estimated demand equations for various food categories. They reported that the coefficient on this variable was positive in a demand equation for fruits and vegetables and negative in a demand equation for meats. Although this methodology implicitly assumes a restrictive model for how time-of-month affects food demand, these intriguing results suggest that the composition of household food bundles may change during the month.

2.3 Hunger and Food Insecurity Surveys

The preceding studies are unusual in that they specifically consider the timing of food intake, food spending, or emergency food use within the month. A greater abundance of existing survey-based research bears on this timing issue only indirectly. For example, the whole rapidly-growing body of research on food insecurity in the United States is concerned with occasional or periodic episodes of hunger, such as might occur at the end of the food stamp month. Highlights of this research are found in the proceedings of a 1994 conference on food security measurement and research (Food and Consumer Service 1994). This section first reviews the three main approaches that have been used in survey questions about hunger and food insecurity and then focuses on those survey questions that shed the most light on the duration and timing of these conditions.

The most parsimonious approach to survey work on hunger is the simple "USDA food sufficiency question" that has appeared in various forms on a number of nationally representative government surveys over the years, including, recently, the Continuing Survey of Food Intake by Individuals (CSFII) for 1989-1991 and the Third National Health and Nutrition Examination Survey (NHANES III). In its NHANES III incarnation, this question asks simply whether respondents and their families have: 1) enough food to eat, b) sometimes not enough to eat, or c) often not enough to eat. In the CSFII, 2.5 percent of respondents reported sometimes or often not getting enough to eat. Preliminary estimates from the NHANES III found that 4 percent of individuals lived in families that reported sometimes or often not getting enough to eat (Rose et al. 1995).

Research by Cristofar and Basiotis has shown how this food sufficiency question relates to a continuous food intake variable. Using data from the 1985-1986 CSFII, a predecessor to the 1989-1991 CSFII survey employed in this dissertation, they found that mean caloric intake falls from 73.6 percent of the RDA for people who always have enough and the kind of food they want, to 70.8 percent for those who always have enough but sometimes not the kind they want, to 65.4 percent for those who sometimes or often do not have enough to eat.[1] These food intake measures are similar to those used later in this dissertation, so this research provides an interesting indication of how different food intake levels correspond to different stages of food insufficiency.

A more extensive battery of survey questions was developed by the Community Childhood Hunger Identification Project (CCHIP). The questions included, for example, "Thinking about the past 12 months: Did you ever rely on a limited number of foods to feed members of your household because you were running out of money to buy food for a meal?" and "Did any of your children ever go to bed hungry because there was not enough money to buy food?" If the response to a question was affirmative, the survey asked how many days in the past month, and how many months in the past year, the family experienced this condition. If five of the eight hunger questions were answered affirmatively, the family was classified as "hungry." This survey, a project of the Food Research and Action Center, an advocacy group on food and hunger issues, led to some of the highest estimates of U.S. hunger that have been published: 19 percent of low-income families were hungry during some part of the preceding year, and another 50 percent were at risk of hunger; in all, four million

[1] In all three cases, caloric intake appears lower than the RDA due to under-reporting.

American children were estimated to be hungry (Food Research and Action Center 1995).

A third set of survey questions on food insecurity, developed at Cornell, refers more directly to a process of running out of food over the course of the month. In these "Radimer/Cornell Food Insecurity Items," survey respondents were asked, for example, whether it is sometimes true or often true that "The food that I bought didn't last and I didn't have money to buy more" or "I worry whether my food will run out before I get money to buy more." In a sample of 193 women with children from a rural New York State county, 25 percent were found to be insecure on the basis of questions that addressed household food anxiety, food quantity, and food quality. Eleven percent were found to experience "child hunger" on the basis of questions that addressed food insecurity for children in particular (Kendall et al. 1995).

Sometimes, in these surveys, a follow-up question inquires about the length of the period during which a household is food insecure (table 2.1). The NHANES III followed the food sufficiency item with the question: "[In the past month,] how many days did (you/your family) have no food or money to buy food." A similar set of questions was asked in the evaluations of the "pure" food stamp cashout demonstrations in San Diego and Alabama (Ohls et al. 1992; Fraker et al. 1992). The San Diego cashout data, for example, indicate that almost 38 percent of food stamp coupon recipients were without food or resources at some point in month, and for these people this condition occurred for 4.99 days of the month, on average. Check recipients were slightly less likely to go without food or resources at some point, but for those who did, this condition occurred for 5.29 days of the month, on average (these differences were not statistically significant).

Table 2.1. Duration of Periods of Food Insufficiency

Selected CCHIP Questions:	**Mean Number of Days in Past 30 Days** (for households classified as hungry only)
1. Did you ever rely on a limited number of foods to feed members of your household because you were running out of money to buy food for a meal?	7.5
8. Did any of your children ever go to bed hungry because there was not enough money to buy food?	1.3
NHANES III:	**Percent** (for all households)
Thinking about the past month, how many days did (you / your family) have no food or money to buy food?	
a) 0 days	31%
b) 1-4 days	31%
c) 5-9 days	21%
d) 10-14 days	12%
e) more than 14 days	4%
"Pure" Cashout Experiments:	**Mean Number of Days in Past 30 Days** (for households that answered "yes" only)
Any days household without food or resources during past month?	
San Diego Coupon Recipients ("yes"=37.77%):	4.99
San Diego Check Recipients ("yes"=33.53%):	5.29
Alabama Coupon Recipients ("yes"=23.43%):	5.51
Alabama Check Recipients ("yes"=21.20%):	5.01
Any household member skip meals due to inadequate food or resources during past month?	
San Diego Coupon Recipients ("yes"=21.63%):	6.10
San Diego Check Recipients ("yes"=17.77%):	5.77
Alabama Coupon Recipients ("yes"=9.90%):	5.62
Alabama Check Recipients ("yes"=8.21%):	5.17

Sources: Food Research and Action Center 1995; Alaimo 1997; Ohls et al. 1992; Fraker et al. 1992.

It is difficult to draw conclusions about the Food Stamp Program from some of the reported results. Two thirds of the CCHIP households received food stamps, about ten percent of the NHANES III sample received food stamps, and all of the cashout respondents received either food stamp coupons or checks for the equivalent value. It may be presumed that for food stamp recipients, days without food or resources tend to be at the end of the food stamp month, but none of the surveys addressed that issue directly.

2.4 Food Stamps and Grocery Shopping Behavior

Food stamp recipients conduct major grocery shopping trips less frequently than other people. "One dramatic difference in expenditure behavior between food stamp recipients and low-income nonrecipients," Fraker wrote in a 1990 review of the literature on the Food Stamp Program, "pertains to the frequency of their major food shopping.... [R]ecipients are far more likely than nonrecipients to conduct their major food shopping on a monthly basis, presumably timed to coincide with their monthly food stamp allotment" (Fraker 1990).

Based on focus group interviews around the country, a recent report for the U.S. Department of Agriculture's Food and Consumer Service (Bradbard et al.), connected this shopping pattern particularly with African American food stamp recipients, although the generality of that ethnic association was not clear in the summary report. "African American focus group participants were most likely to report doing their major shopping once a month at major supermarkets, usually right after receiving their food stamp allotment," the report said. "They go to the store between major trips only to replace perishable food items." This shopping pattern – a single major grocery trip each month with smaller trips to purchase perishables -- will be central to the econometric model of food intake later in chapters four and five.

Almost 40 percent of food stamp recipients in the 1979-80 Survey of Food Consumption in Low-Income Households (SFC-LI) conducted a major grocery shopping trip only once per month (table 2.2, top). Most recipient households make several food shopping trips each month, beyond their "major" shopping trips (table 2.2, middle). Replacing food stamp coupons with check benefits does not appear to affect the number of trips greatly. Replacing coupons with electronic benefits appeared to increase the number of grocery trips in one New Mexico study, but not in another Minnesotta study (table 2.2, bottom).

The only econometric model of shopping frequency and food demand, found in this literature review, reported that participation in the Food Stamp Program reduces the probability of shopping once a week or more frequently (Blaylock). Simulted results suggested that switching from non-participation to participation lowered this probability by 20 percent. Female household headship and distance to the usual shopping location also reduced the probability of shopping frequently. Household size had a positive effect on the odds of shopping frequently, and the author attributed that pattern to "the need for maintaining a fresh and stable supply of perishable food items and larger inventory requirements in general" (again, issues that will be addressed later in this dissertation). "Participants in the Food Stamp Program may shop less often than non-participating households," the author hypothesized, "because food stamps are issued only once a month – perhaps forcing these types of households to be more efficient at holding inventories."

Table 2.2. Frequency of Shopping

	Frequency of "Major" Food Shopping by Households	
USDA Survey of Food Consumption In Low-Income Households, 1979-80:	Coupon Recipients	Low-Income Non-Recipients
More than Weekly	14%	20%
Weekly	26%	51%
Every Other Week	21%	19%
Monthly	39%	10%
	Mean Number of Food Shopping Trips Per Month	
San Diego Cashout (1990):	Coupon Recipients	Check Recipients
Supermarket	5.42	5.38
Neighborhood grocery	3.09	3.1
Convenience store	2.37	3.23
Specialty store	1.22	0.95
All stores	12.09	12.63
Alabama Cashout:		
Supermarket	4.17	3.96
Neighborhood grocery	2.23	2.51
Convenience store	1.29	1.21
Specialty store	0.58	0.58
All stores	8.24	8.23
New Mexico Electronic Benefits Transfer (EBT):	Coupon Recipients	EBT Recipients
All trips using food stamp benefits	3.9	5.0
Ramsey County, Minn., EBT:		
All trips using food stamp benefits	5.5	5.5

Sources: Fraker 1990; Fraker et al. 1992; Ohls et al. 1992; Food and Consumer Service 1993.

2.5 Consequences of the Monthly Food Stamp Cycle

Already in the mid-1980s, Lelyveld summed up both the concern over the monthly cycle's nutritional consequences and the shortage of hard evidence: "The cyclical nature of undernutrition in America -- the monthly slide to a meager diet of starches that will stave off the sensation of hunger -- cannot be good for the health of the poor, but experts on nutrition find it hard to be precise about how bad it is" (Lelyveld 1985).

Advocates on behalf of food and nutrition programs generally emphasize severe nutritional problems associated with underconsumption of food. We noted previously that the CCHIP definition of hunger records symptoms of periodic hunger or food insecurity, such as at the end of the Food Stamp Month. The CCHIP report cites associations between its hunger classification and increased risk of serious illnesses:

> Children from hungry families are more than three times as likely as children from non-hungry families to experience unwanted loss of weight and to have frequent headaches as children from non-hungry families. Hungry children are four times as likely to suffer from fatigue and to have difficulty concentrating. Children from hungry families are significantly more likely to be anemic, to have asthma, allergies, and diarrhea, and to have frequent colds, ear infections, and other infections as children from non-hungry families (Food Research and Action Center 1995).

Research on food insecurity in public health and nutrition journals tends to be less dramatically stated, but it often expresses the same concern. A typical article notes that these clinical symptoms of malnutrition are uncommon in this country and argues that food insufficiency should still be assessed "to capture the effects of chronic, sub-clinical undernutrition among poor families in the United States" (Wehler et al. 1992).

Low-income people in the United States are not just more likely to be undernourished, but also more likely to be overweight (Strunkard and Sorensen 1993). At the 1994 conference on food security measurement and research, William Dietz, the director of clinical nutrition at the New England Medical Center, speculated,

> I think that it may be no coincidence that hunger and obesity occur with an increased prevalence in the same populations. It is paradoxical, because on the one hand, hunger suggests food insufficiency and obesity suggests energy excess. Although it is entirely possible that different social, environmental, or even physiologic mechanisms may independently cause both problems, an alternative possibility is that the two are causally related (Food and Consumer Service 1994).

Dietz put forth the "possibility that episodic exposure to hunger may physiologically increase body fat."

A link between periodic dieting and increased risk of obesity has already been much studied, although experts argue this link is not so severe that overweight people should be deterred from pursuing appropriate weight-loss regimens (National Task Force on the Prevention and Treatment of Obesity 1994). Dietz's suggestion of a further link between involuntary periodic hunger and overweight has received some very preliminary corroboration from further analysis of the same sample of 193 women used by Cornell researchers in their efforts to measure food insecurity, discussed in the previous section (Frongillo et al. 1997). This research found that those experiencing the most severe category of food insecurity were less likely to be overweight than those who were food secure. However, those experiencing a less severe category of food insecurity exhibited the paradox raised by Dietz: they were more likely to be overweight. The authors suggested that food insecurity tends to be directly associated with a lower risk of overweight, but food insecurity is also associated with "disordered" eating patterns, which in turn are associated with a greater risk of overweight.

These proposed links between food insecurity, “disordered” eating patterns, and overweight are not yet considered an established result in the nutrition literature. If further research confirms these associations, then the food stamp cycle studied in this dissertation would be tied to two of the most serious nutritional concerns for low-income Americans: periodic hunger and obesity.

CHAPTER THREE:
MONTHLY PATTERNS IN FOOD EXPENDITURE AND INTAKE

3.1. Introduction

This chapter will describe how food stamp recipients spend benefits and consume food unevenly over time. Food expenditure peaks sharply in the first three days after food stamps are received. Actual food intake drops at the end of the month, for some foods and some people, although food intake over time is always smoother than food expenditure. These patterns show that program participants commonly store food at home to reduce fluctuations in food consumption, but home storage does not eliminate the fluctuations altogether. Many food stamp recipients experience repeated periods of food plenty and food scarcity, with welfare and nutritional consequences that are not yet well understood.

This chapter is organized as follows. Section 3.2 discusses the methodology, which relies on simple comparisons of mean expenditure and intake estimates for different weeks of the food stamp month. Section 3.3 describes the monthly cycle in food expenditure and food intake for the full samples of food stamp recipients. Section 3.4 looks at how different types of people (children and adults, AFDC recipients and nonrecipients) experience different food expenditure and intake cycles. Section 3.5 returns to the full sample, to consider how the cycle differs for different foods. Section 3.6 offers a more detailed look at how the food stamp cycle is influenced by what proves to be a key variable: the frequency of grocery shopping. Section 3.7 summarizes the chapter, and raises some questions that remain to be answered in the remainder of this dissertation.

Section 3.2. Methodology

This research employs two nationally representative surveys. The Diary Consumer Expenditure Survey (CEX), from the Bureau of Labor Statistics, reports spending by consumer units on food and other frequently purchased items (U.S. Department of Labor 1992). The Continuing Survey of Food Intake by Individuals (CSFII), from the U.S. Department of Agriculture, reports actual food intake by household members (U.S. Department of Agriculture 1991). Together, these surveys provide a wealth of information about patterns in food spending and intake over the food stamp month.

The expenditure survey contains highly detailed information on one week of purchases by a consumer unit (usually a family). For most consumer units, the expenditure part of the survey was administered twice, thereby providing 14 days of data. The CEX contains plenty of geographic and demographic information at the level of the consumer unit, but only partial information about individual members.

The intake survey covers a shorter period of time. One day of detailed information on food intake was collected by a trained enumerator. In most cases, two more days of information were reported by recipients using blank forms left by the enumerator. Because there are some systematic differences between the two data collection methods, this study uses three-day means of food intake for only those households with complete intake data. The CSFII contains food intake information at the individual level, and demographic information at both the individual and the household level.

Both surveys asked food stamp recipients the amount of their benefits, and the date on which they last received food stamps. Because the date of each expenditure or intake event is also known, the number of days since food stamps were received can be calculated by subtraction. The food stamp month is defined in terms of this interval. While food stamp benefits tend to become available early in the calendar month, they do not arrive uniformly on the first day of the month, so the food stamp month does not correspond precisely to a calendar month. It is rather a hypothetical month where the arrival of food stamps marks day 0, and the remaining days are numbered from that starting point.

The intake data come from the CSFII for 1989-1991. The following round of this survey began in 1994 and was not completed at the time of this research. Since the CEX is conducted every year, nearby years (1988-1992) were chosen so that the expenditure and intake data generally refer to the same time period. All expenditure values are converted to real January 1990 dollars using the Consumer Price Index (CPI) for all goods. Because the CPI is reported monthly, a linear interpolation is employed to remove small spurious jumps in expenditure between the end of one month and the start of the next.

Even after selecting only food stamp recipients with complete food stamp date information, the sample size for the expenditure data set is more than sufficient for detailed study of the spending cycle (table 3.1). The intake data set is smaller, requiring more judicious splitting of the sample. The food stamp month is divided into just four weeks for purposes of measuring food intake ("Week 1" represents days 0-6 of the food stamp month). In order to compare food expenditure with food intake, most of the expenditure results are also reported on a weekly basis.

Thus, the analysis is conducted with a main expenditure data set that has 12,308 daily spending observations for consumer units in the first four weeks of the food stamp

Table 3.1. Sample Sizes in the CEX and CSFII Data

CEX (1988-1992)		**CSFII (1989-1991)**	
Total CU Observations	58,250	*Total Households*	6,718
Food Stamp CU Observations	3,124	*Food Stamp Households*	1,003
*Food Stamp CU Obervations With Complete Dates**	2,825	*Food Stamp Households With Complete Dates*	979
		*Households With Dates in Four-Week FS Month***	639
Individuals in Food Stamp CU Observations	9,530	*Individuals in Households in Four-Week FS Month*	1,516
CU Spending Days Observed	19,775		
CU Spending Days Observed in Four-Week FS Month	12,308	*Ind. Intake Days Observed in Four-Week FS Month*	4,548

Notes: * One CU observation is a weekly observation on a food stamp consumer unit. Because most CUs in the CEX were surveyed for two weeks, this value represents 1,675 distinct CUs. ** The four-week food stamp month is the first four weeks after food stamps are received.

month. The main intake data set has 1,516 observations, each of which is a 3-day mean for one individual. The final 0-3 days of the food stamp month, from Day 28 onward, are omitted from most of the analysis, because the sample sizes were smaller for this fraction of a week, and also because there are other concerns with the reliability of the data for this period.

Food expenditure appears slightly higher in the final 0-3 days of the food stamp month than it does in Week 4 (see figure 3.1), but this appearance may be due to a measurement problem. Food stamps do not always arrive in precise monthly intervals, so some recipients that seem to be at the very end of one food stamp month may actually be at the start of their next food stamp cycle.

Because food needs differ systematically by age, sex, and pregnancy/lactating status, food intake results are reported using an Adult Male Equivalent (AME) scale that accounts for these differences. An AME scale based on the Recommended Dietary Allowance (RDA) for total food energy intake (National Research Council 1989) is used even when results are reported for specific foods, so that differences between results are always due to real differences in intake and not differences in the scaling factor. For selected micronutrients, by contrast, intake figures are presented as proportion of the corresponding RDAs for those nutrients, so that the seriousness of potential deficiencies can be assessed. The expenditure survey does not include sufficient information on individuals to construct an AME scale, so expenditure results are reported on a per-person basis.

The analytic approach in this chapter is spare, because no further complexity seemed necessary to unearth some key results. Mean values are calculated for each variable of interest -- for example, "food energy intake by children as a percentage of the RDA"

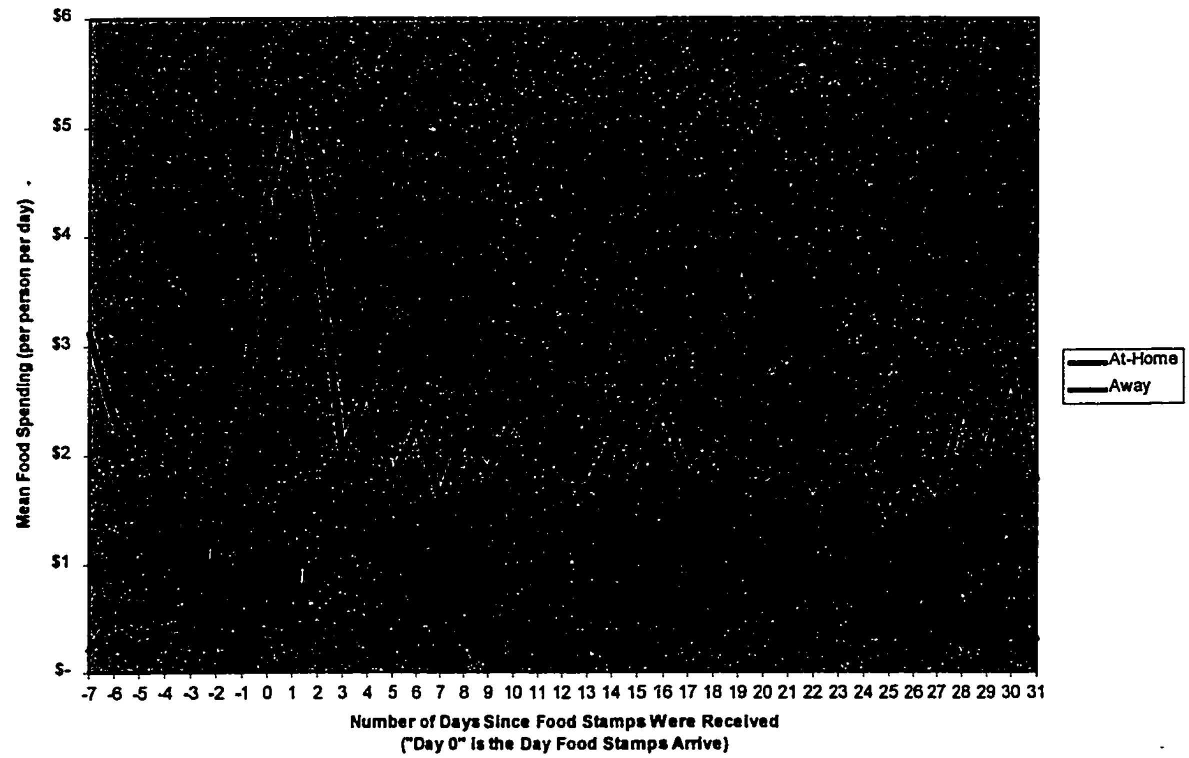
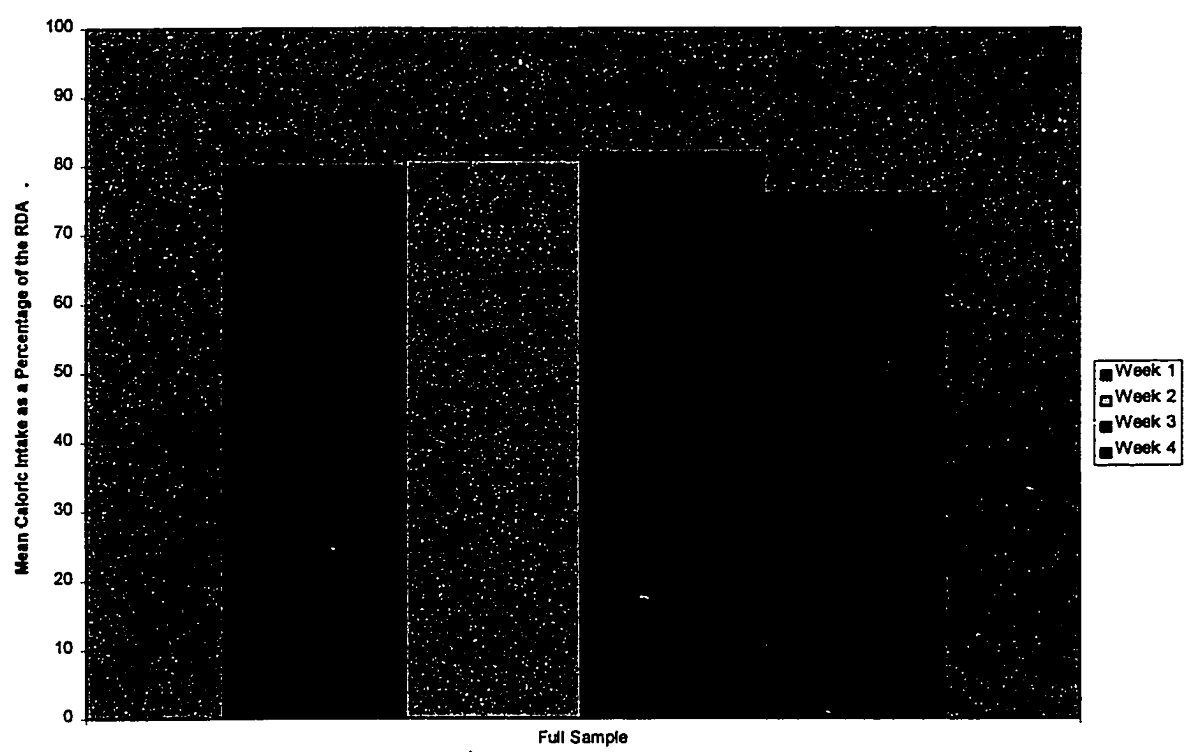


Figure 3.1. Food Spending by Consumer Units, At-Home and Away-From-Home



Note: The *t*-statistic is for a one-tailed test of the difference between Week 4 intake and Week 1 intake.

Figure 3.2. Food Intake by Individuals

or "expenditure on meat per person in the consumer unit" -- in each week of the food stamp month. For each variable, a one-tailed t-test is conducted for the null hypothesis that the Week 1 value is no greater than the Week 4 value. The tests with the CEX data were significant in every case, so this result is not reported repetitiously for the remainder of this chapter. With the CSFII data, significantly lower Week 4 intake means (at alpha equals 0.05) are marked with the traditional star, and "nearly" significant results are marked with the *t*-test statistic so that readers may judge for themselves.

Both surveys use complex sampling designs, and both provide weights to use in generating estimates of population values. The method for estimating population means using weights is straightforward, although calculating unbiased standard errors for these estimates is more difficult. The well-known formulas for standard errors under random sampling generate biased results, whether or not the sampling weights are used. The CEX data contain 44 columns of half-sample weights so that consistent standard errors can be calculated using replication methods. Although these standard errors for the expenditure estimates were computed with the SAS statistical package, they were checked in a small sub-sample using the program WesVarPC, which is designed to analyze complex survey data using replication methods. Standard errors for the food intake estimates from the CSFII data are computed with the statistical software package SUDAAN, which accommodates complex survey designs using analytically-derived formulas for linear statistics, and using Taylor series approximations for non-linear statistics. These standard errors were also checked using WesVarPC, which produced similar estimates.

3.3 Total Food Expenditure and Intake

The pattern in total food expenditure is striking. 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 (figure 3.1). Expenditure on food away from home, which may not be purchased legally with food stamps, is much more steady over the food stamp month. Restaurant food may be purchased more often right after households receive cash, rather than after they receive food stamps, but that pattern would not show up in the CEX and CSFII data.

The monthly pattern in food intake is less dramatic (figure 3.2). Mean food energy intake, measured as the 3-day mean of caloric intake divided by the appropriate RDA for each individual, remains steady for the first three weeks and dips moderately in week 4.[1] This dip is small enough that it could be due to sampling variation. As the next two sections explain, this pattern in total food intake for the full sample is muted by the inclusion of different types of recipients and different foods. Some recipients and some foods do exhibit a significant fall in food intake at the end of the food stamp month.

3.4 Expenditure and Intake for Particular Sub-Samples

This section will consider whether the monthly food stamp cycle described above differs for people in particular sub-samples. In particular, we compare AFDC

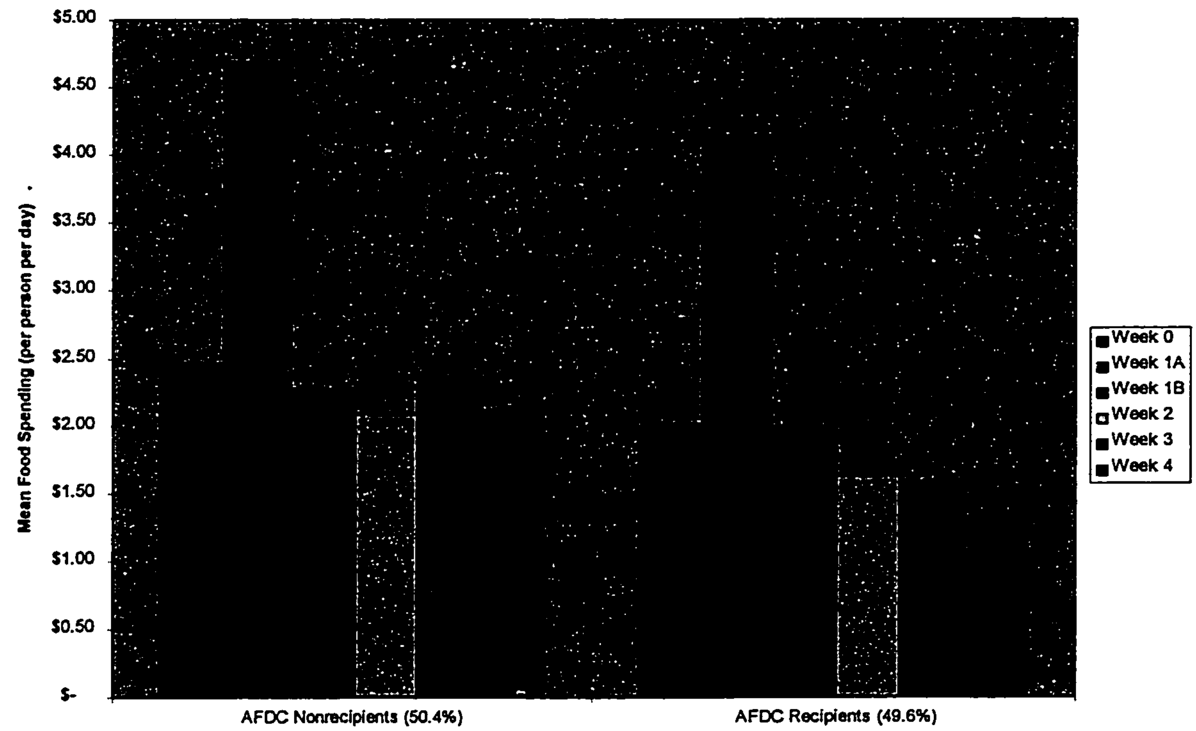
[1] Even in the first three weeks the caloric intake seems low, relative to the RDA, but this reflects the difficulty of collecting complete intake data in a survey, not general undernutrition. Mean food energy intake as a percentage of the RDA is just as low for CSFII respondents who do not receive food stamps (Tippett et al. 1995), probably due to underreporting of intake.

recipients to nonrecipients, female-headed households to other households, and adults to children.

AFDC Receipt

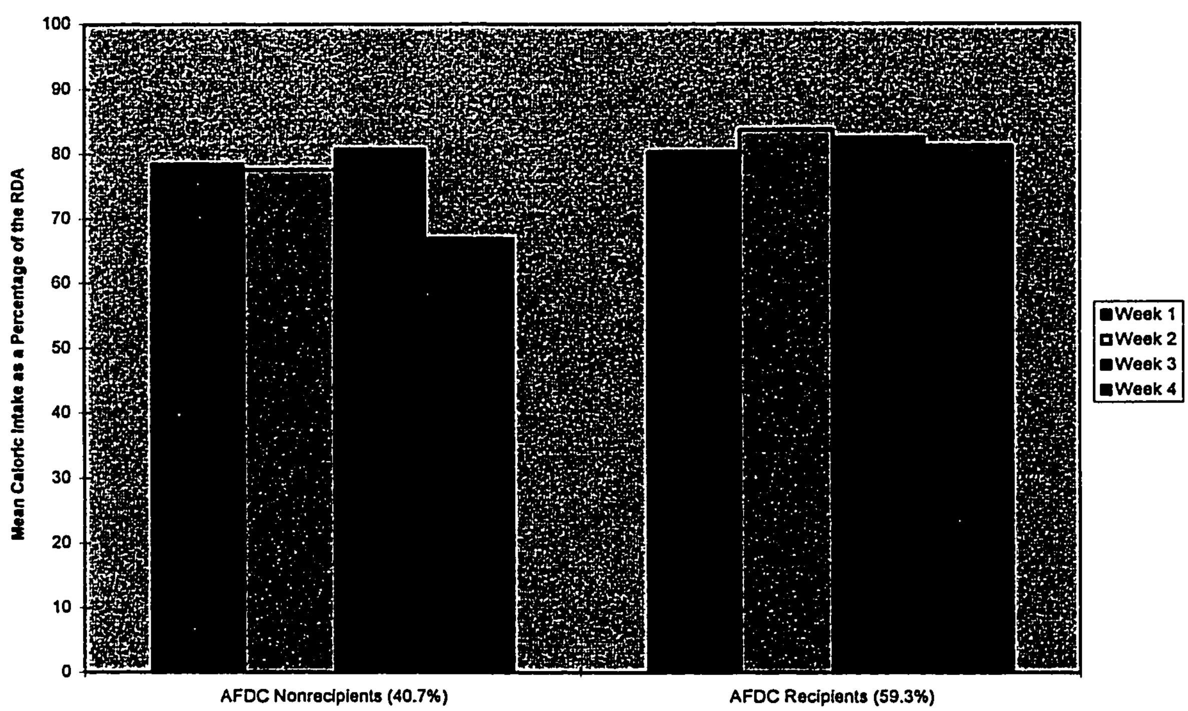
With over 9 million households each month last year, or almost one out of ten Americans, the Food Stamp Program cuts a broader swath through the American population than the archetypal cash welfare program, Aid to Families with Dependent Children (AFDC). Ninety percent of the approximately five million households participating in AFDC receive food stamps. These AFDC households make up about half of all food stamp households (50.6 percent of food stamp households in the CSFII sample received AFDC). Relatively small numbers of food stamp households who receive AFDC have other important sources of cash income such as wage earnings or social security. By contrast, over half of all non-AFDC food stamp households in the CSFII sample receive social security or SSI, and over a third have some wage earnings. As a consequence of their higher levels of cash resources, AFDC nonrecipient families get lower food stamp benefits: AFDC nonrecipient families get \$83 per adult male equivalent per month in the CSFII sample, while AFDC recipient families get \$103 per adult male equivalent per month.

The monthly food cycle is very different for food stamp recipients who receive AFDC and those who do not. The main difference is in food intake patterns, rather than food spending. AFDC recipients and non-recipients both spend heavily on food in the first three days of the food stamp month (figure 3.3). Despite the similar spending patterns, only AFDC non-recipients have a significant dip in food energy in Week 4 (figure 3.4). The estimated difference between Week 1 intake and Week 4 intake for non-recipients is too big to be due to sampling variation. Because AFDC non-recipients receive lower food stamp benefits on average, it is perhaps surprising that they have a



Notes: Week 0 is the seven days before food stamps were received. Week 1A is Days 0-2 days of the food stamp month. Week 1B is Days 3-6 of the food stamp month.

Figure 3.3. Food Spending by Consumer Units, According to AFDC Receipt



Note: * Signifies Week 4 intake is significantly less than Week 1 intake (one-tailed test, alpha=0.05).

Figure 3.4. Food Intake by Individuals, According to AFDC Receipt

more noticeable monthly food intake cycle. This difference could indicate that some aspect of the AFDC program -- perhaps the receipt of cash benefits twice monthly in many states -- ameliorates food shortages at the end of the food stamp month. On the other hand, other household characteristics could be responsible.

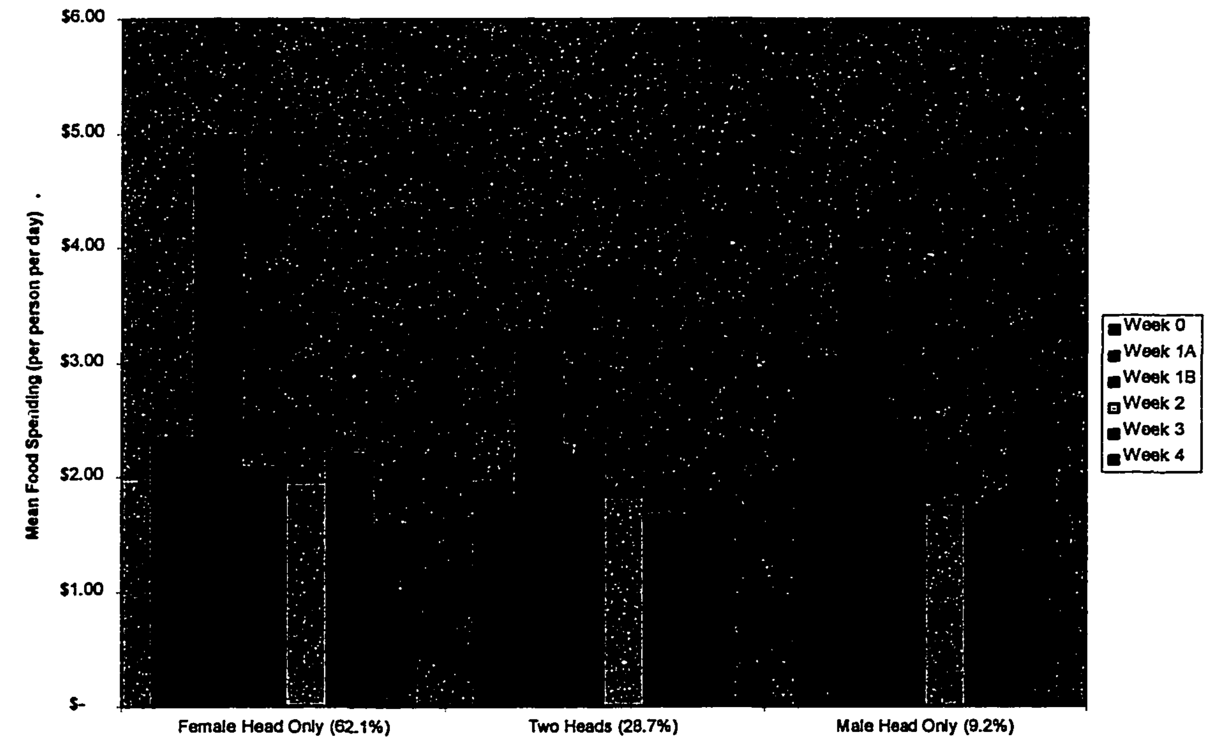
Female Headship

Female-headed households and other households both experience the sharp cycle in food expenditure over the food stamp month (figure 3.5). Purchases at the start of the month appear proportionately heaviest for female-headed households. However, according to the CSFII data, individuals in female-headed households do not experience a dip in food intake at the end of the month (figure 3.6). Individuals in households headed by couples exhibit some drop in food intake at the end of the month, but because the sample size gets smaller as the data are broken down in such detail this pattern could be due to sampling variation. Male-only households appear to have the biggest fall in food intake at the end of the month.

Household headship and AFDC receipt interact to influence the monthly cycle in food intake. AFDC recipients live disproportionately in female-headed households. Almost 70 percent of individuals in AFDC families live in female-headed households, while only 43 percent of individuals in other food stamp families live in female-headed households. The dip in mean food energy intake at the end of the month is most severe for individuals in food stamp households with two characteristics: they do not receive AFDC and they are not headed by a single female.

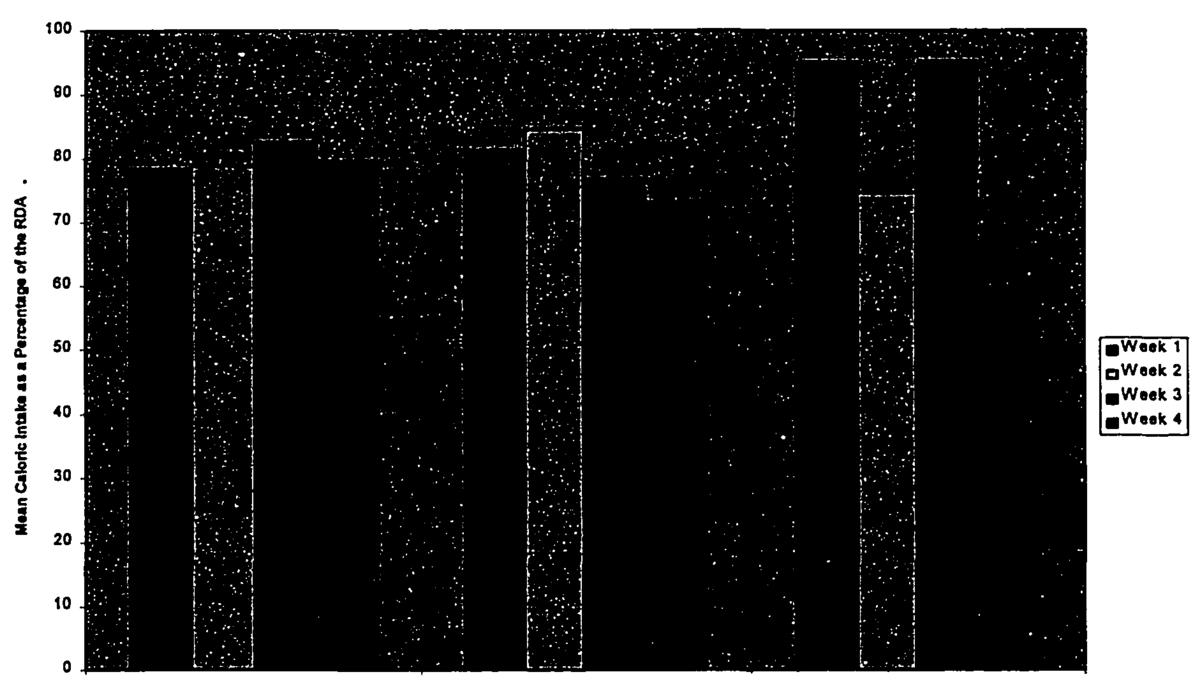
Children

The food intake of children is a special concern for several reasons. In extreme cases, periodic nutritional deprivation can stunt growth and development in children. Also,



Notes: Week 0 is the seven days before food stamps were received. Week 1A is Days 0-2 days of the food stamp month. Week 1B is Days 3-6 of the food stamp month.

Figure 3.5. Food Spending by Consumer Units, According to Household Headship



Note: The *t*-statistic is for a one-tailed test of the difference between Week 4 intake and Week 1 intake.

Figure 3.6. Food Intake by Individuals, According to Household Headship

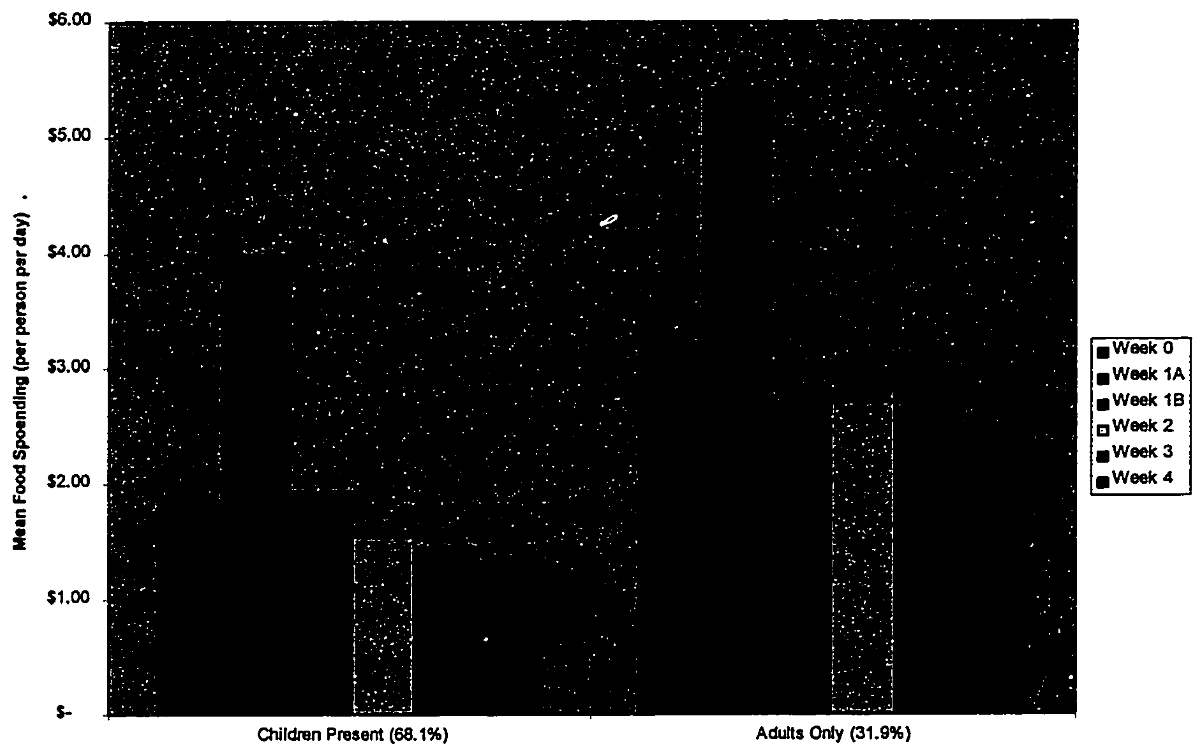
nutritionists and other researchers have identified changes in children's meals as a symptom of the most severe categories of household food insecurity (Food and Consumer Service 1994). Finally, in the rhetoric of U.S. public policy debates, children are held blameless for household food decisions while adults are often held responsible if they fail to acquire or save adequate food resources for themselves.

There is little difference in the amplitude of the spending cycle for families with and without children under age 18 (figure 3.7).[2] In contrast with the expenditure cycle, mean food energy intake is quite different for children and adults (figure 3.8). Adults absorb almost the full drop in food intake, and for them Week 4 intake is significantly less than Week 1 intake. For children, food intake on average remains quite constant over the food stamp month. Children also have higher food energy intake relative to the RDA for their sex and age, indicating that the difference in the RDAs for children and adults is greater than the difference in their actual intake. Relative to the RDAs, children have higher food energy intake as well as a smoother intake pattern over the food stamp month.

3.5 Expenditure and Intake for Selected Foods

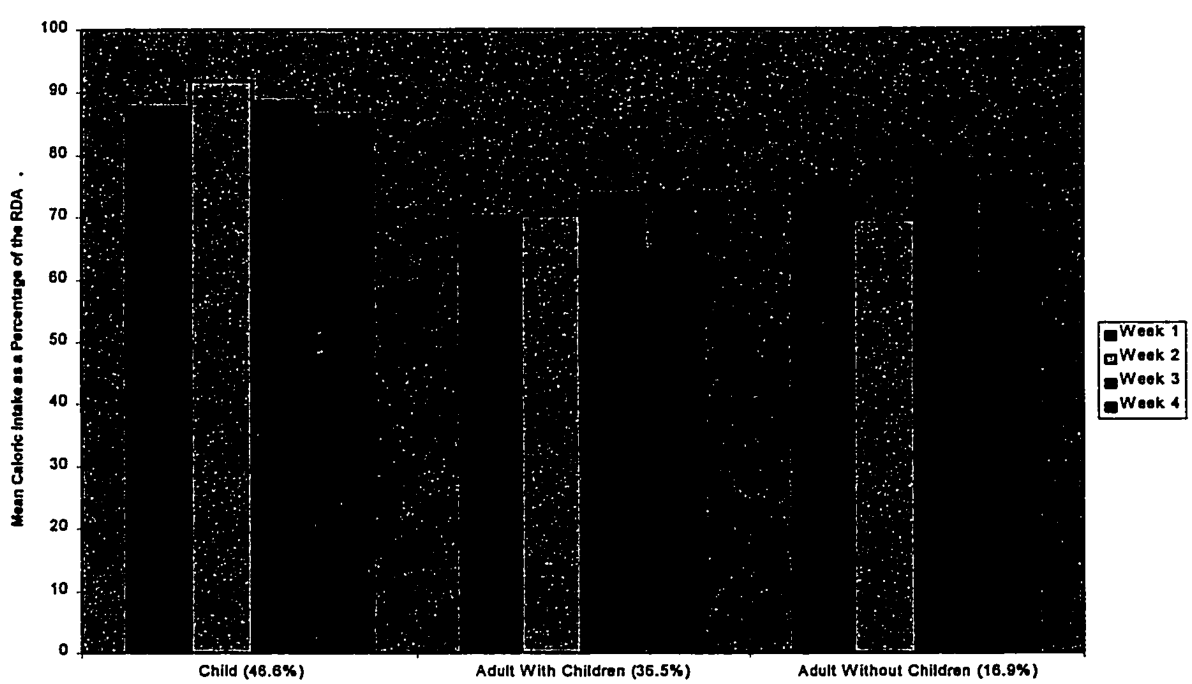
Different foods may exhibit different monthly cycles for at least two reasons: some foods are more perishable than others, and some foods are more expensive than others. This section discusses food expenditure and food intake using six food categories from the "Food Guide Pyramid" (U.S. Department of Agriculture 1992). For food

[2] Food expenditure per person is lower for families with children because children consume less food than adults in absolute terms (teenagers excepted), so this difference in figure 3.7 does not indicate less adequate food supplies for households with children.



Notes: Week 0 is the seven days before food stamps were received. Week 1A is Days 0-2 days of the food stamp month. Week 1B is Days 3-6 of the food stamp month.

Figure 3.7. Food Spending by Consumer Units, According to Presence of Children



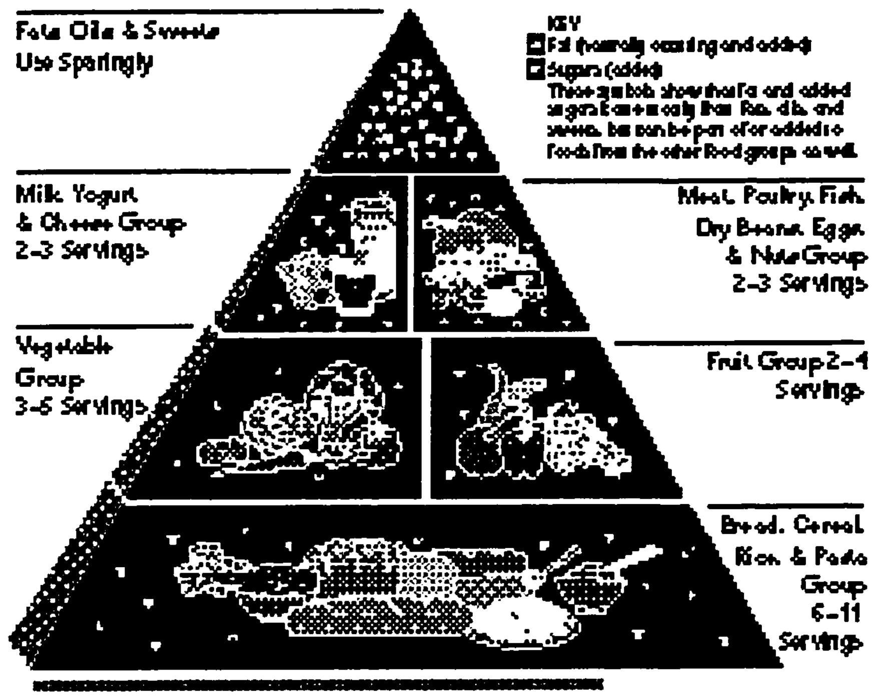
Note: * Signifies Week 4 intake is significantly less than Week 1 intake (one-tailed test, alpha=0.05).

Figure 3.8. Food Intake by Individuals, For Children and Adults

expenditure only, it also compares the monthly food stamp cycle for 19 more detailed foods.

In order to compare expenditure and intake patterns, food items are organized into six categories that approximately represent the cells of the federal government's well-known "Food Guide Pyramid" (figure 3.9), which reflects consensus recommendations regarding the composition of a healthy diet. The existing food categories in the public data files were employed as much as possible, although some changes were made. For example, fresh and processed vegetable expenditures were combined to make the category "VEG", and sweets and oils were combined to make the category "SWTOIL", which is the small triangle at the top of the Pyramid. The only reorganization within food categories was that intake of potatoes was moved from the vegetable category to the starchy staples in "GRAINS," where it finds a better home in terms of carbohydrate content and perishability, if not in terms of biological origin and some vitamins. A disadvantage of combining foods into the Pyramid food categories is that relevant details, such as the difference between processed and fresh vegetables, are hidden. An advantage is that the nutritional implications of the food stamp cycle can be assessed using a small and easily-comprehended set of well-known food categories.

Meats constitute the largest category of food expenditure (figure 3.10). Dairy products make up a higher proportion of food intake than they do of food expenditure, in part because the intake variables for specific food categories are measured by weight including water (figure 3.11). Fruits and vegetables make up a small proportion of both expenditure and intake, in comparison with the recommended amounts. The most-consumed item in the FRUIT intake category is fruit juices, and



Source: USDA. Temporary low-resolution graphic.

Figure 3.9. Food Guide Pyramid

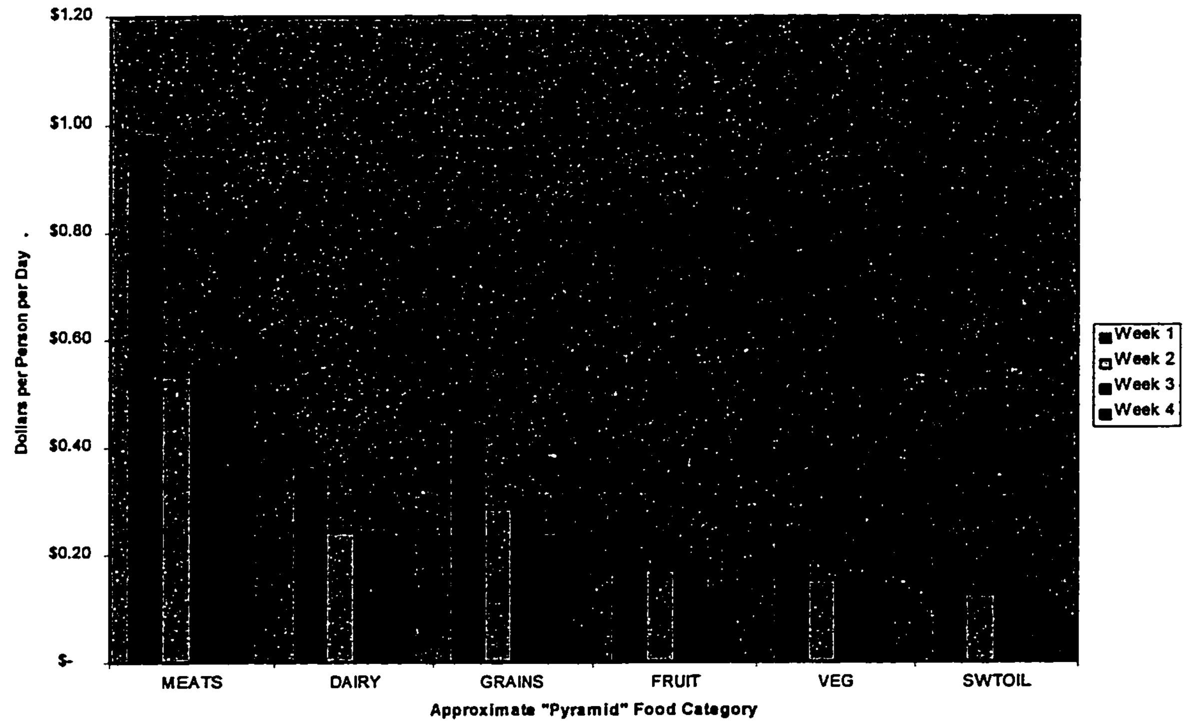


Figure 3.10. Spending by Consumer Units, for Pyramid Food Categories

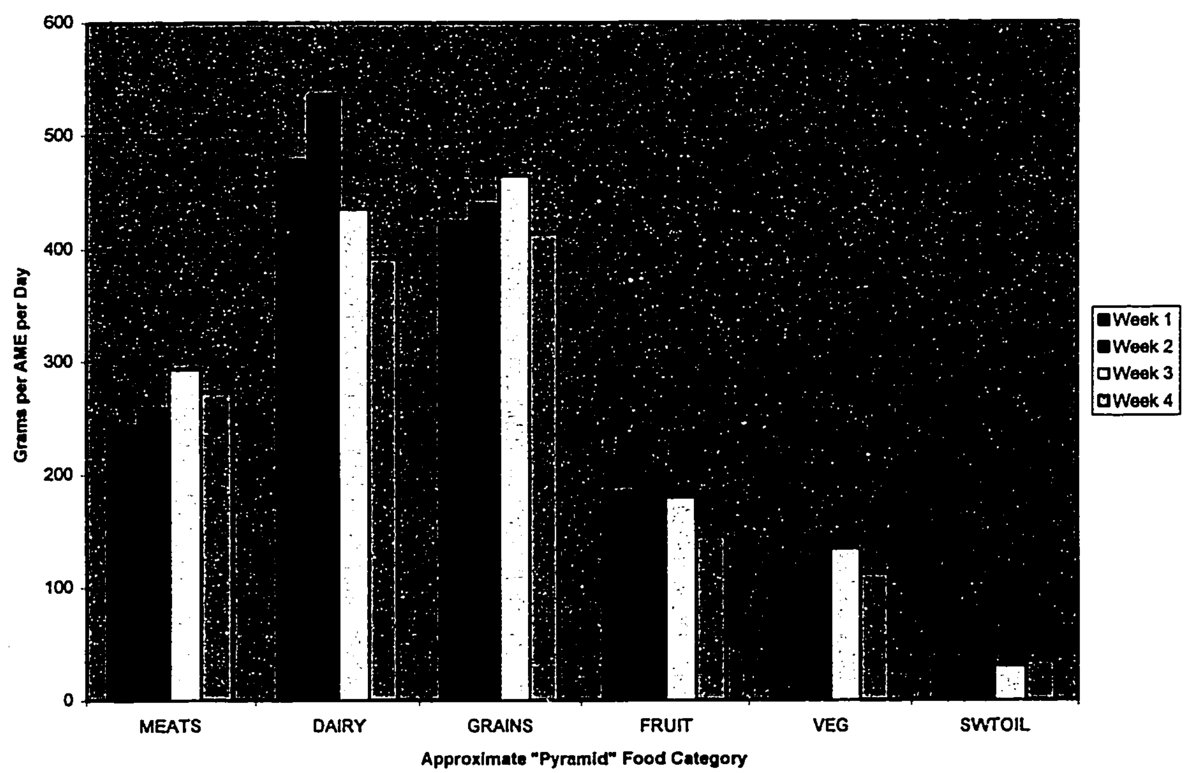


Figure 3.11. Food Intake by Individuals, for Pyramid Food Categories

the most-consumed item in the VEG intake category (after removing potatoes) is tomatoes.

It is easier to perceive relative differences in the monthly expenditure and intake cycles when the variables are expressed as the ratio of Week 4 values to the corresponding values in Week 1 (figure 3.12 and 3.13). Food expenditures are much lower at the end of the month for all Pyramid food categories than they are at the start. The drop is greatest for GRAINS, which contains mainly nonperishable foods that are easily purchased at the start of the month for consumption later.

As for food intake, the dip at the end of the month is concentrated in relatively perishable food categories: dairy and fruits. For these foods, this dip is statistically significant. The comparatively steady intake of meat over the food stamp month is surprising, because even after accounting for low-cost items such as hot dogs one might expect meat to be a relative luxury that is consumed less frequently at the end of the month. The observed pattern does not corroborate anecdotal reports, for example in the *New York Times Magazine* quotation at the start of Chapter 2 (Lelyveld 1985), that only starchy staples are available late in the month. Also, while the intake results otherwise correspond very closely to those found by Emmons (1986) in her Cleveland sample, she found a significant drop in the consumption of "high-protein foods" in Week 4. In our CSFII sample, by contrast, the key feature of foods that are consumed less at the end of the month appears to be their perishability.

The CEX employs hundreds of UCC codes for specific items purchased. The codes for food at-home are organized into 18 categories in the public data files, and there is also a category for food away-from-home. To illuminate differences in the monthly spending cycle for different foods, Week 4 expenditure for each category is measured

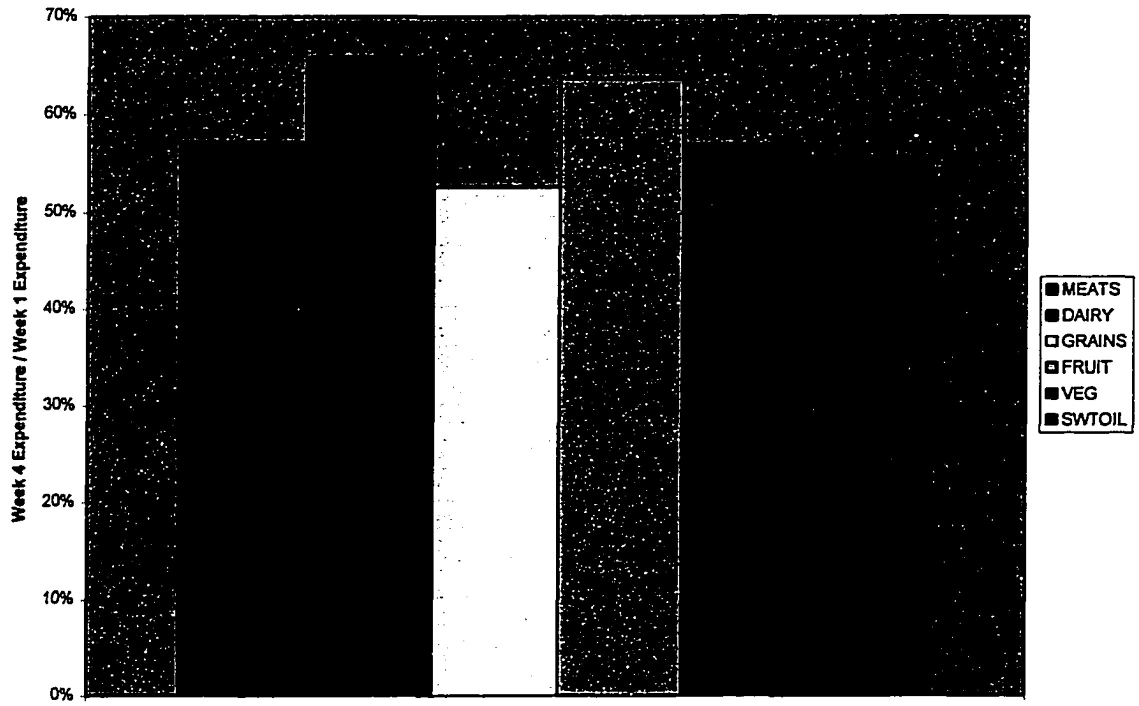
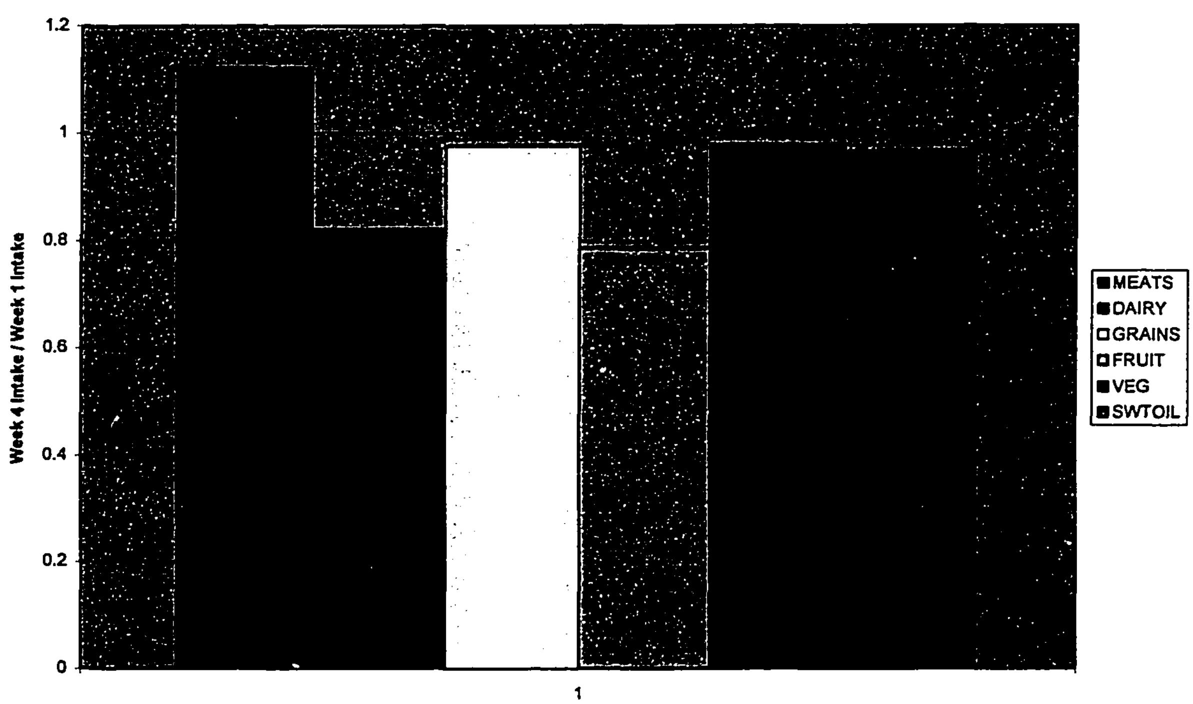


Figure 3.12. Spending by Consumer Units at End of Month, for Pyramid Food Categories



Note: * Signifies Week 4 intake is significantly less than Week 1 intake (one-tailed test, alpha=0.05).

Figure 3.13. Intake by Individuals at End of Month, for Pyramid Food Categories

as a proportion of Week 1 expenditure (figure 3.14). This scale shows the degree to which expenditure drops off over the course of the food stamp month for different foods.

Consider the seven foods for which the relative drop in spending from Week 1 to Week 4 is greatest (at the bottom of figure 3.14). These foods include some low-cost non-perishables, such as canned vegetables and cereals, which are saved for use throughout the month. These foods also include some high-cost items, such as ice cream and seafood, which are probably luxuries consumed mainly at the start of the food stamp month. By contrast, most foods that are highly perishable are purchased more evenly over the month. For example, fresh fruit and fresh vegetables are purchased more steadily over the month than processed fruit and processed vegetables. Food away from home is perishable in the sense that it is generally eaten on the spot, and it also may not legally be purchased with food stamps, so it is purchased quite smoothly over the month. Milk, both highly perishable and relatively inexpensive, is purchased most steadily over the month.

3.6 The Importance of Shopping Frequency

We reported in chapter two that food stamp recipients shop less frequently than low-income nonrecipients. Especially because of the distinct spending and intake patterns for perishable foods, discussed in section 3.5, it seems possible that shopping frequency is an important factor in understanding the food stamp cycle. This section will compare the grocery shopping frequency for food stamp recipients and nonrecipients in the CSFII data. It will then compare the total food energy intake patterns for food stamp recipients who shop more or less frequently. Finally, it will

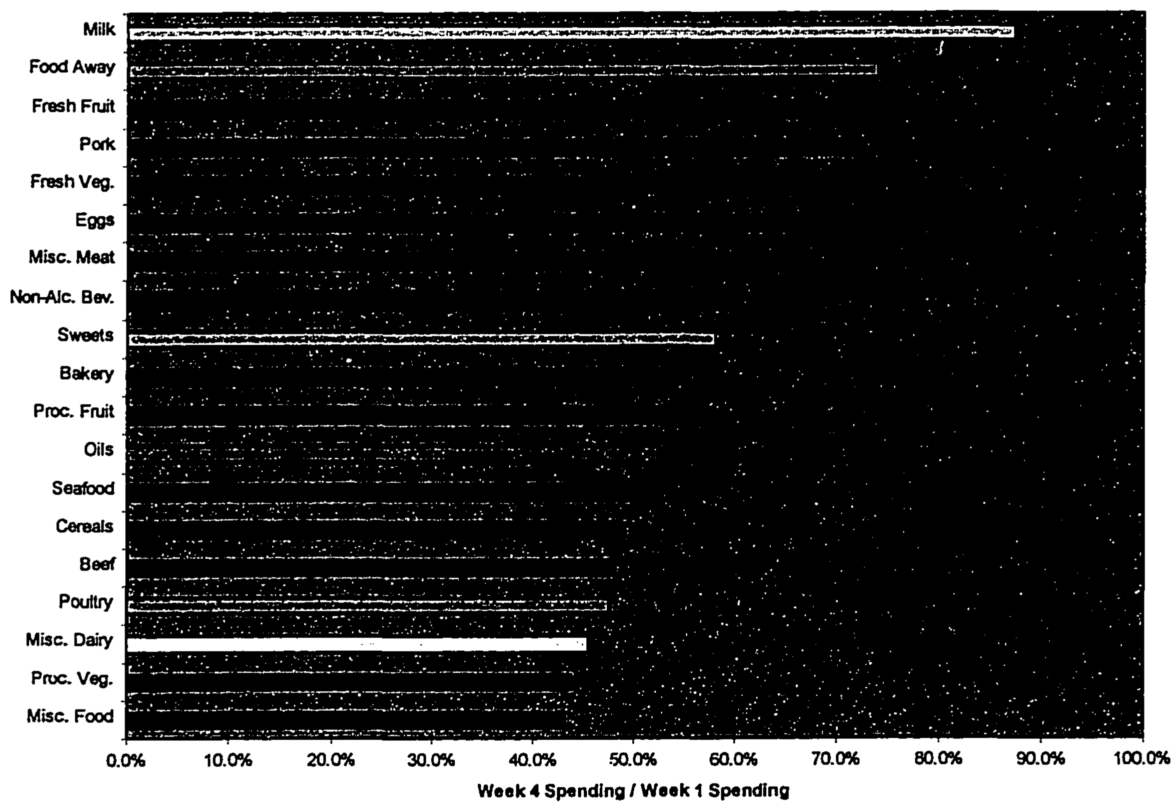


Figure 3.14. Spending by Consumer Units at End of Month, for 19 Specific Foods

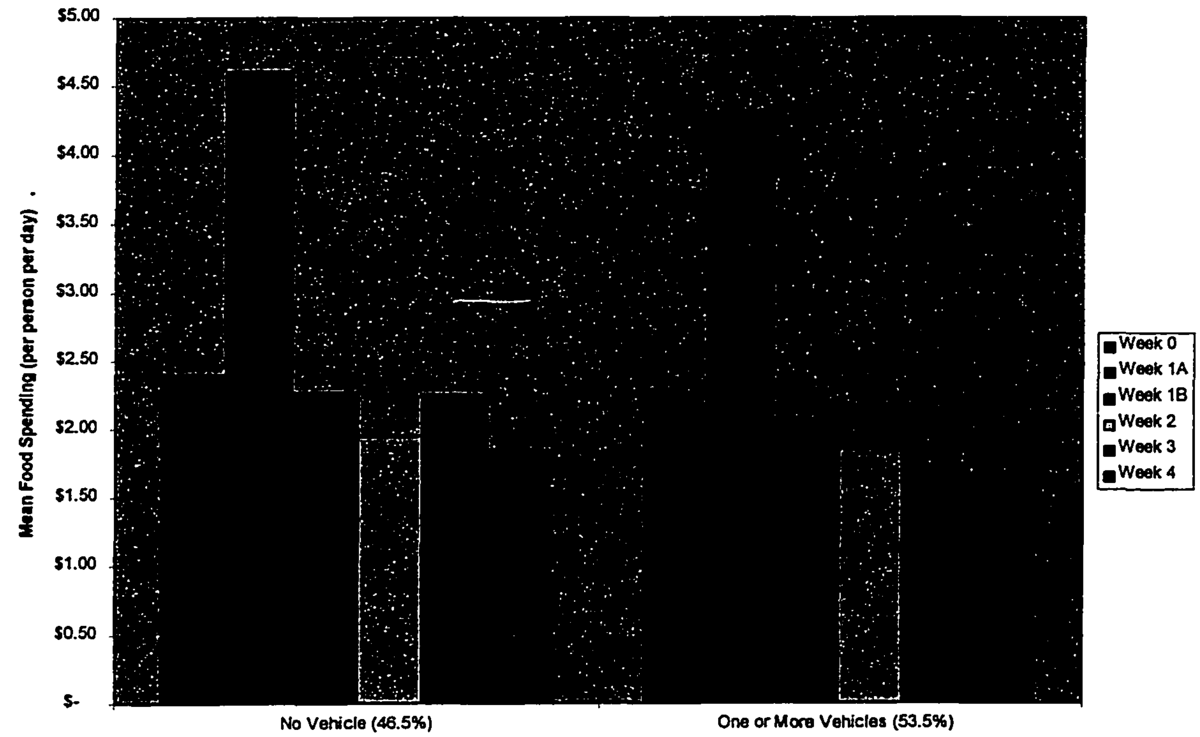
look at how the intake patterns for particular foods and particular nutrients is different for households that shop frequently.

Unfortunately, the food expenditure data do not report the frequency of grocery shopping, and the closest proxy we have in the CEX to compare with the following results on food intake is a variable on automobile ownership. Marginal transport costs are presumably lower for households that own cars. Households that own cars and households that do not own cars both have a sharp cycle in food expenditure (figure 3.15).

The CSFII does report a very useful question on shopping frequency: "On the average, how often does someone do a major shopping for this household?" The response categories are: 1) more than once a week, 2) once a week, 3) once every two weeks, 4) once a month or less, 5) never, 8) don't know, and 9) no answer. For the remainder of this dissertation, households that shop once a month or less frequently will be called "infrequent shoppers" for short. Households that shop more frequently will be called "frequent shoppers."

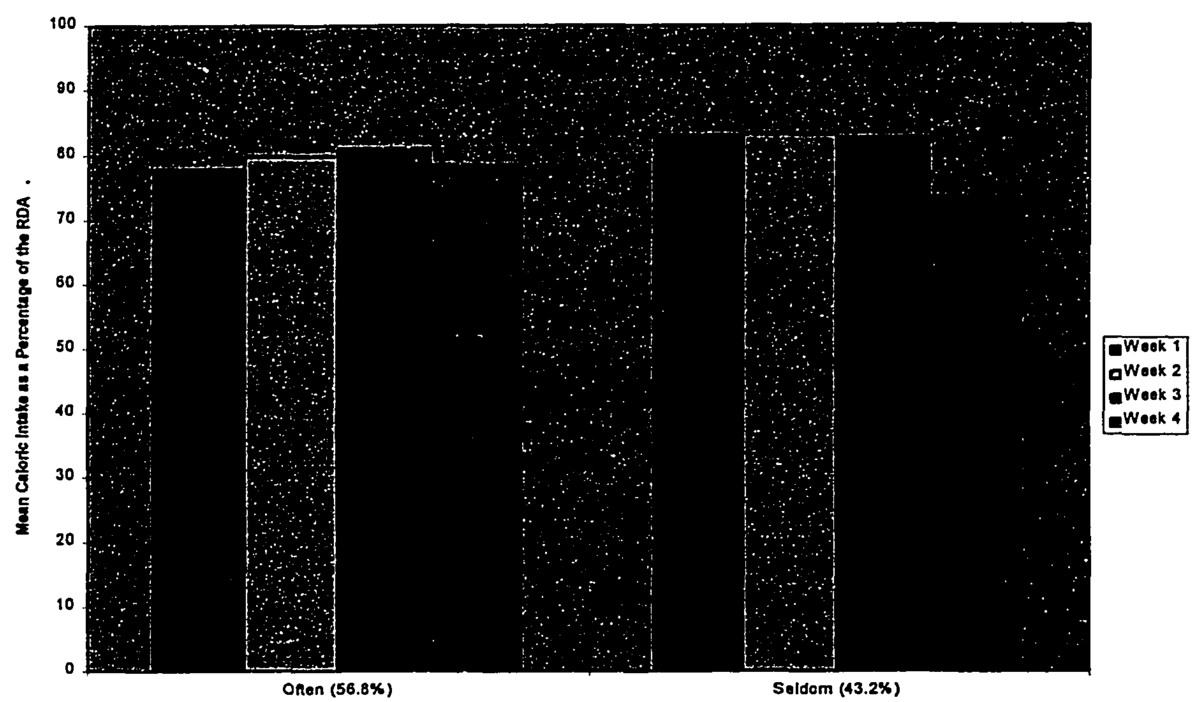
The CSFII corroborates the reports on shopping frequency from previous research. In this sample, 42 percent of food stamp recipients shop infrequently, while only 16 percent of low-income nonrecipients (with income less than 130 percent of the poverty line) shop infrequently (table 3.2). This difference is statistically significant.

Only food stamp recipients who shop infrequently exhibit a statistically significant dip in food intake at the end of the month (figure 3.16). This dip is concentrated in only some Pyramid categories (figure 3.17). In this figure, all food categories exhibit steady food intake for frequent shoppers. Meats and grains exhibit steady food intake



Notes: Week 0 is the seven days before food stamps were received. Week 1A is days 0-2 days of the food stamp month. Week 1B is days 3-6 of the food stamp month.

Figure 3.15. Food Expenditure by Consumer Units, According to Vehicle Ownership



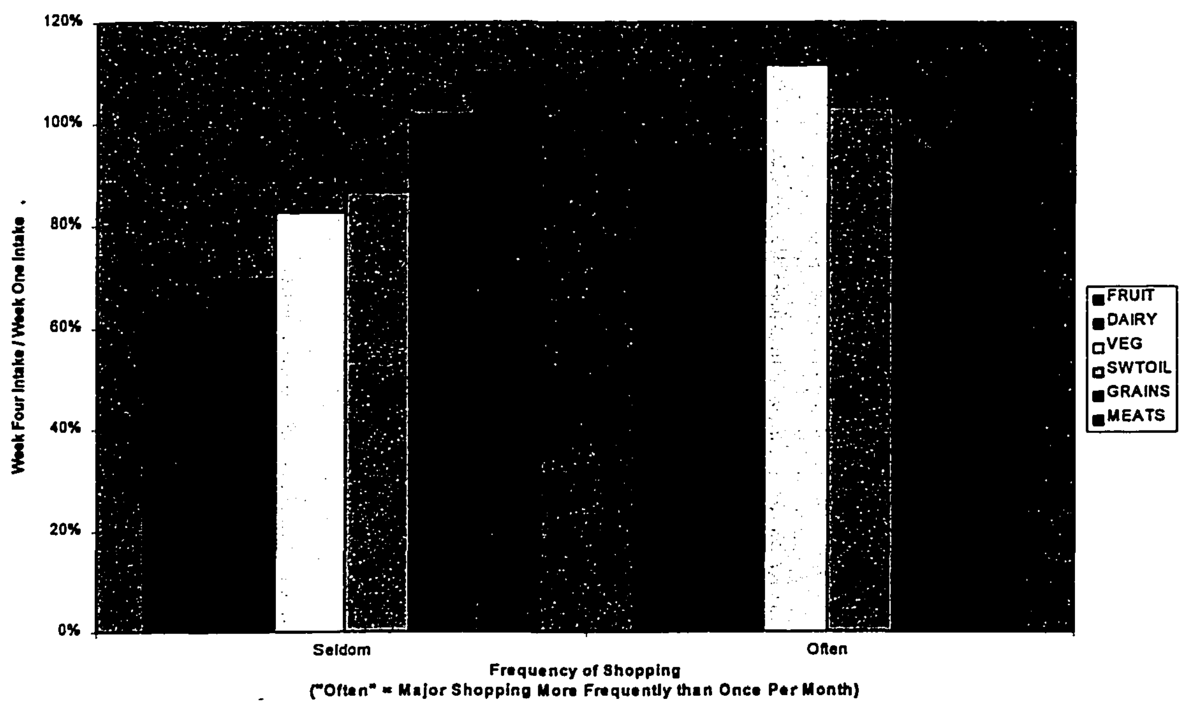
Note: * Signifies Week 4 intake is significantly less than Week 1 intake (one-tailed test, alpha=0.05).

Figure 3.16. Food Intake by Individuals, According to Shopping Frequency

Table 3.2. Shopping Frequency of Food Stamp Recipient Households and Low-Income Nonrecipient Households

		Shopping Frequency		
		Infrequent	Frequent	Total
Low-Income Nonrecipients	N	255	1293	1548
(Income < 130% of poverty)	Percent	11.02	55.88	66.90
	Row Pct.	16.47	83.53	
Food Stamp Recipients	N	318	448	766
	Percent	13.74	19.36	33.10
	Row Pct.	41.51	58.49	
Total		573	1741	2314
		24.76	75.24	100.00

Note: A chi-square test (172.477, 1 d.f.) shows that the difference between shopping frequency of recipients and nonrecipients is significant at alpha=.01.



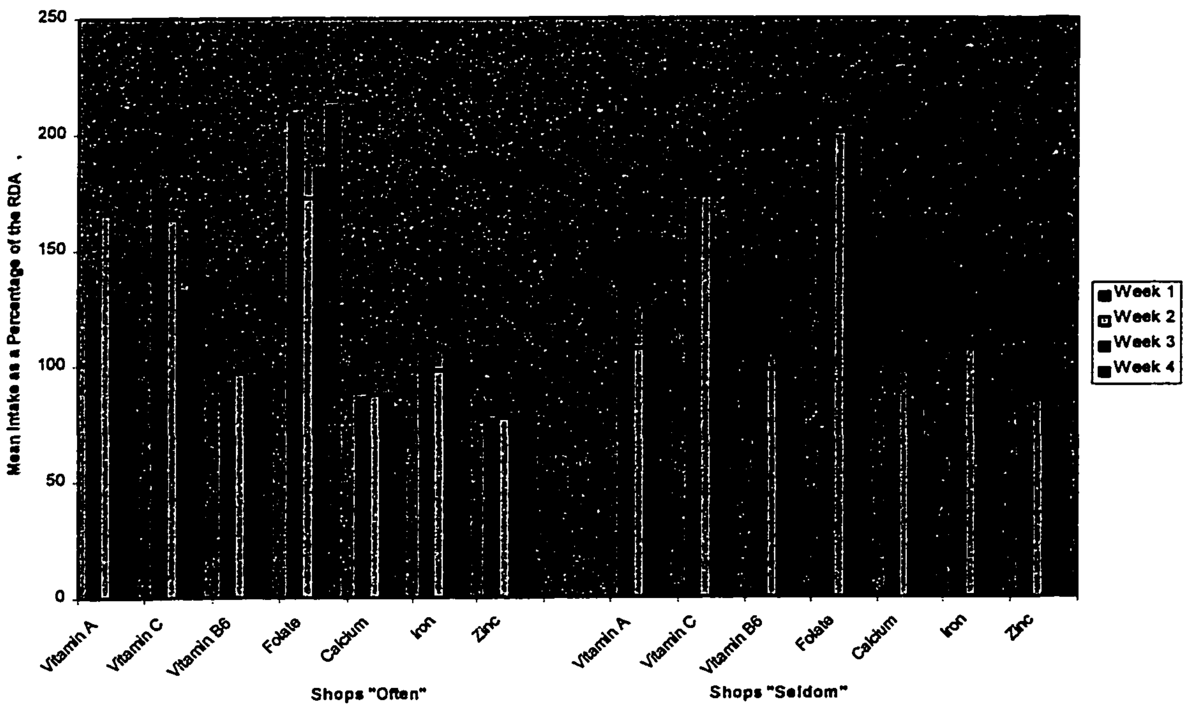
Note: * Signifies Week 4 intake is significantly less than Week 1 intake (one-tailed test, alpha=0.05).

Figure 3.17. Food Intake, by Pyramid Category and Shopping Frequency

even for infrequent shoppers. Only the fruit and dairy categories for infrequent shoppers show a statistically significant drop in food intake.

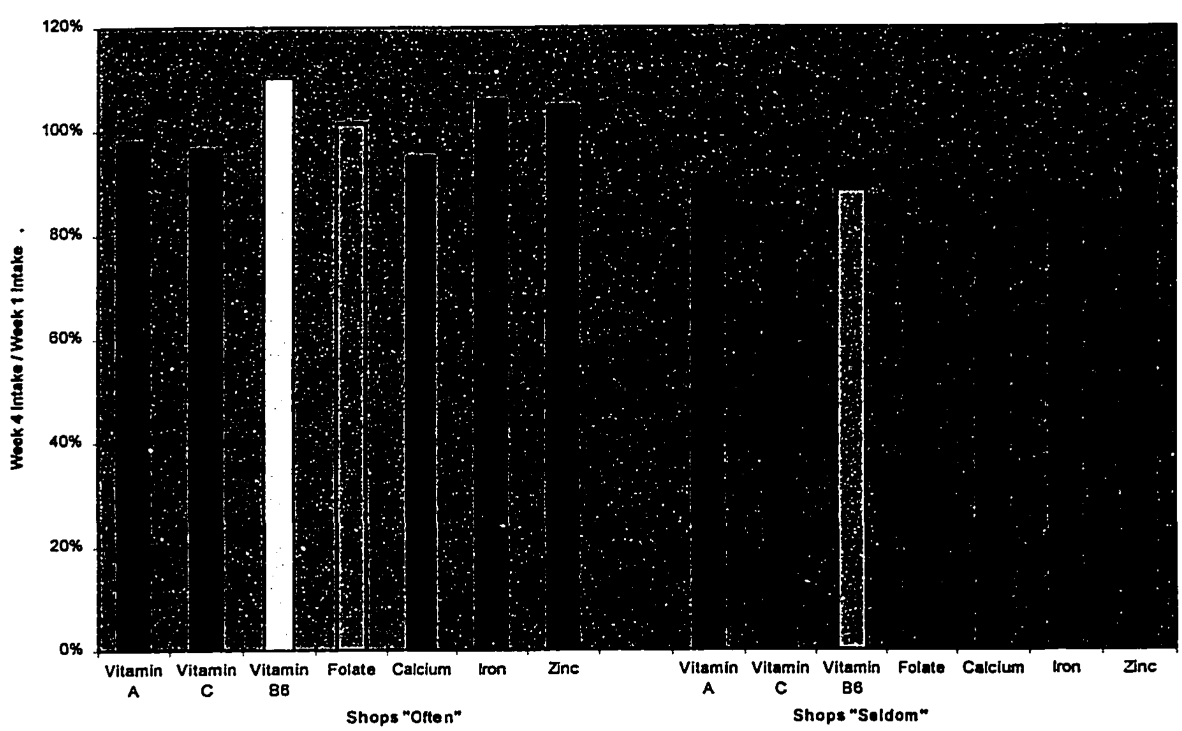
These changes in food intake over time are big enough to affect the intakes of important micronutrients. This section considers seven that are mentioned as "concerns for low-income, high-risk populations" in the *Third Report on Nutrition Monitoring in the United States* (Federation of American Societies for Experimental Biology 1995): vitamin A, vitamin C, vitamin B6, folate, calcium, iron, and zinc. Iron and calcium are also highlighted in *The Surgeon General's Report on Nutrition and* Health (U.S. Department of Health and Human Services 1988) as special concerns for some people. The seven micronutrients are measured as a proportion of the corresponding RDA for each nutrient (figure 3.19). The Recommended Dietary Allowances for micronutrients, unlike the RDA for food energy discussed above, are not recommendations for the typical or median consumer, but higher and more conservative levels that are designed to ensure that almost all consumers who achieve the RDA will be free of symptoms of deficiency.

For the sample of food stamp recipients, the lowest intakes relative to the RDA occurred for vitamin B6 (98 percent), calcium (85 percent), and zinc (80 percent) (figure 3.18). Due to the underreporting of total food intake suspected in the CSFII, these estimates are probably biased downwards. Once again, it is easier to perceive relative differences in the monthly cycle for these micronutrients when their intake is measured as the ratio of Week 4 intake to Week 1 intake (figure 3.19). As with the pattern in specific foods, there is little or no drop in intake at the end of the month for those recipients who shop "often," while for some nutrients there is a significant drop for those who shop "seldom." In particular, intake of vitamin C and calcium is significantly lower at the end of the month for these recipients.



Note: * Signifies Week 4 intake is significantly less than Week 1 intake (one-tailed test, alpha=0.05).

Fig. 3.18. Intake by Individuals, Selected Micronutrients



Note: * Signifies Week 4 intake is significantly less than Week 1 intake (one-tailed test, alpha=0.05).

Fig. 3.19. Intake by Individuals at End of Month, Selected Micronutrients

These results for micronutrients are consistent with the earlier discussion of Pyramid food categories. Dairy products are an important source of calcium, and fresh fruits are an important source of vitamin C. Vitamin C is a water-soluble vitamin, which must be consumed frequently because it is not stored in the body for long periods of time. Calcium is the only micronutrient whose consumption was both lower than the RDA on average, and also significantly lower at the end of the food stamp month.

Section 3.7. Summary and New Questions

This chapter measures intra-monthly patterns in food expenditure and food intake by food stamp recipients, using nationally representative data. Some results are interesting on their own. It is useful to know, for example, that the monthly cycle in food intake is more severe for adults than for children, and more severe for perishable foods than for nonperishables. Public health policy-makers may be concerned that food stamp recipients have significantly lower intakes of some micronutrients at the end of the month, while they may be reassured at least that most food purchased in large trips at the start of the month is stored for later use.

Many of the results, though, raise yet further questions:

- AFDC participation, adulthood, and shopping frequency all affect the monthly food intake cycle, but how do these variables interact?
- The mean level of food intake is lower at the end of the month, at least for some people, but how do changes in food stamp benefit levels affect food intake at different times of month?
- Why is shopping frequency associated with a cycle in food intake? Are some food stamp recipients too impatient to save their benefits for grocery shopping late in

the month, or do they simply do the best they can given food perishability and the constraints on their shopping choices?

To address these questions, we need a multivariate analysis based on a specific model of consumer choice, which simultaneously accounts for both shopping behavior and food intake at different times of the food stamp month. Developing and estimating such a model is the challenge undertaken in the remainder of this dissertation.

CHAPTER FOUR:

LITERATURE REVIEW, PART II

Section 4.1. Introduction

The favored methodologies for economic research on food demand by U.S. food stamp recipients have changed greatly in the last twenty years, reflecting two major developments in applied economics more generally: 1) increased attention to the consistency between empirical specifications and the economic theory of consumer choice, and 2) new methods for modeling censored and categorical choice variables using switching regression equations. These developments have on the one hand raised the standard for an empirical model to be taken seriously as a description of rational behavior by food stamp recipients, and they have on the other hand allowed economists to address a greater part of the complexity of the real phenomena.

Section 4.2 sets up a common framework for a number of applied models that will be reviewed in the later sections. It then discusses two examples of how applied switching regression models of food demand by food stamp recipients can be developed within this framework, from the utility function down to the empirical specification. The first example is a kinked-budget-constraint model of food demand subject to the restriction that food stamps may be spent only on food. The second example is a model of food demand by food stamp recipients, when the decision to participate in the Food Stamp Program is endogenous. The main body of the literature review follows: section 4.3 reviews kinked-budget-constraint models (corresponding to example 1), and section 4.4 reviews endogenous program participation models (corresponding to example 2). Section 4.5 discusses econometric models where the dependent variable is food intake, as opposed to food expenditure or food availability in the household, to provide a foundation for comparisons with the empirical work in the following chapters. A final section evaluates the econometric literature more generally.

4.2 A Common Structure

The structure of the econometric models that now dominate this area of research may be summarized in a stylized framework. This framework consists of two equations describing food consumption (*F*) as a function of a vector (*z*) of independent variables such as prices, income, and food stamp benefits, under each of two regimes (0 and 1) for each individual *i*. A third equation determines which regime in fact applies:

(4.1a) $F_i = f_0(z_i)$ if $D_i = 0$;

(4.1b) $F_i = f_1(z_i)$ if $D_i = 1$;

(4.1c) $D_i = 1$ if $g(z_i) > 0$; otherwise $D_i = 0$.

Food consumption in the first two equations may be unaffected by some elements of *z*, but there is usually an argument for including the full vector of independent variables in the third equation. In principle, a demand framework of this type can be derived explicitly from a theoretical model of constrained choice in the mainstream tradition, although in practice the execution of this derivation varies from application to application.

As examples, consider two models that are most widespread in journal articles that estimate food demand by food stamp recipients: the kinked-budget-constraint model and the food stamp participation model. These examples are described here with some simplifying assumptions that are relaxed in most actual research. In particular, we assume that "food is food" -- food purchased with stamps is the same as food purchased with cash. The goal here is to present the simple models in a consistent framework, from the utility function to the empirical specification, in order to provide a comparison point for later discussion of the many variations and extensions that have been proposed and estimated.

Example 1. The Kinked Budget Constraint

The first example is a model of consumer choice subject to targeted food stamp benefits that may only be spent on food (Southworth; Mittelhammer and West). Suppose the consumer's preferences can be represented by a stricly quasiconcave, differentiable, and monotonically increasing utility function $U(F,X)$, where F is food consumption, X is a composite nonfood good, and the consumer always chooses positive amounts of each good. For the moment, assume the program participation decision is pre-determined, and ignore any stigma attached to using food stamps. If S is the face value of food stamp benefits, C is cash income, p_F is the price of food, and p_X is a vector of prices of other goods, the consumer problem may be stated simply:

$$(4.2) \qquad \underset{F,X}{Max}\, U = U(F,X) \qquad \text{s.t.} \qquad p_F F + p_X X = (C+S) \qquad \text{and} \qquad p_X X \leq C.$$

Together, the two linear constraints constitute a "kinked" or "piecewise linear" budget constraint. Under the given assumptions, this problem may be solved directly using the lagrangian method with two multipliers corresponding to the two constraints. Another intuitive way of describing the solution is to ignore the second constraint for a moment. The remaining problem may be solved easily for a hypothetical food demand function (f^*), sometimes called the "desired" or "underlying" food demand, which would describe consumer choices if there were no restriction on how food stamps are spent. Actual food consumption equals this desired consumption if the desired consumption is greater than or equal to the amount of food that may be purchased with just the food stamp benefits, because in this case the second constraint is non-binding and was therefore properly ignored. Otherwise, the second constraint is binding, and the consumer's food consumption necessarily equals the amount of food that may be purchased with food stamp benefits. This two-part solution may be written in the form of our stylized demand framework (equation 4.1):

(4.3a) $F_i = f_0(p_F, p_X, C_i, S_i) = S_i / p_F \qquad \text{if } D_i = 0;$

(4.3b) $F_i = f_1(p_F, p_X, C_i, S_i) = f^*(p_F, p_X, C_i + S_i) \qquad \text{if } D_i = 1;$

(4.3c) $D_i = 1 \text{ if } g(p_F, p_X, C_i, S_i) = f^*(p_F, p_X, C_i + S_i) - S_i / p_F > 0;$

otherwise $D_i = 0$.

A simple stochastic structure permits empirical estimation of the parameters for desired food demand. A normally distributed mean-zero disturbance is added to the function f^* in equations (4.3b) and (4.3c). If f^* has an intercept, which may interpreted as a parameter of the utility function, this disturbance may be interpreted as representing heterogeneity of consumer preferences. The model may then be estimated using Tobit procedures. The alternative of interpreting the disturbance as measurement error in the dependent variable makes the model more complicated, because it implies that the disturbance also should appear in equation (4.3a) and that the analyst cannot know the true regime for any particular observation.

Example 2. Endogenous Food Stamp Participation

The second example is a simultaneous model of the food stamp participation decision and food demand for those who do or do not participate. Suppose a consumer has preferences over food (F), a composite nonfood good (X), and a dichotomous variable (D) that takes the value one if the consumer chooses to participate, and zero otherwise. Suppose further that preferences with regard to participation are strictly separable from preferences over goods, in the sense that the consumer ranks possible combinations of goods in the same order regardless of the value of D. In this case, a single well-behaved "common" direct utility function $\overline{U}$ may be used to describe preferences over goods under either participation regime. The complete preferences over goods and regimes may then be described by a general utility function $\hat{U}$, which takes $\overline{U}$ as an argument:

$$(4.4) \quad U = U(F,X,D) = \hat{U}(\overline{U}(F,X),D).$$

A frequently-used special case of equation (4.4) comes from the model of "flat" welfare stigma, due to Moffitt (1983). In that model, program participation induces a fixed reduction in utility, so that the participation dummy variable is a simple additive term on the common direct utility function:

$$(4.5) \quad U = \hat{U}(\overline{U}(F,X),D) = \overline{U}(F,X) - \phi D.$$

Equation (4.5), though intuitive, is more restrictive than has been generally recognized. In the modern economic theory of choice, utility functions are not cardinal: they are merely an ordinal representation of a consumer preference ranking. Customarily, a positive montonic transformation of a utility function represents the same preferences. A positive monotonic transformation of the utility function $\overline{U}$ similarly will represent the same ranking of preferences over F and X, conditional on participation regime D. The problem is that such a transformation may alter the represented preferences over participation regimes. For example, the well-known logarithmic and multiplicative forms of Stone-Geary preferences for $\overline{U}$, which are usually considered equivalent, will represent different preferences over participation regimes.

The consumer problem is to make a participation decision and choose a bundle of goods, subject to two linear budget constraints that correspond to the two regimes. For nonparticipants, full income is just cash income (C). For participants, full income includes cash income plus food stamp benefits (S). In this example, prices p_F and p_X will be the same under both regimes, although that assumption easily could be relaxed to account for a food stamp program with a purchase requirement. This example also assumes that all recipients spend at least some cash on food, so the kinked budget constraint in the previous example may be ignored.

The easiest solution method is to maximize the common direct utility function $\overline{U}$ with respect to a generic linear budget constraint ($p_F F + p_X X = M$), where M is full income, to derive common demand functions ($\overline{F}$ and $\overline{X}$) with prices and income as arguments. Of course, the actual quantities demanded will still differ, due to the distinct income levels under the two regimes. The common demand functions may be inserted back into the direct utility function to derive an indirect utility function, which takes the same form under the two regimes:

$$
\begin{aligned}
(4.6)\quad \overline{V}(p_F, p_X, M) &= \overline{U}(\overline{F}(p_F, p_X, M), \overline{X}(p_F, p_X, M)) \\
&= \underset{\{F,X\}}{Max}[\overline{U}(F, X) | p_F F + p_X X = M].
\end{aligned}
$$

The following "conditional" indirect utility functions may be calculated:

$$
(4.7a)\quad V_1(p_F, p_X, C, S) = \hat{U}(\overline{V}(p_F, p_X, S + C), 1), \text{ and}
$$

(4.7b) $V_0(p_F, p_X, C, S) = \hat{U}(\bar{V}(p_F, p_X, C), 0)$.

Under Moffitt's model of flat welfare stigma, these conditional indirect utility functions may be written more simply:

(4.8) $V_D = \bar{V}(p_F, p_X, (C + DS)) - \phi D$.

The general model of the simultaneous food demand and participation decisions may be written in the form of the stylized framework as follows:

(4.9a) $F_i = f_0(p_F, p_X, C_i, S_i) = \bar{F}(p_F, p_X, C_i)$ iff $D_i = 0$;

(4.9b) $F_i = f_1(p_F, p_X, C_i, S_i) = \bar{F}(p_F, p_X, C_i + S_i)$ iff $D_i = 1$;

(4.9c) $D_i = 1$ if $g(p_F, p_X, C_i, S_i) = V_1(p_F, p_X, C_i, S_i) - V_0(p_F, p_X, C_i, S_i) > 0$; otherwise $D_i = 0$.

In practice, two alternatives to the general utility-theoretic switching equation (4.9c) have been used for empirical estimation. The more common method has been to use an ordinary probit, where *g* is simply assumed "as a first-order approximation" to be a linear function of the relevant exogenous variables including ordinary income and food stamp benefits. Alternatively, in the special case of Moffitt's model of flat stigma, the switching equation takes a nonlinear form that may still be feasible to estimate:

(4.9d) $D_i = 1$ if $g(p_F, p_X, C_i, S_i) = \bar{V}(p_F, p_X, C_i + S_i) - \bar{V}(p_F, p_X, C_i) - \phi > 0$; otherwise $D_i = 0$.

For a stochastic specification, suppose e_{iD} is an additive normally distributed mean-zero disturbance on the food demand function for individual i under regime D in equations (4.9a) and (4.9b). Under either a simple probit specification or Moffitt's model of flat stigma, one can suppose u_i is an additive disturbance on the third equation. In Moffitt's model, this may be seen as a disturbance in the scalar parameter ϕ, representing heterogeneity in the level of flat welfare stigma perceived by different people. This disturbance will generally be correlated with the e_{iD}. If this correlation is ignored, empirical estimates will be subject to "self-selection bias." To correct for this bias, the system of equations in (4.9) may be estimated either by maximum likelihood (Moffitt 1983) or by a consistent two-step estimator (Heckman 1976; Lee 1978).

4.3 The Literature on Kinked-Budget-Constraint Models

The theoretical foundation for kinked-budget-constraint models was originally developed by Southworth (1945). He described the consumer problem of choice between food and a composite nonfood good, subject to the traditional budget constraint and the additional constraint that food stamps may not be used for nonfood purchases. Southworth's model predicted that inframarginal or "unconstrained" food stamp recipients, who spend some of their own cash on food, should have the same marginal propensity to consume food out of cash or food stamp benefits. By contrast, extramarginal or "constrained" food stamp recipients, who spend only their food stamp benefits on food, should have a much higher marginal propensity to consume food out of food stamps. The latter marginal propensity to consume should equal unity. This popular theoretical framework has been thoroughly discussed elsewhere (Mittelhammer and West 1975; Fraker 1990).

The econometric background for these models begins with the "Tobit" specification, which accounts for zero expenditures in some observations (Tobin). This model was extended and developed into a general model of kinked budget constraints by Hausman (1985) and Moffitt (1986). The econometrics of the Tobit model is discussed at length in Maddala (1983), and various models of "kinks" are reviewed in Pudney (1989).

An early use of a Tobit specification to study the U.S. Food Stamp Program was Huang, Fletcher, and Raunikar (1981). This article began with a graphical indifference-curve exposition of the Southworth model, with and without a purchase reqirement for food stamps. However, the article employed the Tobit just for its more usual purpose of adjusting for observations with no food expenditures in the short survey period. The kinked budget constraint from food stamp benefits was ignored in the empirical work, as was consistent with the literature on the program to that date.

Senauer and Young (1986) more specifically accounted for the kinked budget constraint and formally tested the Southworth hypothesis (see table 4.1). The food expenditure variable in their data, from the Panel Study of Income Dynamics (PSID), contained only cash food expenditures above and beyond any food stamp spending. Thus, while their empirical model explicitly followed Huang, Fletcher, and Raunikar's Tobit specification for "zero" food expenditures, the economic content of their model was entirely different. A zero food expenditure corresponded to an extramarginal recipient, and a positive food expenditure corresponded to an inframarginal recipient.

Under their null hypothesis that the Southworth theory is correct, Senauer and Young's model was just like example 1, with a semi-logarithmic functional form for the underlying food demand function f^*. For their alternative hypothesis, the authors

Table 4.1. Econometric Models of the "Kinked" Budget Constraint

	Senauer and Young (1986)	Moffitt (1989)	Wilde and Ranney (1996)
Data:	PSID (1978-1979)	Puerto Rico survey (1977)	San Diego and Alabama cashout surveys (1990)
Sample size:	2257 obs.	1147 obs.	1078-2289 obs.
Data clustered at the kink.	Yes	No	No
Tests several functional forms.	No	Yes	Yes
Tests for heteroskedasticity.	No	No	Yes
Tests for normality of error terms.	No	No	No
Tests selection bias due to endogenous participation.	No	Yes (but not in kinked-budget model)	No
Has error term for preference heterogeneity.	Yes	Yes	Yes
Has error term for measurement error.	No	Yes	No
Allows unconstrained MPC out of food stamps to differ from MPC out of cash.	Yes	Yes (but not in kinked-budget model)	Yes
Conclusions about marginal effects:	Marginal effect of food stamps on unconstrained food spending is greater than the marginal effect of cash income, showing that the Southworth model is incorrect.	Marginal effect of food stamps is no different from marginal effect of cash benefits, even for recipients who seem likely to be extramarginal, suggesting program is already "cashed out" by illegal trafficking.	Marginal effect of coupons on unconstrained food spending is greater than the marginal effect of ordinary income. In San Diego, not Alabama, marginal effect of stamps exceeds the marginal effect of cash benefits.

added an extra variable, measuring the ratio of food stamp benefits to total income, which should be irrelevant under the null hypothesis. Because the parameter on this variable was significantly different from zero, Senauer and Young concluded that the marginal propensity to consume food out of food stamps was higher than the corresponding marginal propensity out of cash, even for unconstrained food consumption, so they rejected the Southworth model.

Senauer and Young did not estimate a correction for endogenous program participation, but they did cite Ranney's (1983) evidence in a different sample that the resulting selection bias was not significant. In attempting to explain the rejection of the Southworth hypothesis, they offered some comments on the monthly cycle studied in this dissertation:

> When a household receives a monthly food stamp allotment, larger and more expensive food purchases are typically made early in the month. As the food purchased with food stamps runs out later in the month, the family may begin to eat less well, but will also spend cash to buy additional food (Senauer and Young 1986).

Moffitt's (1989) article on the food stamp cashout in Puerto Rico was in several respects more ambitious than anything else in this literature. The data for the kinked-budget-constraint models come from 1977, when there was still a purchase requirement, so Moffitt accounted for three demand regimes rather than just the usual two: recipients may use less than their full authorized amount of food stamps, they may use exactly the full benefit amount, or they may add some of their own cash for food purchases at full price. In his stochastic specification, Moffitt also used two distinct types of disturbance: one representing heterogeneity of preferences tends to produce "clumping" at the kink in the budget constraint; another representing measurement error in the dependent variable tends to smooth out the clumping at the kink. Finally, Moffitt considered linear, log-linear, and linear expenditure system (LES) functional forms for his underlying food demand equation.

Moffitt's model was otherwise similar to the framework in example 1. He allowed the marginal propensity to consume food out of food stamps and cash to differ in a simpler specification, but not in his final kinked-budget-constraint specifications. In a footnote, he also reported estimates for a selection bias correction model, but again, not while simultaneously considering the kinked budget constraint. There was no evidence of selection bias.

Moffitt's main results were varied. Iterative computation of his maximum likelihood problem converged for the linear and LES functional forms, and with these forms there were positive variances for both types of disturbance: preference heterogeneity and measurement error. The log-linear form did not converge, but a graphical analysis suggested the "best" estimates that could be found for this form fit the data better than the converged estimates from the other two forms. The level of "clumping" at the kink appeared much higher with the log-linear functional form, which yielded evidence of preference heterogeneity but no evidence of measurement error in the dependent variable.

Unlike Senauer and Young (1986) above and Wilde and Ranney (1996) discussed below, the main contrast with the Southworth theory in Moffitt (1989) was not that the marginal propensity to consume food out of food stamps was so high for inframarginal recipients, but rather that it was so low for extramarginal recipients. Moffitt suggested that the food stamp program may have already been effectively "cashed out" by illegal trafficking, which would also explain why food spending did not fall much in response to cashing out food stamps in Puerto Rico.

Using data from two cashout experiments, Wilde and Ranney (1996) estimated a kinked-budget-constraint model that allowed different marginal propensities to consume food out of food stamp coupons, food stamp program checks, and ordinary income. If these three marginal propensities were equal, the model would be consistent with the Southworth theory, and it could be written just like example 1. In this article, we used an innovation from Moffitt (1983;1989) to set up the model when these marginal propensities differ. We supposed that each dollar of ordinary income was "equivalent" to a fixed fraction of a dollar of food stamp coupon or cash benefits, so "full income" or "effective income" could be written: $FY = Y + \gamma_1 Y_{ch} + \gamma_2 Y_{co}$, where Y was ordinary income, Y_{ch} was check benefits and Y_{co} was coupon benefits. This specification had a clearer economic interpretation than the alternative (non-Southworth) hypothesis in Senauer and Young (1986), but the general utility function that might yield this relationship between different types of benefits was still not formally developed. In our conclusion, we discussed two non-traditional theoretical approaches that might cause coupons to be different from cash, even for inframarginal recipients, and we argued "as an approximation" that the empirical specification from these approaches would "share some of the essential characteristics" of the model we actually estimated.

Our results indicated that the marginal propensity to consume food out of coupons was consistently much higher than the corresponding marginal propensity out of ordinary income. Check benefits from the food stamp program fell in between. In one study site (Alabama) they were treated more like food stamp coupons, and in the other site (San Diego) they were treated more like ordinary income. We concluded that empirical research should not assume food stamps are the same as ordinary income for inframarginal recipients. However, mainly due to the small proportion of the sample that appeared to be extramarginal, we concluded that the whole effort to model the kinked budget constraint formally did not make a great difference in the empirical results.

4.4 The Literature on Endogenous Program Participation Models

The switching regime model in example 2 was developed by Heckman (1976) and Lee (1978) in the context of labor economics problems with many comparable elements. Heckman emphasized the structural similarites between this econometric model and other limited dependent variable models such as the Tobit. As an example, he simultaneously modeled the decision of women to participate in the wage labor market and their wage conditional on choosing to participate.

Although empirical studies of food stamp participation even in the 1990s cited Heckman (1976) as their principal econometric source, Lee's (1978) model is more strictly parallel. Lee considered the wage that a person would earn as a union or nonunion worker and, simultaneously, the person's endogenous decision about union participation. Two wage equations, conditional on each participation regime, described the log of wages as a linear function of several exogenous explanatory variables. The worker chooses to participate if the difference in the log-wages is greater than a "reservation" difference, which is a linear function of personal characteristics and the costs of being a union member.

Presumably, this "reservation" wage difference could be described as the solution to a utility-theoretic problem of finding the wage that produces indifference between the two participation regimes, but this theory was not explicitly developed. Lee's functional form for the participation decision allowed estimation in reduced form by probit. Because the structural participation equation included the union and nonunion wages, the reduced form participation equation included all variables that affect either participation or the wage or both. The reverse was not true. Some variables (such as a dummy for full time work) could appear in the participation equation but not in the wage equation. Indeed, although in principle the model is estimable without such identifying variables due to its strong distributional assumptions, the consensus in the econometric literature is that results will be more robust if there are some variables in the switching (probit) equation that do not appear in the others. In Lee's model, selection bias correction factors from the reduced form probit equation were used, in the second step, to obtain consistent estimates of the parameters for the wage equations.

Models in this spirit have been used many times to describe food stamp participation and food demand simultaneously. In this section, I focus on six detailed models that have appeared in the peer-reviewed literature (see table 4.2), but these methods have also been used in other sources (Chen 1983; Devaney, Haines, and Moffitt 1989; Devaney and Fraker 1989; Fraker, Long, and Post 1990).

An early journal article in the food stamp literature was Akin et al. (1985), who studied a sample of elderly people from the 1977-78 Nationwide Food Consumption Survey. The authors verbally discussed constrained maximization of a utility function defined over "nutrients and other goods." The stigma associated with program participation was treated not as a variable in the utility function, but rather as an unobserved "cost." The empirical framework was asserted: linear nutrient demand functions, conditional on participation regime, and a probit equation that determines the choice of regime. In contrast with example 2 above, different categories of income were assumed to affect nutrient demand differently, although there was no discussion

Table 4.2. Econometric Models of Endogenous Program Participation

	Akin et al. (1985)	Smallwood and Blaylock (1985)	Ranney and Kushman (1987a)
Data:	NFCS 1977-78 (elderly in basic sample)	NFCS 1977-78 (low income sample)	Consumption survey, four states 1979-1980
N (participants):	262	1845	310
N (nonparticipants):	1053	2655	346
Theoretical framework:	Little utility-theoretic discussion	Discusses Southworth model verbally	Explicit model of joint participation and food demand.
Functional form for food demand:	Linear, with quadratic terms for income	Linear, including interactions with participation	Linear in the parameters, with special vars.
Motivation for participation equation:	Reflects the "benefits and costs" of participation	Participation depends on a "cost/benefit ratio"	Based on difference between utility of participating or not
Discussion of stigma:	"Costs" include "social stigma"	"Psychic costs of program stigma," excluded	Stigma tackled using hh prod. function.
Treats selection bias.	Yes	No	Yes
Estimation method:	Two-step	Recursive, not simultaneous, max. lik.	Two-step
Discussion of kinked budget constraint:	None	Explains that few observations are extramarginal.	Discussed in theory. Later assumes inframarginality.
Conclusions:	Program participants have better dietary status, but selection bias not important in most cases	Marginal effects of food stamps greater than corresponding effects of cash	Food stamps have more effect than cash on food demand, but little difference in effect on utility

Table 4.2. Continued.

	Devaney and Fraker (1986)	Devaney and Moffitt (1991)	Butler and Raymond (1996)
Data:	Puerto Rico Cashout: 1977, 1984	SFC-LI 1979-80	RIME 1969-1973; Eld'ly Cashout '80-'81
N (participants):	1381 and 883	Approx. 1450	85 and 774
N (nonparticipants):	1559 and 1540	Approx. 1450	969 and 768
Theoretical framework:	Little utility-theoretic discussion	Utility function over goods, but not participation	Little utility-theoretic discussion
Functional form for food demand:	Linear (most params. equal across regimes)	Linear (most params. equal across regimes)	Linear (most params. equal across regimes)
Motivation for participation equation:	Just characteristics "that affect program participation"	Reflects "propensity" to participate	Reflects "propensity" to participate
Discussion of stigma:	None	None	States: "Stigma is created by assets."
Treats selection bias.	Yes	Yes	Yes
Estimation method:	Maximum likelihood	Max. lik. with two selection bias specifications	Two-step and instrumental vars.
Discussion of kinked budget constraint:	None	None	None
Conclusions:	No selection bias. FS and cash benefits both affect demand more than ordinary income	Food stamps have more effect than cash on nutrient demand, but selection bias not important	Evidence of selection bias in Demo. but not RIME. Also, stamps may not have strong effect on nutrition

(along the lines of the kinked-budget-constraint models above) of why that might be so. The probit equation was said to reflect the "benefits and costs" of participation, but it was not derived as a solution to the consumer's utility-maximization problem. In fact, some variables such as urban residence appeared in the nutrient demand equations but not the participation equation, even though it seems reasonable that the participation decision would depend on the nutrient consumption under each regime. Akin et al. estimated their system with a Heckman-type "two step" consistent estimator. They found for most nutrients that food stamp participants behaved differently than nonparticipants with respect to their nutrient intakes. The selection bias correction factors were statistically insignificant in all but one case.

Almost the same methodology was used in three of the remaining five articles reviewed in this section (Devaney and Fraker 1986; Devaney and Moffitt 1991; Butler and Raymond 1996). Devaney and Fraker studied food consumption survey data from before and after the Puerto Rico food stamp program was cashed out in the early 1980s. They commented on the potential hazard of selection bias, and they simultaneously estimated a linear food demand equation and a participation equation by maximum likelihood. The variables in the participation equation were described as "characteristics ... that affect program participation."

Unlike Akin et al. (1985), Devaney and Fraker had only one demand equation to describe behavior under the two participation regimes. This restriction was equivalent in effect to assuming that all parameters are equal across regimes, except for the parameter on food program benefits. Furthermore, it is not clear how they handled the identification issues discussed above in the context of Lee (1978). Devaney and Fraker appear to have included all explanatory variables in their food demand equations (see their Table 2, p. 733), but I don't find that they ever reported specifically what variables were in their participation equation.

In any case, Devaney and Fraker found little evidence of selection bias due to endogenous program participation. Food program benefits -- whether coupons or cash -- were found to have a greater effect on the money value of food used at home, compared with ordinary income. There was little difference between the two types of food program benefits.

Devaney and Moffitt (1991) developed a utility-based model of nutrient demand more explicitly than Akin et al. (1985). However, they still gave no specific basis in their utility function, which is defined over goods, either for the distinction between food stamps and other income or for the consumer's choice of participation regime. The probit for program participation was simply said to reflect "the 'propensity' to participate." Apparently, like Devaney and Fraker (1986) but unlike Akin et al. (1985), Devaney and Moffitt (1991) assumed most parameters to be equal across the two participation regimes. Furthermore, there was once again little explanation for the choice of variables that help to identify the demand and participation equations: household size, the number of guest meals, and dummy variables for region of the country and urbanization all appeared in the demand equation but not the participation equation, even though the participation decision would seem to depend in part on food consumption under each regime.

Devaney and Moffitt employed both the now familiar specification for selection bias correction and also an alternative specification where the error term on the participation equation was correlated with a normally-distributed variable slope parameter in the nutrient demand equation. They estimated their system by maximum likelihood. As in the preceding articles, Devaney and Moffitt found that neither specification yielded evidence of selection bias, and their results indicated strong evidence that food stamps have a distinct effect on nutrient intake.

A final recent article along these lines was Butler and Raymond (1996), who used two older data sets: the Rural Income Maintenance Experiment (RIME) in Iowa and North Carolina from 1969-1973, and the Supplemental Social Insurance / Elderly Food Stamp Cashout Project ("Cashout Demo.") in New York, South Carolina and Oregon from 1980-1981. In this article, there was no utility-theoretic motivation, but the empirical specification was similar to those discussed previously. Nutrient intake conditional on participation regime was a linear function of several variables, including both food stamps and other income. The participation decision was described by a probit model, representing once again a "propensity" to participate.

Like Devaney and Fraker (1986) and Devaney and Moffitt (1989), Butler and Raymond (1996) assumed that the parameters for most variables are the same across participation regimes, although they commented more explicitly on the restrictiveness of this assumption. In principle, their choice of variables was more consistent with Lee (1978) (although they did not cite that article) in the sense that they included all demand variables in their participation equation but not vice versa. However, their choice for a single identifying variable unique to the participation equation may be questioned. They hypothesized that a family's assets affect the participation decision, because "assets can affect the perception by the particpants themselves and others viewing them of how appropriate their behavior is, i.e. stigma is created by assets." However, they excluded assets from the nutrient demand equations on the grounds that income from assets -- which does affect nutrient demand -- is already captured in the income variable. "Assets which do not produce a cash flow," they argued, "probably do not improve the diet." It could be argued instead, though, that assets are so correlated with important class and human capital variables that one should not simply assume assets have no effect on nutrient demand. It is difficult to assess Butler and Raymond's use of their key assets variable, becuase it was scaled in such away that their parameter estimates for their two data sets appeared as "-0.001" and "-0.000" in their results tables, but with highly significant t-statistics of -3.558 and -2.964.

Unlike the preceding studies, Butler and Raymond found evidence of selection bias in one of their two data sets. Furthermore, after correcting for selection bias, they failed to find the strong positive effects of food stamps noted in the preceding studies. Instead, they reached an unusual conclusion: "We find that adequate income is no guarantee of adequate nutrition; increased income, either restricted to food stamps or otherwise, is associated with reduced nutrient intake in both data sets" (Butler and Raymond 1996). Just as with the assets variable, this conclusion is difficult to assess, because the calorie demand parameters for their income variable in their two data sets appeared as "0.000" and "-0.000" in their results tables, in one case with a highly significant associated t-statistic.

The remaining two articles (Smallwood and Blaylock 1985; Ranney and Kushman 1987a) gave more explicit consideration to how food stamp recipients' food demand and program participation decisions relate. Smallwood and Blaylock began with a theoretical framework based on the Southworth model. To address the possibility that food stamps are different from cash, even though few observations in their data set are extramarginal, they gave a verbal discussion of several possible explanations for distinct marginal propensities to consume food out of coupons and cash. Like Akin et al. (1985), they discussed the participation decision in terms of the "expected costs and benefits" of participation, although they appeared to have had in mind personal preferences about participation as well as budgetary factors.

Like the preceding articles, Smallwood and Blaylock estimated both a food expenditure equation and a program participation equation. The expenditure equation applied to participants and eligible nonparticipants, but it included dummy-variable interactions allowing several slope parameters to differ under the two regimes. The participation equation described the log probability of participating, relative to not participating, as a linear function of a "food expenditure enhancement" and a "nonfood expenditure enhancement." These enhancements reflected the increase in per capita food expenditures or nonfood expenditures, respectively, that would accrue from program participation.

Smallwood and Blaylock assumed that the error terms on their demand and participation equations are independent, so they didn't use a selection bias correction procedure. To support this assumption, they held that the same random disturbance would appear in the food demand equation whether an individual participates or not, so therefore the error terms canceled in the "food expenditure enhancement." In effect, although the food demand functions conditional on participation and nonparticipation were stochastic, the difference between the two functions was assumed to be nonstochastic. The expenditure enhancements thus were used as exogenous explanatory variables in the participation equation, and no tests for endogeneity were reported.

Smallwood and Blaylock estimated their model with data from the 1977-78 Nationwide Food Consumption Survey (NFCS) low-income sample. The same data were later studied by Devaney and Fraker (1989) with a selection bias correction model, which found no evidence of selection bias. Because the estimated parameters for the "food expenditure enhancement" and the "nonfood expenditure enhancement" in the participation equation were effectively equal, Smallwood and Blaylock concluded, "there was no indication that households with a greater preference for food (larger food expenditure enhancement) were more likely to participate than other households." This interpretation of their results does not appear consistent with the assumption that the enhancement is nonstochastic, unless the "greater preference for food" refered only to preferences fully picked up by the explanatory variables and not to idiosyncratic preferences. As in most of the articles described above, Smallwood and Blaylock also found that food stamps have a greater marginal effect than cash income on food expenditure.

Finally, Ranney and Kushman (1987a) offered the only empirical model derived from an explicit utility-theoretical framework that incorporated both the program participation and food demand decision for food stamp recipients (as in example 2). They defined a utility function over food, a nonfood good, and also a home-produced composite good reflecting "prestige and privacy," which were affected by the stigma of program participation. This utility function was maximized with respect to a kinked budget constraint (as in example 1), although in practice the derivation of demand functions by way of Roy's identity relied implicitly on the assumption of an interior (non-zero) solution for food purchased with cash. Because only inframarginal recipients optimally have non-zero solutions for food purchased with cash, this assumption was equivalent to assuming inframarginality, as in most of the applied literature discussed in this section.

Ranney and Kushman's model was similar in spirit to Moffitt's (1983) model of labor supply decisions for welfare recipients subject to stigma. Like Moffitt, Ranney and

Kushman derived demand functions conditional on choosing to participate or not participate, and then they determined the optimal regime by comparing the conditional indirect utility functions under each regime.

Ranney and Kushman estimated their model using data on food stamp participants and nonparticipants from consumption surveys in four states in 1979-1980. They chose tractable specifications for their indirect utility and food demand functions, rather than deriving these functions from a single direct utility function as their model permits in principle. In their journal article (Ranney and Kushman 1987a), they estimated the participation and demand equations separately, but in a monograph version (Ranney and Kushman 1987b) they also estimated the system using a two-step selection bias correction. They reached the conclusions, well-corroborated in this literature, that selection bias appears insignificant and that food stamps have a strong and distinct impact on food spending.

4.5 Econometric Analysis of the Effect of Food Stamps on Food Intake

In his review of the literature on the Food Stamp Program, Fraker (1990) observed that nutrient intake is a different type of dependent variable from food expenditure and nutrient availability in the home food supply. Because food stamps may not be legally used to purchase prepared food, in most cases, the program is mainly designed to augment food availability from the home food supply. "Thus," he wrote,

> nutrient availability (from the home food supply) is a well-focused measure of the behavior that the FSP is designed to influence, whereas nutrient intake is a more inclusive measure that encompasses behavior that the FSP is not designed to influence as directly. For that reason, we expact that the FSP would have weaker effects on nutrient intake then on nutrient availability.

> Existing research findings confirm our expectation that the effects of the FSP on nutrient intake are weaker than its effects on nutrient availability (Fraker 1990).

Fraker based this conclusion on a review of eight studies that measure the effect of the Food Stamp Program on nutrient intake. Two of the studies reviewed above in section 4.4 are of this type. For example, the study by Aiken et al. (1985) found positive but statistically insignificant effects of food stamp benefits on the intake of various nutrients. Butler and Raymond found, counterinuitively, that food stamp benefits have a negative effect on most nutrients, in some cases significantly so. In summarizing this literature, Fraker said, "Two notable patterns in the estimates of the effects of food stamps on nutrient intake ... are the scarcity of statistically significant estimates and the presence of a substantial proportion (one-fourth) of negative estimates."

4.6 Conclusions

It is clear from the wide variety and large number of empirical studies reviewed here that many applied economists believe this family of switching regression models has a high potential for expanding our understanding of food demand by food stamp recipients. However, in many applications, the more complicated statistical techniques turned out not to make a big difference in the empirical estimates: the number of extramarginal observations is often small in the kinked-budget-constraint models, especially since the elimination of the purchase requirement for food stamps almost two decades ago, and there has been minimal evidence for selection bias due to unobserved correlation between program participation and food demand equations.

Moreover, the most important empirical result in this literature still stands outside the theoretical framework that in most articles undergirds the estimation. This result is the often-replicated finding that food stamps have a greater effect than cash income on food spending, even after accounting for the kinked budget constraint or for self-selection bias.

One theoretical framework that could account for this result is Moffitt's (1983) model with variable stigma, meaning stigma that increases proportionally with program benefits. Levedahl (1996), for example, cited that model as background for a specification that allows the marginal propensity to spend on food out of food stamps to differ from the corresponding marginal propensity for cash. Like Wilde and Ranney (1996) and Devaney and Moffitt (1991), discussed above, Levedahl (1996) made use of Moffitt's special constructed income variable, where a dollar of food stamps is "equivalent" to a fixed proportion of a dollar of ordinary income.

A disadvantage of the variable stigma framework for explaining the distinct impact of food stamps is that, on its face, this framework appears to require that stigma is associated with the actual consumption of food-stamp food rather than with its purchase. It is hard to believe either that increased consumption of food-stamp food implies a proportionally increased sensation of stigma at the grocery store, or that households continue to perceive food-stamp food as stigmatized relative to cash food once both kinds of food are on the shelf in the kitchen.

The main conclusion from this review is that the existing literature leaves the door open for a particular line of further research. First, given that it is difficult to model several regime-switching issues at once -- or at least that no articles have yet done so -- it may be worthwhile to look beyond the two such issues that have received the most attention and consider new ones. Second, to account for the distinct effect of food stamps in a manner that is consistent with the stated theoretical framework, it may be desirable to consider food purchases and food consumption separately. The model of shopping behavior choice and food demand in the next chapter was developed to satisfy these criteria.

CHAPTER FIVE:
THEORY AND METHODS

5.1 Introduction

This chapter first presents a theoretical framework for considering how consumers make rational choices between food and non-food goods and, at the same time, about how frequently to conduct major grocery shopping trips (section 5.2). Then, it discusses the framework's theoretical implications for food intake demand functions under two shopping frequency regimes (section 5.3) and for the shopping frequency decision itself (section 5.4). The chapter develops a corresponding econometric model of food intake and shopping regime choice (section 5.5). Finally, section 5.6 considers alternative functional forms for the key conditional food intake functions.

This chapter builds on the analysis available in earlier chapters. Chapters two and three reported that food stamp recipients are more likely than other low-income people to conduct a major grocery shopping trip infrequently. Chapter three showed that those households which do shop infrequently experience significantly lower food intake late in the food stamp month, while more frequent shoppers experience no such cycle in food intake. Chapter three also noted, however, that this simple comparison did not hold constant other relevant economic variables. Chapter four discussed the large economic literature on how food stamp recipients make decisions about food demand, while simultaneously facing other options and constraints that may be modeled in a regime-switching framework. Although these models hold promise for capturing some of the greater complexity of the food decisions of food stamp recipients, the conclusion to chapter four identified a need for exploration of regime choices other than the two that have received most attention in the literature (participate in the program or not, choose an inframarginal consumption bundle or not). This chapter incorporates the empirical findings about shopping patterns and the monthly food stamp cycle into an endogenous switching regression demand model of the type discussed in chapter four.

In this model, the consumer chooses between two shopping regimes (frequent or infrequent major grocery trips). Simultaneously, conditional on the shopping regime choice, he or she chooses a level of food energy intake in each half of the month. One advantage of this approach is that it explains food shopping and food intake behavior together, in a manner consistent with the economic theory of rational choice. Another advantage is that it replaces the univariate comparisons from chapter three with a coherent multivariate framework, so that the distinct effects of various independent variables may be sorted out.

Partly offsetting these advantages, we have limited the analysis in other respects. For tractability, given the data set and sample size, the econometric approach focuses on a single type of food intake measure: food energy intake as a percentage of the RDA. Although an awareness of food storage difficulties motivates the model here, this approach sacrifices some of the detailed insight into specific more perishable and less perishable foods that was available with the simpler methodology in chapter three (especially in sections 3.5 and 3.6). Also, this approach requires a heavy reliance on a particular interpretation of the implications of "infrequent" major grocery shopping trips, as the following section explains.

Despite these constraints on the model, the following chapters will show how this combined model of food shopping frequency and food intake yields interesting empirical results about the Food Stamp Program. The simple empirical comparisons in chapter three and the more analytic approach in the next three chapters complement each other in describing and explaining the food stamp cycle.

5.2 Theoretical Framework

Consider again the finding that infrequent major shoppers have a significant food intake cycle, but frequent major shoppers do not. The direction of causation for this relationship is not obvious. As the quotation from the *New York Times Magazine* in chapter two suggests, 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 so long. Without resources to shop with, there would be little reason to conduct a second major grocery trip in the last half of the month, even if shopping costs were negligible. Alternatively, food stamp households that face transportation difficulties, time constraints, or stigma may choose to shop only once monthly, and they may have trouble storing food for consumption four weeks later as a consequence. Stated simply, a reluctance to save food resources for the end of the month may lead to infrequent food shopping, or infrequent food shopping may lead to low food intake at the end of the month.

The theory developed here is in the spirit of the latter explanation.[1] This approach depends on the proposition that storage and perishability issues are significant. This proposition is supported in part by the observations concerning the particular foods that infrequent shoppers were most likely to consume in lower quantities at the end of

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[1] A model in the spirit of the former explanation is considered in Wilde and Ranney (1997). That model describes the food consumption of impatient consumers, subject to both liquidity constraints and the constraint that food stamps may only be used to purchase food.

the month. Chapter three reported that this drop in food intake was concentrated in the dairy and fruit Food Guide Pyramid categories. We tentatively interpreted that finding as evidence that infrequent major shoppers may face additional constraints in acquiring or retaining perishable food for consumption towards the end of the food stamp 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. These preferences may depend in part on a vector of individual-specific variables (θ), including demographic and geographic characteristics. These characteristics may also include an idiosyncratic individual-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 quasiconcave utility function *U*:

(5.1) $U = U(F_1, X_1, F_2, X_2; \theta)$.

The consumer must choose between two shopping regimes: less frequent major grocery trips ($D = 0$) or more frequent major grocery trips ($D = 1$). In the empirical work below, the shopping regime is determined using a survey question that asks, "On the average, how often does someone do a major food shopping for this household?" The household is said to shop infrequently if the response is once per month or less frequently. The survey provides little instruction on what constitutes a "major" shopping trip, so some interpretation is needed below to employ this question in the empirical model.

More frequent grocery shopping involves a loss of leisure time and also perhaps a greater sensation of stigma from using food stamps in the checkout line. The consumer's ranking of bundles of food and non-food was described above without reference to a particular shopping regime, which means that preferences over goods and shopping regimes are weakly separable. Here, this assumption is strengthened so that preferences may be described by a utility function U^* that is strongly separable between goods and shopping regimes:

$$(5.2) \quad U^*(F_1, X_1, F_2, X_2, D; \theta, \theta^*) = U(F_1, X_1, F_2, X_2; \theta) + \phi(\theta^*)D,$$

where ϕ reflects the additional inherent utility or disutility of shopping more frequently, rather than less frequently, and θ^* is a vector of characteristics that affect preferences over shopping regime.[2]

Although it is internally consistent to describe preferences over shopping regimes in this fashion, one could alternatively have defined the utility function over more fundamental underlying goods that affect shopping decisions, such as leisure and freedom from stigma. In empirical practice, that approach would not have gained much insight here. If one continues to make the same separability assumption and to consider only two shopping regimes, and one takes labor supply as preallocated, there would still be only two possible values for the final term in equation 5.2. If future data availability would permit separate measurement of the effects of leisure and stigma on shopping frequency or permit a model of the labor supply decision within an otherwise similar framework, it would be worthwhile to pursue the alternate approach. The

[2] This assumption of strong separability 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.

empirical work here, however, will be able to measure the effects of several independent variables on shopping frequency, but not to distinguish whether these variables act through their consequences for leisure or for stigma. In this case, therefore, the specification in equation 5.2 above is most concise and appropriate.

If grocery shopping with food stamps is sufficiently time-consuming and/or subject to enough unpleasant stigma, ϕ is a negative value indicating the disadvantages of shopping more frequently. To see the offsetting advantages of shopping more frequently, one must consider the budget constraint. The expense of food perishability is described using the concept of the "effective" price of food, or the cost per unit of food *consumed* rather than per unit of food *purchased*. For a household in regime 0 (where $D = 0$), if some proportion of food spoils in storage between period 1 and period 2, the effective price of a unit of food consumed in period 2 is higher. Or, if the same household in regime 0 chooses instead to buy some perishable foods in more expensive local stores later in the month (purchases that do not qualify as a "major" grocery shopping trip), then one can again say that the effective price of food in period 2 is higher. Because the model's substantive interest and the data used below both concern food intake rather than food expenditures, it turns out that it can afford to be agnostic about the precise source of the higher effective price, so long as this price is correctly defined in terms of food intake.

In contrast to infrequent shoppers, frequent shoppers are assumed to face an effective food price that is constant for the two periods. This restriction on food prices under regime 1 assumes that the first major grocery trip occurs early in the food stamp month and that at least one major grocery trip occurs enough later in the month to limit food spoilage problems. Two empirical observations from chapter three support these assumptions: 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 non-food, 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:

$$(5.3) \quad \underset{F_1,X_1,F_2,X_2,D}{Max} \quad U^*(F_1,X_1,F_2,X_2,D;\theta,\theta^*), \text{ s.t.}$$

$$(D0) \quad p_F F_1 + p_X X_1 + q_F F_2 + p_X X_2 = \overline{M} \text{ if } D = 0,$$

$$(D1) \quad p_F F_1 + p_X X_1 + p_F F_2 + p_X X_2 = \overline{M} \text{ if } D = 1,$$

where full income $\overline{M}$ includes monthly cash income plus food stamp benefits. Note that this model assumes that the consumer is inframarginal (not constrained by the legal restrictions on food stamps), which is reasonable for most U.S. food stamp recipients, who spend some of their own cash on food. The empirical work below necessarily allows food stamps and cash income to have distinct effects on food intake.[3]

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[3] One might describe a food demand model that is sufficiently simple to estimate and yet capable of fully explaining why inframarginal recipients treat coupons and cash differently as the "Holy Grail" of applied food stamp research.

5.3 Food Demand Functions Under the Two Regimes

Because the CSFII data are cross-sectional and they do not report prices, the empirical work below will focus mainly on "Engel" relationships, describing the impact of household resources on food intake. The price effects that are addressed concern the differences in the effective price for food in the second period under the two shopping regimes. Thus, although one could write the food demand functions that solve equation 5.3 as functions of all prices and income (and do so in appendix D), that would mean carrying around in the notation many prices that never change. It is more straightforward here to describe food demand in period *t* conditional on the two regimes as distinct functions of income, so the different effective food prices are absorbed into the notation for the functions themselves:

$$(5.4)\quad \begin{aligned} F_t &= F_t^0(\overline{M};\theta) && \text{if } D=0\text{, and} \\ F_t &= F_t^1(\overline{M};\theta) && \text{if } D=1. \end{aligned}$$

In all, there are four such conditional food intake functions, for the two time periods and two shopping regimes: $F_1^0(\overline{M};\theta)$, $F_2^0(\overline{M};\theta)$, $F_1^1(\overline{M};\theta)$, and $F_2^1(\overline{M};\theta)$.

If Giffen goods are ruled out, the negative own-price effect of a higher effective food price ($q_F > p_F$) implies that the second-period conditional food intake function is lower for regime 0 than for regime 1:

$$(5.5)\quad F_2^0(\overline{M};\theta) < F_2^1(\overline{M};\theta).$$

However, no such unambiguous statement can be made for the first period. The substitution effect of the higher price q_F would tend to raise the first-period conditional food intake function in regime 0, while the income effect would tend to lower this function, so:

$$(5.6)\quad F_1^0(\overline{M};\theta) \geq F_1^1(\overline{M};\theta) \qquad \text{or} \qquad F_1^0(\overline{M};\theta) < F_1^1(\overline{M};\theta),$$

depending on whether the substitution effect or the income effect is greater. Appendix D demonstrates the claim that this inequality can take either direction. It also discusses a reasonable special case where only the last inequality in equation 5.6 is true. Basically, under the commonly-made assumption that preferences are strongly separable between time periods and a plausible assumption about the price elasticity of food in the second period, the conditional food intake in the first period is lower for regime 0 than for regime 1. Neither of those assumptions is needed for the empirical work below, so the direction of the inequality in equation 5.6 is left as an empirical question.

5.4 Choice of Shopping Regime

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

$$(5.7)\quad V^0(\overline{M};\theta) = U(F_1^0(\overline{M};\theta), X_1^0(\overline{M};\theta), F_2^0(\overline{M};\theta), X_2^0(\overline{M};\theta);\theta), \qquad \text{and}$$
$$V^1(\overline{M};\theta) = U(F_1^1(\overline{M};\theta), X_1^1(\overline{M};\theta), F_2^1(\overline{M};\theta), X_2^1(\overline{M};\theta);\theta).$$

The consumer chooses to shop frequently if the difference in these indirect utilities is enough to compensate for the disutility of shopping more frequently:[4]

(5.8) $D(\overline{M};\theta,\theta^*)=1$ if $V^*(\overline{M};\theta,\theta^*)=V^1(\overline{M};\theta)-V^0(\overline{M};\theta)+\phi(\theta^*)\geq 0$, and $D(\overline{M};\theta,\theta^*)=0$ otherwise.

Once the shopping regime is determined, the model for unconditional food intake is:

$$(5.9)\quad F_t(\overline{M};\theta,\theta^*)=[1-D(\overline{M};\theta,\theta^*)]F_t^0(\overline{M};\theta)+[D(\overline{M};\theta,\theta^*)]F_t^1(\overline{M};\theta).$$

This model provides a starting point for considering food choices by food stamp recipients, when their monthly food consumption cycle is thought to stem from their unusual shopping behavior rather than just from impatience. This framework provides a basis for the econometric model discussed next.

5.5 Econometric Model

In this section, a switching regression model with endogenous switching is developed to capture the simultaneous food shopping and intake decisions in a manner consistent with the theoretical framework. This type of model was developed by Heckman (1976) and Lee (1978), and it was applied by Moffitt (1983) to a welfare application similar to this one. The model's main features are an equation that describes the choice of shopping regime and two equations for food intake conditional on each of the shopping regimes.

[4] If the consumer's level of ϕ is such that she actually prefers to shop frequently, all else equal, then she will necessarily choose regime 1.

As discussed above, the empirical model differs from the theoretical framework by allowing food stamps and cash income to have distinct effects on the conditional food intake equations. 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 inframarginal food stamp recipients and even after accounting for selection bias (Fraker 1990). Thus, the model here allows food stamps (S) and cash income (M) to appear separately in the conditional Engel functions.

Equations 5.7 and 5.8 show that the choice of shopping regime depends on all the stochastic and non-stochastic variables in the conditional food intake functions (including the variables in θ), and also on factors that affect the choice of shopping regime directly (the variables in $\theta*$). Thus, all variables in the model appear in the econometric equation for choice of regime. However, there may be some variables in $\theta*$ that do not appear in the conditional food intake functions in equation 5.4.

The stochastic elements of θ -- stochastic from the analyst's point of view – appear in the conditional food intake equations for the two shopping regimes as the additive disturbances ε^0 and ε^1. The corresponding disturbance in the equation that determines shopping regime, which is denoted ε^R, is a function of the stochastic elements of both θ and $\theta*$, for the reasons given in the preceding paragraph. Thus, even if the stochastic elements of θ and $\theta*$ are statistically independent, the disturbance in the empirical regime choice equation (ε^R) may be correlated with the disturbances in our conditional food intake equations (ε^0 and ε^1).

The non-stochastic individual-specific geographic and demographic elements of θ, which appear in all equations, will be denoted Z^F. The non-stochastic elements of $\theta*$ that appear in the regime choice equation only are denoted Z^R.

With this notation, the empirical equations that correspond to the theoretical food intake functions in equation 5.4 may be written:

$$(5.10)\quad \begin{aligned} F_t &= \widetilde{F}_t^0(S,M,Z^F)+\varepsilon^0 && \text{if } D=0\text{, and} \\ F_t &= \widetilde{F}_t^1(S,M,Z^F)+\varepsilon^1 && \text{if } D=1. \end{aligned}$$

The empirical equation that corresponds to the theoretical regime choice specification in equation 5.8 may be written:

$$(5.11)\quad \begin{aligned} &D=1 \ \text{ if } \widetilde{V}(S,M,Z^F,Z^R)+\varepsilon^R \geq 0\text{, and} \\ &D=0 \ \text{ otherwise.} \end{aligned}$$

Finally, taking account of the fact that each independent variable and disturbance term may differ across individuals, the full econometric model for food intake in period t by individual i (F_{ti}) may be written:

$$(5.12)\quad F_{ti}=(1-D_i)[\widetilde{F}_t^0(S_i,M_i,Z_i^F)+\varepsilon_i^0]+(D_i)[\widetilde{F}_t^1(S_i,M_i,Z_i^F)+\varepsilon_i^1],$$

where

$D_i=1$ if $\widetilde{V}(S_i,M_i,Z_i^F,Z_i^R)+\varepsilon_i^R \geq 0$;

$D_i=0$ otherwise.

The equations in this system must be estimated simultaneously, because the error terms for the conditional food intake functions may be correlated with the error term for choice of regime. Intuitively, a household that chooses an idiosyncratically high food intake may also be more or less likely to choose to shop frequently.

An additional complication is that limited dependent variable models such as in equation 5.12 are known to yield inconsistent estimates in the presence of mispecifications of the error structure, such as heteroskedasticity. A lively and current field of research has developed around semi-nonparametric methods for relaxing the distributional assumptions required in these models. The model here, however, uses a parametric functional form for multiplicative heteroskedasticity:

$$(5.13)\quad \varepsilon_i^D = \varepsilon *_i^D \exp(\delta^{D\,\prime} W_i),$$

where $\varepsilon *_i^D$ is an "underlying" homoskedastic disturbance, W is a vector of variables that affect the standard deviation of ε_i^D, and δ^D is a vector of parameters to be estimated. The underlying variance-covariance structure may be written:

$$(5.14)\quad (\varepsilon *_i^0, \varepsilon *_i^1, \varepsilon_i^R) \sim N(0, \Sigma), \qquad \text{where}$$

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

5.6 Functional Form

For estimation, a parametric form for the conditional Engel functions should have several characteristics. First, it should permit food intake to be concave in food stamp benefits. Second, because the dependent variable is food intake rather than food expenditures, it should permit the Engel function to "flatten out" entirely at higher benefit levels. Third, because sample size is an issue and a powerful test is needed to pick up an important effect, the functional form should be frugal in its number of parameters. Some familiar functional forms failed by one or more of these standards. For example, a quadratic Engel function that is concave would misbehave at high benefit levels, where the function is decreasing.

The main results are reported in chapter six for two functional forms: an "inverse" form (I) and a "spline" form (II). With the inverse form (I), the conditional Engel function in period t and regime D may be written:

$$(5.15)\quad F_t^D = \beta_t^{0D} + \frac{\beta_t^{1D}}{(S-\alpha)} + \frac{\beta_t^{2D}}{(S-\alpha)^2} + \beta_t^{3D} M + \beta^{4D}{}' Z^F ,$$

where the β s are parameters to be estimated by maximum likelihood. The special parameter α is a horizontal shifter that is needed to avoid imposing the unattractive characteristic that food intake tends toward negative infinity as food stamp benefits tend toward zero. Except for this special parameter, the functional form is linear in the parameters, so for mechanical reasons it is convenient to use a grid search to estimate α. The β s are estimated conditional on each possible value of α, and the α that leads to the highest estimated log-likelihood value is selected. The statistical results in chapter six are reported conditional on this value of the parameter α being the true value.

With the spline form (II), the conditional Engel function in period t and regime D may be written:

$$(5.16)\quad F_t^D = \beta_t^{0D} + \beta_t^{1D} S + \beta_t^{2D} S^* + \beta_t^{3D} M + \beta^{4D}{}' Z^F ,$$

where S^* is a spline variable. The spline variable is calculated as follows:

$$(5.17)\quad S^* \quad = S - \mu \qquad \text{if } S - \mu > 0 ,$$

$S^* \quad = 0 \qquad\qquad$ otherwise,

where μ is the value of food stamp benefits at the "kink" or knot between two linear segments in the food intake function. Just as with the inverse form, this function is linear in the beta parameters, but not in μ, so it is convenient to use a grid search to select μ. The βs are estimated conditional on each possible value of μ, and the μ that leads to the highest estimated log-likelihood value is selected. The statistical results in chapter six are reported conditional on this value of the parameter μ being the true value.[5]

Both functional forms specify a simple linear effect for cash income. This assumption would be unattractive in many consumer demand applications. Here, however, our prior expectations, based on Fraker's (1990) literature review, are that for food stamp recipients the marginal effect of cash income on food spending is substantially smaller than the marginal effect of food stamp benefits. When the dependent variable is food intake instead of food spending, we expect the effect of cash income to be yet smaller. In this context, we were not confident in the potential for estimating a more complex form for the effect of cash income.

For both the inverse (I) and spline (II) forms, the specification for the switching equation is linear:

(5.18) $$V^* = \gamma^0 + \gamma^1 S + \gamma^2 M + \gamma^{3\prime} Z^F + \gamma^{4\prime} Z^R .$$

Although this equation will be estimated simultaneously with the conditional food intake equations by maximum likelihood, the parameters may be interpreted as in the probit model. Each parameter indicates the marginal change in the z-score for the

[5] Appendix C reports parallel results for two simpler functional forms, which do not have the special parameters estimated by grid search.

probability of being in regime 1, in response to a change in the corresponding independent variable.

While the true test of any choice of functional form is in empirical application, this section concludes with some comments *a priori* on the strengths and weaknesses of the two functional forms. The spline form has the advantage that it is a simple and easily-interpreted generalization of a linear functional form, and it takes the linear form as a special case. One disadvantage is that the estimated function has a kink or non-differentiable point at some value of food stamp benefits, while presumably there is not such a kink in the true economic relationship. The inverse form is more elegant in the sense that the estimated function has no kink.[6] Furthermore, with this form, the marginal effect of food stamp benefits on food intake necessarily approaches zero as food stamp benefit levels increase beyond a certain point. This pattern is reasonable if food energy intake (as opposed to food expenditure) tends to level off at high food stamp benefit levels. Both functional forms satisfy the three criteria identified at the start of this section. The two functional forms differ in the structure they impose on empirical estimates of the effect of food stamp benefits, so agreement between the main empirical patterns under both functional forms will increase confidence in the results.

This econometric model forms the basis for the following two chapters. Results and discussion of the endogenous switching regression estimation appear in chapter six. These results will be used in chapter seven in simulations that show the impact of changes in food stamp benefit levels and also policy changes that affect the propensity or incentive to conduct major grocery shopping trips more frequently.

[6] Professor Mount first suggested the inverse form, and pointed out that it satisfies our main criteria for choice of functional form while avoiding the "inelegance" of the kink in the spline form.

CHAPTER SIX

RESULTS AND DISCUSSION

6.1 Introduction

This chapter contains results and discussion for the econometric model described in chapter five. It presents the maximum likelihood parameter estimates and illustrates what these estimates reveal about the shopping frequency and food intake decisions under each of the two shopping regimes. Section 6.2 discusses the data and the independent variables. Section 6.3 considers results that concern the whole system of econometric equations. Section 6.4 considers the regime choice equation, which determines the probability of being a frequent shopper. Section 6.5 presents key results concerning the effect of food stamps on food intake under the two shopping regimes. Section 6.6 contains a discussion and assessment of these results on food stamps and food intake. Finally, section 6.7 considers the effects of variables other than food stamps on food intake.

6.2 Data and Variables

The data utilized are drawn from the Continuing Survey of Food Intake by Individuals (CSFII) for 1989-1991, which was described in chapter three. The household is the unit of analysis for the econometric estimation, because all income variables and many demographic variables are reported only at the household level. Addressing systematic patterns in intra-household allocation along with the food stamp cycle will have to await future research.

The information on food intake by individuals in the first four weeks of the food stamp month was combined by household, to create a data set with 638 household observations (table 6.1). Of these, 28 had missing data that rendered them unusable. Those households that had been excluded earlier, because it had been more than four weeks since they received food stamps, were scrutinized to ensure that they had not been unnecessarily deleted.[1] This effort led to re-coding of the dates dates of eight observations. Three households that were listed as current food stamp recipients had responses that, taken literally, indicated that it had been just over 365 days since food stamps were received. It was presumed that the year column of their food stamp date had been misreported by one year (or they could not have been "current" recipients), and their dates were adjusted accordingly. For five households that were listed as current food stamp recipients, the date of food stamp receipt appeared several days *after* the date to which food intake data referred, suggesting that the interviewer had some sort of follow-up contact with the household, during which the more recent date of food stamp receipt was reported. We re-coded these five observations so that the food intake observations appear at the appropriate place in the preceding food stamp month. Lastly, one observation was excluded due to an implausibly high caloric intake measurement. The final sample size is therefore 617 observations (see table 6.1).

[1] We considered taking as given that food stamps arrive on a regular cycle, so that an observation reporting for example 33 days since food stamps were "last received" could be relabeled as day two or three of the subsequent food stamp month. However, we were too concerned that the household might actually be late in receiving food stamps, or be in the process of leaving the program.

Table 6.1. Missing Observations and Adjustments to Data

Individuals in First Four Weeks of Food Stamp Month (see chapter three):		1516
Households with Individuals in First Four Weeks of Food Stamp Month, For Which: HH Mean Food Intake and Food Stamp Benefits Could be Calculated:		638
Households Deleted Due to Missing Data on Income Variables or Distance to Store:		28
Previously Excluded Housholds That Could Be Included if Date of Most Recent Receipt Is Adjusted by One Year:	*	3
Previously Excluded Households That Could Be Included if Small Negative Values of "NUMDAYS" Are Changed to the Appropriate Day in the Preceding Food Stamp Month:	*	5
Households Deleted Due to Implausibly Large Reported Food Intake		1
Final Sample Size for Econometric Estimation:		617

*These inclusions are explained on page 92.

The main dependent variable is each household's food energy intake as a percentage of the appropriate food energy RDA.[2] The binary variable indicating frequent shopping is also a dependent variable. For the independent variables, each income and benefit variable is measured per adult male equivalent (AME) in the household. The vector Z^F (variables affecting choice of regime and conditional food intake) includes household size (in AME) and binary variables for cash welfare receipt, female headship, receipt of WIC food, urban residence, and residence in the Southern states. Some candidates for inclusion in Z^R (variables affecting choice of shopping regime but not conditional food intake) could not be excluded from Z^F with certainty, but the one important variable that qualifies for inclusion in Z^R is distance from home to the store where major grocery shopping occurs.

The variables in the heteroskedasticity vector W are household size (in AME) and food stamp benefits. Household size is included here, because the main dependent variable is a household mean, which therefore may be measured more precisely as household size increases. Food stamp benefits are included here, because discretionary tastes for food may be more variable than basic needs for food, so households with more food resources may have a higher standard error in the conditional food intake equations.[3]

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[2] The sum of all household members' food energy intake is divided by the sum of all members' reference food energy levels in the RDA, where each member's reference food energy level is based on that member's age, sex, and pregnancy/lactating status.
[3] One committee member has observed that another natural variable for inclusion in this vector is cash income per AME. Cash income had originally been excluded out of concern that the data would not permit reliable estimation of the distinct effects of food stamps and cash income on the standard deviation of the error terms. The model was re-estimated with the cash income variable. Just as with food stamp benefits in the results below, the parameter on cash income is not statistically significant at the 0.10 level under either shopping regime or either functional form.

In light of Devaney and Fraker's cautionary findings regarding the fragility of econometric estimation with sample weights, the CSFII sample weights are not used in the econometric analysis. The demographic variables should capture the same effects that are treated by the sample weights in our descriptive results in chapter three. We would have liked to include a more complete array of geographic and demographic independent variables, but were prevented by concerns over multicolinearity and the modest sample size. Variable names and mean values appear in table 6.2.

6.3 Econometric Results for the System of Equations

This section describes econometric results for the system of econometric equations as a whole. It contains tables for the maximum likelihood parameter estimates under the two final functional forms. It then discusses goodness-of-fit measures and, finally, the estimated parameters that describe the joint distribution of the error terms. The most important economic results, from the regime choice and food intake equations, are treated in greater detail in the following two sections.

Maximum Likelihood Parameter Estimates

The model is estimated by maximum likelihood using routines written for GAUSS (Aptech Systems 1996a) and its MAXLIK add-on package (Aptech Systems 1996b). The log-likelihood function and the corresponding gradients for the econometric model in chapter five are derived in appendix A. The computer code is included and documented in appendix B.[4] Starting values were generated with a Heckman-Lee

[4] The code was tested using simulated data generated from known parameters, to confirm that that it works correctly. For a simpler homoskedastic case, these tests were compared to those generated by the "mover/stayer" endogenous switching regression procedure in LIMDEP (Greene 1995). Appendix A discusses this comparison.

Table 6.2. Mean Values and Definitions for Regression Variables

Name	Notation in Eq. (5.15)-(5.18)	Definition	Mean
Dependent:			
Food Intake		Mean HH Caloric Intake as Pct. of RDA	73.940
D		Dum: Frequent Major Grocery Trips	0.579
Independent:			
STAMPS		Monthly Benefits per AME in $100s	0.970
CASHINC		Monthly Cash Income per AME in $100s	4.550
AMETOT	*beta4[1]*	HH Size in Adult Male Equivalents (AME)	1.807
WELF	*beta4[2]*	Dum: AFDC Receipt	0.509
FHEAD	*beta4[3]*	Dum: Unmarried Female Head	0.648
WICFOOD	*beta4[4]*	Dum: WIC Receipt	0.207
URBAN	*beta4[5]*	Dum: Urban Residence	0.462
SOUTGEO	*beta4[6]*	Dum: Southern U.S. States	0.444
DIST	*gamma5[1]*	Distance to Grocery Store in Miles	4.046
Special:			
INTCEPT1	*beta01*	Dum: First Half of the Month	0.506
INTCEPT2	*beta02*	Dum: Second Half of the Month	0.494
STAMPS1	*beta11 (5.16)*	Interaction: INTCEPT1 with STAMPS	0.472
STAMPS2	*beta12 (5.16)*	Interaction: INTCEPT2 with STAMPS	0.498
SPLINE1	*beta21 (5.16)*	Interaction: INTCEPT1 with Spline*	0.152
SPLINE2	*beta22 (5.16)*	Interaction: INTCEPT2 with Spline*	0.179
INST1	*beta11 (5.15)*	Interaction: INTCEPT1 with (1/STAMPS)	0.422
INST2	*beta12 (5.15)*	Interaction: INTCEPT2 with (1/STAMPS)	0.402
INSTSQ1	*beta21 (5.15)*	INST1 Squared	0.411
INSTSQ2	*beta22 (5.15)*	INST2 Squared	0.383
CASH1	*beta31*	Interaction: INTCEPT1 with CASHINC	2.200
CASH2	*beta32*	Interaction: INTCEPT2 with CASHINC	2.348

The spline variable S is defined in equation (5.17).

two-step consistent estimator, using GAUSS routines that are also included in appendix B. For the final maximum likelihood estimation under heteroskedasticity, the log-likelihood function was maximized using an iterative Newton algorithm. For both functional forms, the maximization program converged smoothly in six iterations.

For the inverse functional form (I), an initial grid search over intervals of 0.05 determined the maximum likelihood value for the special parameter α, which is essentially a horizontal shifter, to be 0.50. For the spline functional form (II), a similar grid search over intervals of 0.05 determined the maximum likelihood value for the special parameter μ, which represents the amount of food stamps at the "kink" (in $100s per AME), to be 0.50. These parameters have different meanings in the two functional forms, and it is coincidence that the grid searches generate the same values.[5]

The maximum likelihood estimates for the remaining parameters are given for the inverse form (I) in table 6.3 and for the spline form (II) in table 6.4. In each table, the top section describes the food intake functions under each of the two regimes 0 and 1 (infrequent and frequent shopping, respectively). The middle section contains the estimated parameters that determine the probability of being a frequent shopper. The bottom section contains the estimated parameters that describe the joint distribution of the error terms for the three equations.

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[5] Appendix C reports results for two alternate functional forms where reasonable values for the special parameters are simply chosen *a priori*. These alternate forms are of course inferior on grounds of goodness-of-fit, but they avoid the issue of reporting the remaining maximum likelihood values conditional on the initial grid search.

Table 6.3. Endogenous Switching Regression Model with Form I (Inverse)

Food Intake Functions:		Regime 0 Estimates	Regime 0 Std. err.	Regime 1 Estimates	Regime 1 Std. err.
INTCEPT1	*beta01*	43.078	24.561	75.177	11.483
INTCEPT2	*beta02*	58.688	21.233	56.925	11.484
INVERSE1	*beta11*	65.510 **	38.830	-3.187	22.963
INVERSE2	*beta12*	16.192	32.300	45.406 **	22.304
INV-SQUARE1	*beta21*	-39.582 **	20.029	4.789	11.419
INV-SQUARE2	*beta22*	-12.713	16.607	-25.722 **	11.556
CASH1	*beta31*	0.168	0.967	-0.033	0.427
CASH2	*beta32*	0.237	0.303	0.279	0.610
AMETOT	*beta4[1]*	2.815 **	1.524	0.168	1.276
WELF	*beta4[2]*	-0.485	4.115	4.286 *	2.965
FHEAD	*beta4[3]*	0.956	3.723	1.019	2.761
WICFOOD	*beta4[4]*	7.134 **	3.553	5.296 **	3.077
URBAN	*beta4[5]*	-0.414	2.955	-4.853 **	2.461
SOUTGEO	*beta4[6]*	0.416	3.603	-2.851	2.811

Switching Function:		Estimates	Std. err.
INTCEPT	*gamma0*	0.770	0.213
STAMPS	*gamma1*	-0.008	0.072
CASHINC	*gamma3*	0.000	0.012
AMETOT	*gamma4[1]*	0.008	0.058
WELF	*gamma4[2]*	-0.270 **	0.124
FHEAD	*gamma4[3]*	-0.218 **	0.119
WICFOOD	*gamma4[4]*	-0.094	0.134
URBAN	*gamma4[5]*	-0.148 *	0.109
SOUTGEO	*gamma4[6]*	-0.281 **	0.110
DIST	*gamma5[1]*	-0.021 **	0.008

Distributional Parameters:		Estimates	Std. err.
std. dev. 0	*sig0*	26.463	3.023
std. dev. 1	*sig1*	24.655	2.392
cov. (0,R)	*sig0R*	-1.991	12.319
cov. (1,R)	*sig1R*	-3.844	6.956
AMETOT-R0	*delta0[1]*	-0.112 **	0.042
STAMPS-R0	*delta0[2]*	0.042	0.053
AMETOT-R1	*delta1[1]*	-0.067 **	0.035
STAMPS-R1	*delta1[2]*	-0.003	0.048

* Indicates significant at alpha=.10, one-tailed test. ** Indicates significant at alpha=.05.
Estimation is contitional on special parameter alpha=0.5.

Table 6.4. Endogenous Switching Regression Model with Form II (Spline)

Food Intake Functions:		Regime 0 Estimates	Regime 0 Std. err.	Regime 1 Estimates	Regime 1 Std. err.
INTCEPT1	*beta01*	41.449	19.717	84.955	7.951
INTCEPT2	*beta02*	52.372	20.068	60.329	9.606
STAMPS1	*beta11*	55.784 **	23.147	-19.063	15.007
STAMPS2	*beta12*	16.711	22.717	33.583 **	16.621
SPLINE1	*beta21*	-59.019 **	24.989	18.433	16.424
SPLINE2	*beta22*	-14.201	23.946	-36.943 **	17.590
CASH1	*beta31*	0.253	1.012	-0.024	0.426
CASH2	*beta32*	0.237	0.303	0.319	0.613
AMETOT	*beta4[1]*	3.340 **	1.511	0.274	1.263
WELF	*beta4[2]*	-0.977	4.081	4.218 *	2.972
FHEAD	*beta4[3]*	1.153	3.800	0.914	2.771
WICFOOD	*beta4[4]*	6.913 **	3.555	5.285 **	3.076
URBAN	*beta4[5]*	-0.373	2.968	-5.026 **	2.459
SOUTGEO	*beta4[6]*	0.262	3.653	-3.043	2.824

Switching Function:		Estimates	Std. err.
INTCEPT	*gamma0*	0.772	0.212
STAMPS	*gamma1*	-0.010	0.071
CASHINC	*gamma3*	0.000	0.012
AMETOT	*gamma4[1]*	0.008	0.057
WELF	*gamma4[2]*	-0.269 **	0.124
FHEAD	*gamma4[3]*	-0.218 **	0.119
WICFOOD	*gamma4[4]*	-0.094	0.134
URBAN	*gamma4[5]*	-0.148 *	0.109
SOUTGEO	*gamma4[6]*	-0.280 **	0.110
DIST	*gamma5[1]*	-0.020 **	0.008

Distributional Parameters:		Estimates	Std. err.
std. dev. 0	*sig0*	27.006	3.209
std. dev. 1	*sig1*	24.486	2.395
cov. (0,R)	*sig0R*	-2.229	13.043
cov. (1,R)	*sig1R*	-3.412	7.274
AMETOT-R0	*delta0[1]*	-0.112 **	0.042
STAMPS-R0	*delta0[2]*	0.022	0.057
AMETOT-R1	*delta1[1]*	-0.067 **	0.035
STAMPS-R1	*delta1[2]*	0.003	0.050

* Indicates significant at alpha=.10, one-tailed test. ** Indicates significant at alpha=.05.
Estimation is conditional on special parameter mu=0.5.

Goodness-of-Fit

In non-linear maximum likelihood estimation, there is no single goodness-of-fit measure for comparing the two functional forms, equivalent to the *R*-square in ordinary least squares. Veall and Zimmermann (1994; 1996) observe that different "pseudo *R*-square" measures serve different purposes that are all handled by *R*-square alone in OLS. These purposes include: 1) measuring "significance-of-fit" or the probability that the true slopes are flat, 2) measuring "explained variation" or the proportion of the variation in the dependent variable that is explained by the model, and 3) measuring correlation between the dependent variable and the set of independent variables.

Veall and Zimmermann's preferred pseudo *R*-square measure, due to McKelvey and Zavoina, falls into the "explained variation" class, while the more popular McFadden pseudo *R*-square measure falls into the "significance-of-fit" class. Veall and Zimmermann argue that the McFadden measure is only appropriate for discrete choice models, not for mixed models with discrete and continuous variables. They also argue that the McKelvey and Zavoina measure does the best job of estimating the most intuitive goodness-of-fit concept for limited dependent variable models: the *R*-square statistic that would have been estimated if the dependent variable were not censored. The McKelvey and Zavoina pseudo *R*-square statistic for a particular estimated equation may be calculated:

$$(6.1) \quad R^2_{MZ} = \frac{\sum_i (\hat{F}_i - \overline{F}*)^2}{\sum_i (\hat{F}_i - \overline{F}*)^2 + N\hat{\sigma}_i^2},$$

where N is the number of observations, $\hat{F}_i$ is the predicted dependent variable, $\overline{F}* = (1/N)\sum_i \hat{F}_i$, and $\hat{\sigma}_i$ is the estimated standard deviation for a particular observation.

Here, the functional forms are compared using the log-likelihood values, a simple Wald chi-square statistic for significance-of-fit, and the McKelvey and Zavoina pseudo R-square measure (table 6.5). The first two columns of table 6.5 contain the goodness-of-fit measures for the final inverse (I) and spline (II) functional forms. The third and fourth columns contain comparison measures for two alternate functional forms discussed in appendix C, which avoid the use of an initial grid search.

The estimated log-likelihood values in the first row of table 6.5 have no easy interpretation on their own, but they serve to compare the different functional forms, which have the same number of parameters. Because the signs are negative, a smaller absolute value for the log-likelihood values in the final inverse and spline functional forms indicates better "fit" than we find for the alternate functional forms.

In the middle section of the table, the Wald test for significance-of-fit in the food intake functions corresponds in purpose to the F-test reported for OLS in standard statistical packages. The null hypothesis that the slope parameters in the food intake functions are jointly equal to zero is rejected for all four functional forms. The Wald statistic for this test is higher for the two final functional forms, and lower for the two alternate forms.

At the bottom of the table, the McKelvey-Zavoina "explained variation" measure is intended to approximate the R-square that would be estimated for each equation if the underlying latent variables were in fact observed and the equation were estimated by

Table 6.5. Log-likelihood Values and Goodness-of-fit Measures

	Functional Form			
	Final Inverse (I)	Final Spline (II)	Alternate Inverse	Alternate Spline
Log-likelihood Value:	-5.1689	-5.1691	-5.1701	-5.1724
Wald Test -- All Food Intake Slopes=0:				
Chi-Squared Statistic	45.450	44.891	43.913	40.367
Degrees of Freedom	24.000	24.000	24.000	24.000
p-Value	0.005	0.006	0.008	0.020
McKelvey-Zavoina Pseudo R-Square:				
Regime 0	0.099	0.090	0.101 *	0.070
Regime 1	0.059	0.061	0.050	0.059
Switching Equation	0.062	0.062	0.062	0.062

Results for the two final forms appear in tables 6.3 and 6.4, respectively. Results for the two alternate forms appear in appendix C in tables C.1 and C.2, respectively.

* For the alternate inverse functional form, the model generated negative predicted food intake values for five observations (from regime 0). These observations were dropped in calculating the pseudo R-square measure, so this calculation is not directly comparable to the others.

least squares. For the three equations in each of the final forms, these pseudo *R*-square measures ranged from 0.059 to 0.099. These values are quite low but not atypical for limited dependent variable models with cross-sectional survey data.

By all three criteria, the two final functional forms "fit" as well as or better than the two alternate functional forms. The difference in goodness-of-fit between the two final functional forms is very small. The fact that these functional forms are estimated conditionally on the special parameters, chosen by grid search, precludes testing this difference with a non-nested hypothesis test such as the *J*-test. However, it seems unlikely that such a test would select one of the two final functional forms as significantly superior to the other, because they are so closely equal on statistical grounds.

Distributional Parameters

The estimates for the distributional parameters appear in the bottom sections of tables 6.3 and 6.4. These are very similar for the two functional forms. The estimated "underlying" standard deviations for food intake in the two regimes (std. dev. 0 and std. dev. 1) must be adjusted using the heteroskedasticity parameters to calculate the estimated standard deviations for a given observation. The mean estimated standard deviations appear in table 6.6. These large estimates, like the pseudo *R*-square measures above, indicate that a large amount of heterogeneity in the food intake variables remains unexplained by the model.

The cross-equation covariances are small relative to these standard deviations, and they are not significantly different from zero. This means that the main estimates would not have been far different if the food intake functions had been estimated separately for the two shopping regimes. Note, however, that this does not mean that

Table 6.6. Mean Standard Deviations For Each Shopping Regime, With Parameter Estimates from Both Functional Forms

I. Inverse Functional Form

Regime 0 (Infrequent Shoppers)		*Regime 1 (Frequent Shoppers)*	
Underlying Homoskedastic Std. Dev.	Actual Mean Std. Dev.	Underlying Homoskedastic Std. Dev.	Actual Mean Std. Dev.
26.463	22.725	24.655	21.838

II. Spline Functional Form

Regime 0 (Infrequent Shoppers)		*Regime 1 (Frequent Shoppers)*	
Underlying Homoskedastic Std. Dev.	Actual Mean Std. Dev.	Underlying Homoskedastic Std. Dev.	Actual Mean Std. Dev.
27.006	22.741	24.486	21.808

shopping regime is unimportant. There are substantial differences in the effect of food stamps in the food intake functions for the two shopping regimes (indicated in the top sections of tables 6.3 and 6.4). Estimating the two regimes separately might have been innocuous, but estimating the two regimes jointly with corresponding parameters restricted to be equal would have been a serious misspecification. Also, one could not have known the cross-equation covariances would be small without estimating the full endogenous switching regression model.

The final four estimated parameters in tables 6.3 and 6.4 are the heteroskedasticity parameters, indicating the effect of household size and benefit levels on the standard deviation of error terms for the food intake functions under the two shopping regimes. The food stamp benefit level does not significantly affect the standard deviation of the disturbance under either regime, as hypothesized. Increased household size does significantly reduce the standard error under both regimes. The latter results are sensible, because the dependent variable is a household mean that may be more precise if the household size is larger. Because ignoring heteroskedasticity induces bias as well as inefficiency in limited dependent variable models, it proved important to account for heteroskedasticity with respect to household size.

6.4 Choice of Shopping Regime

This section reports results for independent variables that affect the probability of shopping frequently. The parameter estimates for the switching function appear in the middle sections of tables 6.3 and 6.4. They are almost identical for the two functional forms, because both forms have the same specification for the choice of shopping regime. Cash welfare receipt, female headship, urban residence, residence in the U.S. South, and increased distance to "major" grocery store (in miles) significantly reduce the probability of being in regime 1 (major grocery shopping trips more than once monthly). For both functional forms, the signs on food stamp benefits and household size in AME are sensible, but these parameter estimates are not significantly different from zero. The effect of cash income on the probability of being a frequent shopper was estimated to be almost precisely zero.

These parameter estimates indicate the marginal effects of a change in each independent variable on the z-score for the probability of being a frequent shopper. However, a given change in the z-score may imply different changes in actual probabilities, depending on the initial value for the z-score. To perceive the economic meaning of these estimates, it helps to restate them in a manner that shows directly how the independent variables affect the probability of being a frequent shopper.

Table 6.7 contains the actual mean values for the independent variables in the switching equation, and also "low" and "high" values for comparison. For the continuous variables, for example, the low comparison food stamp value is 0.5 units ($50 per AME) below the actual mean, and the high value is 0.5 units above the actual mean. The low comparison cash income value is one unit ($100 per AME) below the actual mean, and the high value is one unit above. For the discrete or dummy variables, the low value is zero and the high value is one.

Fifty-eight percent of the food stamp households are frequent shoppers. The probability of being a frequent shopper is adjusted from this starting point using the parameters from the switching equation and the difference between the actual mean value of the independent variable and the low or high comparison values. Then, the new comparison probability of being a frequent shopper is reported. This calculation,

Table 6.7. Illustration of the Parameters in the Regime Choice Equation, in Terms of the Probability of Shopping Frequently

Regime 1 Households (Frequent Shoppers)
as a Propcrtion of All Households: **57.9%**

Independent Variable	Mean Value	"Low" Comparison Value	Probability of Choosing Regime 1	"High" Comparison Value	Probability of Choosing Regime 1
STAMPS	0.970	0.470	58.0%	1.470	57.7%
CASHINC	4.550	3.550	57.8%	5.550	57.9%
AMETOT	1.807	0.807	57.5%	2.807	58.2%
WELF	0.509	0	63.1%	1	52.6%
FHEAD	0.648	0	63.3%	1	54.8%
WICFOOD	0.207	0	58.6%	1	54.9%
URBAN	0.462	0	60.5%	1	54.7%
SOUTGEO	0.444	0	62.7%	1	51.7%
DIST	4.046	2.046	59.5%	6.046	56.3%

For STAMPS, the low value is 0.5 units below the actual mean, and the high value is 0.5 units above. For CASHINC and AMETOT, the low value is one unit below the actual mean, and the highvalue is one unit above. For DIST, the low value is two units below the actual mean, and the high value is two units above. For all other variables, the low value is zero and the high value is one.

though simpler than the simulations using the full sample in the next chapter, serves to illustrate what the switching parameter estimates mean in terms of actual probabilities.

For food stamp benefits per AME, cash income per AME, and household size in AME, table 6.7 indicates the probability of choosing regime 1 is almost unchanged from 58 percent in the low and high scenarios. The small effect of changes in food stamp benefit levels deserves some further comment. Food stamp participants are far less likely even than low-income nonparticipants to be frequent shoppers, as chapter three describes. The small effect here means just that, in a sample of food stamp recipients only, increases in the benefit level lead to insignificant further reductions in the probability of shopping frequently, beyond the initial effect of being a program participant. Overall, participation in the Food Stamp Program may still have a large effect on shopping frequency.

The binary variables for cash welfare receipt, female headship, urban residence, and residence in the U.S. South have more substantial marginal effects on shopping frequency. The probability of being a frequent shopper is 6 to 11 percentage points lower for people in each of these categories, compared with those who are not. Distance to major grocery store in miles, though statistically significant, does not have as large an effect in practical terms. A household whose store is two miles closer than the mean distance is only about three percentage points more likely to shop frequently than a household whose store is two miles further than the mean distance.

These effects of each variable individually may understate what the model has to say about the shopping frequency decision. Consider a combined effect of the three most influential dummy variables in the calculations above. Using the same calculation method as in table 6.7, a household without cash welfare, with two household heads, and living outside the U.S. South would have a 73 percent probability of shopping frequently. By contrast, a household with cash welfare, a female head only, living in the U.S. South would have a 43 percent probability of shopping frequently.

6.5 The Effect of Food Stamps on Food Intake: Results

Key results in this dissertation describe the effect of food stamp benefits on food intake in the two time periods and two shopping regimes. This section begins with two technical matters: 1) how to calculate expected food intake values to use in a graphical illustration of the main food stamp effects, and 2) whether the main results are statistically significant in three different ways. The remainder of this section discusses at greater length two figures that describe the main effects of food stamp benefits.

Expected Food Intake Values

The effect of food stamp benefits on food intake in the two time periods is described by the first six parameters for each shopping regime in the top section of tables 6.3 and 6.4. These parameters have a different meaning under the two functional forms, so they are not directly comparable in the two tables. Instead, the effects of food stamp benefits are best explained graphically. This sub-section considers two methods of calculating expected food intake values, which will be used in generating such graphs. The first method uses the expected value of the latent food intake variables for each shopping regime, and the second method uses the expected value of actual food intake variables conditional on being in each shopping regime.

The expected value of the latent food intake variable is calculated directly from the parameter estimates for the food intake functions. For example, with the inverse functional form, the expected food intake in period *t* and shopping regime *0* for a shopper with mean values of the independent variables (denoted with bars) is:

$$(6.2) \quad E[F_t^0] = \hat{\beta}_t^{00} + \frac{\hat{\beta}_t^{10}}{(\bar{S}-\hat{\alpha})} + \frac{\hat{\beta}_t^{20}}{(\bar{S}-\hat{\alpha})^2} + \hat{\beta}_t^{30}\bar{M} + \hat{\beta}^{40}{}'\bar{Z}^F ,$$

where the $\hat{\alpha}$ and $\hat{\beta}s$ are estimated parameters.

By contrast, the expected value of actual food intake conditional on being shopping regime *0* may be written:

$$(6.3) \quad E(F_t \mid D=0) = \hat{\beta}_t^{00} + \frac{\hat{\beta}_t^{10}}{(\bar{S}-\hat{\alpha})} + \frac{\hat{\beta}_t^{20}}{(\bar{S}-\hat{\alpha})^2} + \hat{\beta}_t^{30}\bar{M} + \hat{\beta}^{40}{}'\bar{Z}^F - \hat{\sigma}_{0e}\frac{\phi(\hat{\gamma}'\bar{Z})}{1-\Phi(\hat{\gamma}'\bar{Z})},$$

where $\hat{\gamma}$ is the vector of parameter estimates in the switching equation and $\bar{Z}$ includes the variables in both $\bar{Z}^F$ and $\bar{Z}^R$. Equations 6.2 and 6.3 clearly differ only in the last term of equation 6.3. This term is an adjustment that takes account of the additional information from knowing that an individual has chosen shopping regime 0. If the cross-equation covariance $\hat{\sigma}_{0e}$ is nonzero, then knowing that the shopper has chosen regime 0 also generates information about the expected value of the error term on the food intake function, conditional on being in regime 0.

Either equation 6.2 or equation 6.3 may be preferred for generating expected values, depending on the application. As the preceding paragraph indicates, equation 6.3 is preferred if the analyst is interested in a set of people who have themselves chosen to be in a particular shopping regime, and the analyst wants to know the expected food intake for that set. By contrast, equation 6.2 would be preferred if the analyst is interested in predicting food intake for a set of people who will be assigned to a particular regime. Equation 6.2 may also be preferred for the purpose simply of describing the main estimated results, where it is clearly understood that this estimated latent food intake may differ from the expected value of food intake conditional on a particular shopping regime. A rough analogy to the better-known tobit model may help: equation 6.2 corresponds to the latent relationship described by the tobit parameter estimates, and equation 6.3 corresponds to the actual expected value of the dependent variable for non-limit observations. There are some purposes for which it is sensible to report the tobit parameters directly, so long as these are not confused with conditional effects (see Macdonald and Moffitt).

Figures 6.1 and 6.2 illustrate the meaning of the food stamp parameter estimates in the top section of tables 6.3 and 6.4, respectively. Each of the four curves in each figure describes the "Engel" relationship between food stamp benefits and the expected value of latent food intake (as in equation 6.2) for a particular time period and shopping regime, where the other independent variables are held constant at their mean values. To perceive changes in food intake over time, one compares the curve for the first half of the month (marked with squares) to the corresponding curve for the second half of the month (marked with circles), in a given shopping regime.

Wald Tests of Three Null Hypotheses

To test whether the main results in these figures are statistically significant, there are several hypotheses one might consider. This sub-section presents results for Wald tests of three types of null hypotheses. The first type inquires whether food stamp benefits have no marginal effect on food intake, under each time period and shopping regime. For the spline form only, the second type makes a similar inquiry separately for food stamp benefit levels below or above the kink in the food intake function. The

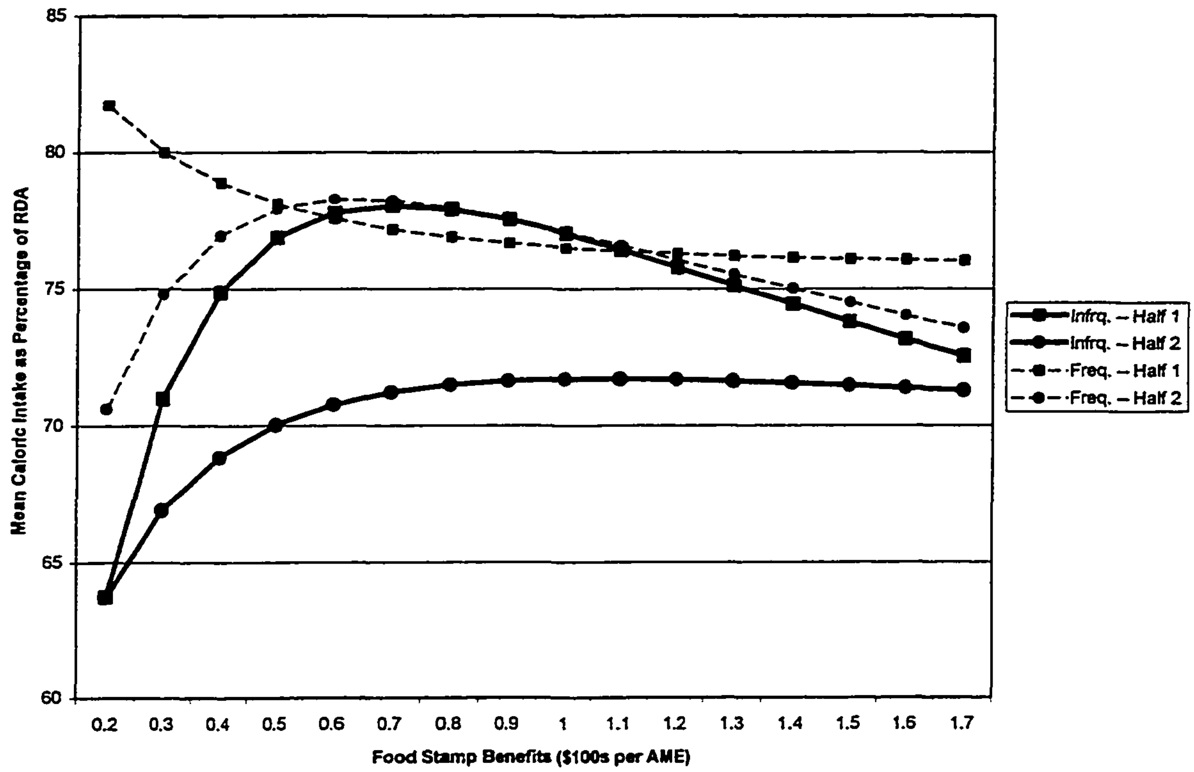

Figure 6.1. Expected Value of Latent Food Intake in Each Time Period and Shopping Regime, as a Function of Food Stamp Benefits, With the Inverse Functional Form

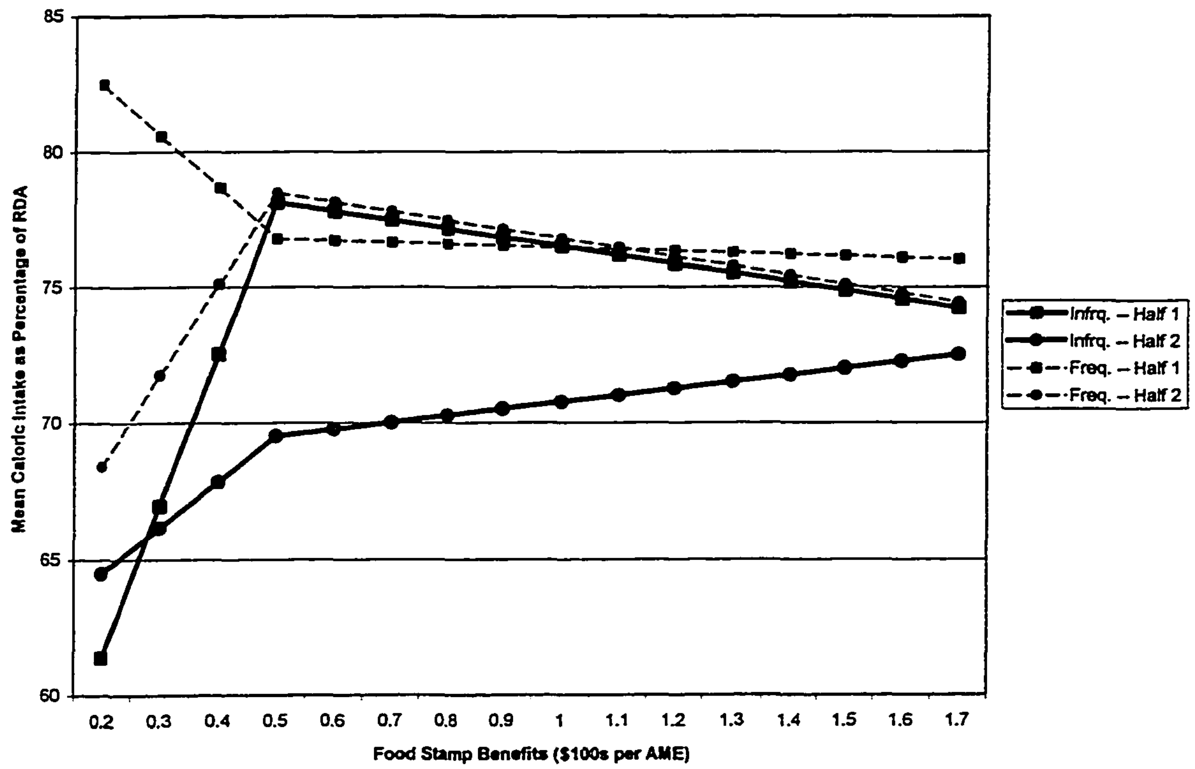

Figure 6.2. Expected Value of Latent Food Intake in Each Time Period and Shopping Regime, as a Function of Food Stamp Benefits, With the Spline Functional Form

third type asks whether there are no differences in the effects of food stamps between the two shopping regimes.

For the null hypothesis that food stamps have no marginal effect, table 6.8 reports Wald statistics for the food intake functions in each time period and shopping regime. Using a lenient significance level of $\alpha = 0.10$, the null hypothesis is rejected for two cases: infrequent shoppers in the first half of the month, and frequent shoppers in the second half of the month. The null hypothesis could not be rejected for the remaining two cases: infrequent shoppers in the second half of the month and frequent shoppers in the first half of the month.

For the spline functional form only, there is a natural break point in the food stamp variable for testing a similar null hypothesis separately for benefit levels below or above the kink in the food intake functions. Table 6.9 reports Wald statistics for each time period and shopping regime. These tests find that when benefit levels are below the kink, food stamps have a significant marginal effect on food intake for just the same two categories identified above: infrequent shoppers in the first half of the month, and frequent shoppers in the second half. When benefit levels are above the kink, food stamps no longer have a significant marginal effect on food intake in any time period or shopping regime.

The third type of Wald test indicates whether the effect of food stamp benefits is the same in the two shopping regimes (table 6.10). Here the null hypothesis is that the six parameters describing the food stamp effect in the two time periods are identical for the two shopping regimes. The p-values were 0.161 for the inverse functional form and 0.090 for the spline functional form. On purely statistical grounds, these Wald tests suggest but do not prove that the effect of food stamps is different under the two

Table 6.8. Wald Tests of Null Hypotheses that Food Stamps Have No Effect, For Each Time Period and Shopping Regime Separately

I. Inverse Functional Form

Description of Null Hypothesis	Parameter Restricitons*	Wald Chi-Square	*p*-Value
Food stamps have no marginal effect for:			
Infrequent Shoppers -- First Half	$\beta_1^{10} = \beta_1^{20} = 0$	5.652 *(2 d.f.)*	0.059
Infrequent Shoppers -- Second Half	$\beta_2^{10} = \beta_2^{20} = 0$	1.795 *(2 d.f.)*	0.408
Frequent Shoppers -- First Half	$\beta_1^{11} = \beta_1^{21} = 0$	1.932 *(2 d.f.)*	0.381
Frequent Shoppers -- Second Half	$\beta_2^{11} = \beta_2^{21} = 0$	5.271 *(2 d.f.)*	0.072

II. Spline Functional Form

Description of Null Hypothesis	Parameter Restricitons**	Wald Chi-Square	*p*-Value
Food stamps have no marginal effect for:			
Infrequent Shoppers -- First Half	$\beta_1^{10} = \beta_1^{20} = 0$	5.827 *(2 d.f.)*	0.054
Infrequent Shoppers -- Second Half	$\beta_2^{10} = \beta_2^{20} = 0$	1.527 *(2 d.f.)*	0.466
Frequent Shoppers -- First Half	$\beta_1^{11} = \beta_1^{21} = 0$	2.225 *(2 d.f.)*	0.329
Frequent Shoppers -- Second Half	$\beta_2^{11} = \beta_2^{21} = 0$	4.649 *(2 d.f.)*	0.098

* Parameter symbols are defined in equation 5.15. ** Parameter symbols are defined in equation 5.16.

Table 6.9. Wald Tests of Null Hypotheses that Food Stamps Have No Effect, In the First and Second Segments of the Spline Functional Form

II. Spline Functional Form			
Description of Null Hypothesis	Parameter Restricitons**	Wald Chi-Square	*p*-Value
First Segment			
Food stamp benefit levels less than $50 per AME ("to the left of the kink") have no marginal effect for:			
Infrequent Shoppers -- First Half	$\beta_1^{10} = 0$	5.808 *(1 d.f.)*	0.016
Infrequent Shoppers -- Second Half	$\beta_2^{10} = 0$	0.541 *(1 d.f.)*	0.462
Frequent Shoppers -- First Half	$\beta_1^{11} = 0$	1.614 *(1 d.f.)*	0.204
Frequent Shoppers -- Second Half	$\beta_2^{11} = 0$	4.082 *(1 d.f.)*	0.043
Second Segment			
Food stamp benefit levels greater than $50 per AME ("to the right of the kink") have no marginal effect for:			
Infrequent Shoppers -- First Half	$\beta_1^{10} + \beta_1^{20} = 0$	0.626 *(1 d.f.)*	0.429
Infrequent Shoppers -- Second Half	$\beta_2^{10} + \beta_2^{20} = 0$	0.538 *(1 d.f.)*	0.463
Frequent Shoppers -- First Half	$\beta_1^{11} + \beta_1^{21} = 0$	0.045 *(1 d.f.)*	0.833
Frequent Shoppers -- Second Half	$\beta_2^{11} + \beta_2^{21} = 0$	1.964 *(1 d.f.)*	0.161

** Parameter symbols are defined in equation 5.16.

Table 6.10. Wald Tests of Null Hypotheses that Food Intake Parameters are Identical For Both Shopping Regimes

I. Inverse Functional Form

Description of Null Hypothesis	Parameter Restrictions*	Wald Chi-Square	*p*-Value
The intercept and regression parameters describing the effect of food stamps on food intake are identical for the two shopping regimes.	$\beta_1^{00} = \beta_1^{01}$ $\beta_2^{00} = \beta_2^{01}$ $\beta_1^{10} = \beta_1^{11}$ $\beta_2^{10} = \beta_2^{11}$ $\beta_1^{20} = \beta_1^{21}$ $\beta_2^{20} = \beta_2^{21}$	9.240 *(6 d.f.)*	0.161

II. Spline Functional Form

Description of Null Hypothesis	Parameter Restrictions**	Wald Chi-Square	*p*-Value
The intercept and regression parameters describing the effect of food stamps on food intake are identical for the two shopping regimes.	$\beta_1^{00} = \beta_1^{01\prime}$ $\beta_2^{00} = \beta_2^{01\prime}$ $\beta_1^{10} = \beta_1^{11\prime}$ $\beta_2^{10} = \beta_2^{11\prime}$ $\beta_1^{20} = \beta_1^{21}$ $\beta_2^{20} = \beta_2^{21}$	10.945 *(6 d.f.)*	0.090

* Parameter symbols are defined in equation 5.15. ** Parameter symbols are defined in equation 5.16.

shopping regimes. However, these statistics test equally against all alternative hypotheses, while some alternatives are actually more plausible than others. The modest statistical evidence is reinforced by the plausible economic meaning of the differences between the two shopping regimes – in particular, that expected food intake is lowest for infrequent shoppers in the second half of the month. It appears likely that the differences between food intake patterns under the two regimes are not spurious, but rather they reflect real differences between frequent and infrequent shopping.

6.6 The Effect of Food Stamps on Food Intake: Discussion

Even though the two functional forms are quite different mathematically, figures 6.1 and 6.2 show that the two forms agree closely on the main food stamp effects. As expected from the theoretical framework in chapter five, food intake in the second half of the month is higher for frequent shoppers than for infrequent shoppers at every level of food stamp benefits. In the first half of the month, food intake is higher for frequent shoppers than for infrequent shoppers, except for a small region of the domain where food intake under the two regimes is almost precisely equal.

We organize our discussion of these figures into three sections: 1) the large region of the domain where benefit levels exceed $50 per AME and three of the four curves appear to reach some type of satiation level in food intake; 2) the distinct curve for infrequent shoppers in the second half of the month, who have a lower food intake level; and 3) the region where food stamp benefit levels are below $50 per AME and food intake patterns are more erratic but generally more strongly affected by marginal changes in food stamp benefits.

Satiation Food Intake

The literature review in chapter four discussed how previous research found small or even occasionally negative marginal effects of food stamp benefits on food intake, in contrast with the strong effects that have been found on food expenditure. Similarly, in figures 6.1 and 6.2, when food stamp benefits exceed $50 per AME, three of the four curves describe a relatively flat relationship between benefit levels and food intake, and at a relatively high level of food intake. These are the curves for frequent shoppers in both halves of the month and for infrequent shoppers in the first half of the month only.

The slight downward slope of the curves in this region, found in both functional forms, has several possible explanations. First, the actual relationship in this region may be flat, and the apparent moderate downward slope may be a product of sampling variation. The hypothesis tests in tables 6.8 and 6.9 above support this explanation. Second, the slight downward slope may be a correct estimate of the true relationship. However, it is difficult to explain why food stamp benefits beyond a certain point would actually depress food energy intake. Third, we mention the possibility that the estimation methods could attribute an effect of cash income in part to the food stamp benefit level. The concern here is that if higher benefit levels correspond closely to households with lower cash income levels, then an inadequately specified model could incorrectly attribute lower food intake to higher food stamp benefits, when the lower food intake should more reasonably be attributed to lower cash income. However, the discussion of policy simulations in the next chapter finds that the functional relationship between food stamp benefits and cash income is not as tight as one might think from a brief reading of the benefits formula in the program regulations. Instead, the food stamp and cash income variables have enough independent variation for their effects to be distinguished.

In sum, for these three of the four food intake curves under both functional forms, when food stamp benefits exceed approximately $50 per AME, food intake appears to reach a satiation level with food energy measured at about 75-78 percent of the RDA.[6] In this region, additional increases in food stamp benefits have little or no marginal effect on food energy intake.

Infrequent Shoppers in the Second Half of the Month

The effect of food stamps appears substantially different for infrequent shoppers in the second half of the month. This case is particularly interesting, given this dissertation's focus on the interaction between the shopping frequency decision and food intake in two halves of the food stamp month.

The moderate, but not steep, estimated upward slope of this curve is reasonable. Because food intake is lower for this case, one may expect that a household with additional food stamp resources would make it a priority to increase food intake here. Offsetting that effect, households that conduct a major shopping trip only once monthly may have difficulty converting additional food stamp resources at the start of the food stamp month effectively into additional caloric intake at the end of the month, due to food perishability and food storage difficulties. Indeed, the hypothesis tests in table 6.8 could not reject the null hypothesis that the marginal effect of food stamps is zero for infrequent shoppers in the second half of the month.

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[6] As noted in chapter three, this measure of food energy intake includes some underreporting. Our methodology requires the frequently-made assumption that the degree of underreporting does not vary with the level of food stamp benefits or other independent variables.

In figures 6.1 and 6.2, expected food energy intake for infrequent shoppers in the second half of the month ranges from 3 to 11 percent lower than the corresponding value for frequent shoppers. Under the theoretical framework in chapter five, this difference indicates that, for infrequent shoppers, the effective price of food[7] is higher in the second half of the month. This higher effective price influences household consumption decisions sufficiently to reduce food energy intake, which suggests substantial economic stress for these households in the second half of the month.

Very Low Food Stamp Benefit Levels

The patterns in food intake are more erratic where monthly food stamp benefit levels are less than $50 per AME. With both functional forms, the marginal effect of food stamps appears more steeply positive for three of the four curves at these benefit levels. Also, both functional forms find the strange negative slope for the fourth curve – frequent shoppers in the first half of the month.

As with the discussion above for benefit levels higher than $50 per AME, there is a natural test of the statistical significance of these findings for the spline functional form, due to the obvious break point at the kink (see table 6.9). The steep positive slopes for infrequent shoppers in the first half of the month and frequent shoppers in the second half of the month are statistically significant. The positive slope for infrequent shoppers in the second half of the month and the odd negative slope for frequent shoppers in the first half of the month are not statistically significant. Only 25 percent of the sample has benefits below $50 per AME, so these hypothesis tests less powerful than others discussed earlier.

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[7] The effective price of food, once again, is the price per unit actually consumed. It may be higher in the second period because some portion of the food spoils or because the household must make some smaller food purchases in more expensive stores.

In sum, for frequent shoppers in the second half of the month and infrequent shoppers in the first half of the month, the marginal effect of food stamp benefits on food intake is significantly positive when benefit levels are less than $50 per AME. For the remaining two cases, there may be different reasons why food stamp benefits have smaller marginal effects or none at all. Frequent shoppers in the first half of the month appear to reach the relatively high "satiation" level of food intake, as discussed above, even at very low benefit levels. For infrequent shoppers in the second half of the month, by contrast, the marginal effect of benefits on food intake in this region may be somewhat lowered because these recipients may not be able easily to convert additional food stamp benefits into additional food intake.

With the exception of frequent shoppers in the first half of the month, who appear more secure at a high level of food intake, it appears that very low food stamp benefit levels can lead to substantially lowered food energy intake levels. Both the low levels and steeper positive slopes for the remaining three food intake functions in this region may indicate that food shortages are being felt in these households.

6.7 The Effect of Other Variables on Food Intake

This final section considers the effect of variables other than food stamps on the food intake functions in the two time periods and two shopping regimes. These variables appear similarly under the inverse (I) and spline (II) functional forms, so it is not surprising that the corresponding parameter estimates are very similar in tables 6.3 and 6.4.

The effect of monthly cash income (measured in hundreds of dollars per adult male equivalent) on food intake in either time period or either shopping regime is not significantly different from zero. This result, which may seem surprising to economists, may in part be a product of our sample of food stamp recipients, whose cash income levels do not vary nearly as widely as those in the population at large. It may also reflect the observation that most recipients in the sample reach a "satiation" level of food energy intake, so additional cash income may be spent on some combination of non-food goods and food characteristics other than food energy content. In general, the marginal effect of monthly cash income on food intake is estimated to be at least as high or slightly higher in the second half of the month, compared with the first. This pattern makes sense if variation in cash income affects food intake more strongly during the period when food stamps are running out. Again, however, these differences were not statistically different, and the main result here is that the marginal effect of cash income is near zero.

Under both functional forms, 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 is measured on a per AME basis, the positive household size parameter may reasonably be interpreted as scale advantages for larger households in producing food intake.

The estimated parameter for cash welfare (AFDC) participation is insignificant and near zero under regime 0, and positive and weakly significant under regime 1. The parameter for urban residence is negative, and significantly so for regime 1 only. It is not clear why these effects should be stronger for frequent shoppers, or that this result has substantial economic implications.

Female headship and residence in the South generally have small and insignificant effects on food intake under either regime. This result is interesting, because these variables have strong effects on the shopping frequency decision, as discussed in section 6.4 above. Univariate comparisons in chapter three raised the possibility that female headship in particular is related to the monthly food stamp cycle, and one reason for pursuing the full multivariate model was to sort through this relationship. 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 intake functions for each regime directly. Given the choice of shopping regime, the food intake behavior of people in these categories is the same as that of other households. This result makes sense if female heads, for example, are too busy to shop or if they face additional transport costs and difficulties shopping with children, but their preferences about food are the same as those of other people.

By contrast, participation in the WIC program appears to affect food intake directly. For both functional forms, the WIC binary variable has a large, positive, and statistically significant parameter under both shopping regimes. The WIC program is targeted at particular foods that supply nutrients needed by women, infants, and children, and it also includes a stronger nutrition education component than most food programs. All else equal, WIC participation raises food energy intake relative to the RDA by about 7 percentage points of the RDA for infrequent shoppers, and by about 5 percentage points for frequent shoppers. None of the other demographic and geographic binary variables have as strong an effect on food intake as WIC does.

This chapter has reported the main effects of various independent variables on the probability of shopping frequently or infrequently. It then discussed how food stamp benefits affect food intake under each shopping regime. Finally, this section considered how variables other than food stamp benefits affect food intake. The parameter estimates reported in this chapter will be used in the next chapter in simulations that indicate the main policy implications.

CHAPTER SEVEN

POLICY SIMULATIONS

7.1 Introduction

This chapter contains simulations that show the implications of the empirical results in several ways. Section 7.2 focuses on the bottom line: the full impact of different food stamp benefit levels on food intake after all direct and indirect effects are taken into account. This section allows us more easily to compare results from our endogenous switching regression model with the previous literature. Section 7.3 considers the actual lever used in food stamp policy: the benefit formula that determines the food stamp allotment as a function of income, household size, and other factors. This section considers three methods for modifying the benefit formula, which may imply different effects on food intake even for policy alternatives that involve equal changes in the program budget. Finally, section 7.4 considers a type of program change that cannot easily be considered under more traditional models: changes in the incentive or propensity to shop frequently. We have in mind policy options such as the introduction of electronic benefit transfer (EBT) or the delivery of food stamp benefits twice monthly, either of which might encourage major grocery trips more than once per month.

7.2 The Overall Impact of Food Stamps on Food Intake

In the previous chapter, section 6.5 discusses at length the distinct effect of food stamps on the latent food intake variable under the two shopping regimes. The exposition there aimed to explain the empirical results from the food intake equations of the endogenous switching regression model. This section, by contrast, focuses on what may be for some policy purposes the bottom line: the overall impact of food stamp benefit levels on food intake after all direct and indirect effects are taken into account. This section considers the expected value of food intake at different food stamp benefit levels and uses the whole sample to calculate the mean elasticity of food intake in the two time periods with respect to food stamp benefits.

The analysis in this section differs from the previous chapter in two respects. First, rather than give illustrative results for a "typical" observation (with mean values for all independent variables other than food stamps), it calculates an expected food intake value for each observation and then reports the mean expected food intake for the full sample.[1] Second, rather than calculate an expected value for the latent food intake variable under each shopping regime, it calculates for each observation a weighted mean of expected food intake conditional on being in each shopping regime, where the conditional expectations are calculated as in equation 6.3 of the previous chapter and the weights are the probabilities of being in each regime. This calculation gives, for each observation, a single expected value for food intake in each time period.

First, consider the effects of different food stamp benefit levels. We suppose that a single food stamp benefit level may be assigned to all observations, but all other independent variables are distributed as they are in the real sample. This assignment of benefits is unrealistic in comparison to simulations using the actual benefit formula, discussed in the next section of this chapter, but it serves to illustrate the expected value of food intake in the two time periods at each level of food stamp benefits.

[1] For non-linear functions, of course, the expectation using the mean values of the independent variables will differ from the mean of the expectations calculated separately for each observation.

These expected values are reported in figure 7.1, based on parameter estimates from the final inverse functional form. This figure illustrates some of the features that were noted in the previous chapter: 1) expected food intake is moderately lower in the second half of the month, compared with the first half; 2) over most of the domain, the marginal effect of food stamp benefits on food intake is small; and 3) when food stamp benefit levels are very low, this marginal effect is larger. In contrast with the figures in the previous chapter, each curve in figure 7.1 is a weighted average of the expected food intake values conditional on being in each shopping regime, so the figure does not indicate distinct food intake patterns under the two regimes.

Second, consider the mean elasticity of food intake in the two time periods with respect to food stamp benefits, using the actual food stamp benefit level observed for each household. Conditional on being in regime 0 (for example), the elasticity of food intake with respect to food stamp benefits is calculated from the first derivative of the conditional expected food intake in equation 6.3:

$$(7.1)\quad \partial E[F_t \mid D=0]/\partial S = -\beta_t^{10}(S-\alpha)^{-2} - \beta_t^{20}(S-\alpha)^{-3} + \sigma_{0e}[-\gamma' Z\lambda^0(\gamma' Z) + (\lambda^0(\gamma' Z))^2]\gamma^1,$$

where $\lambda^0(\gamma' Z) = -\phi(\gamma' Z)/[1-\Phi(\gamma' Z)]$ and γ^1 once again is the element of the vector γ that corresponds to the food stamp benefit variable. Using this first derivative, the elasticity conditional on being in regime 0 may be written:

$$(7.2)\quad e_t^0 = \frac{\partial E[F_t \mid D=0]}{\partial S}\frac{S}{E[F_t \mid D=0]}.$$

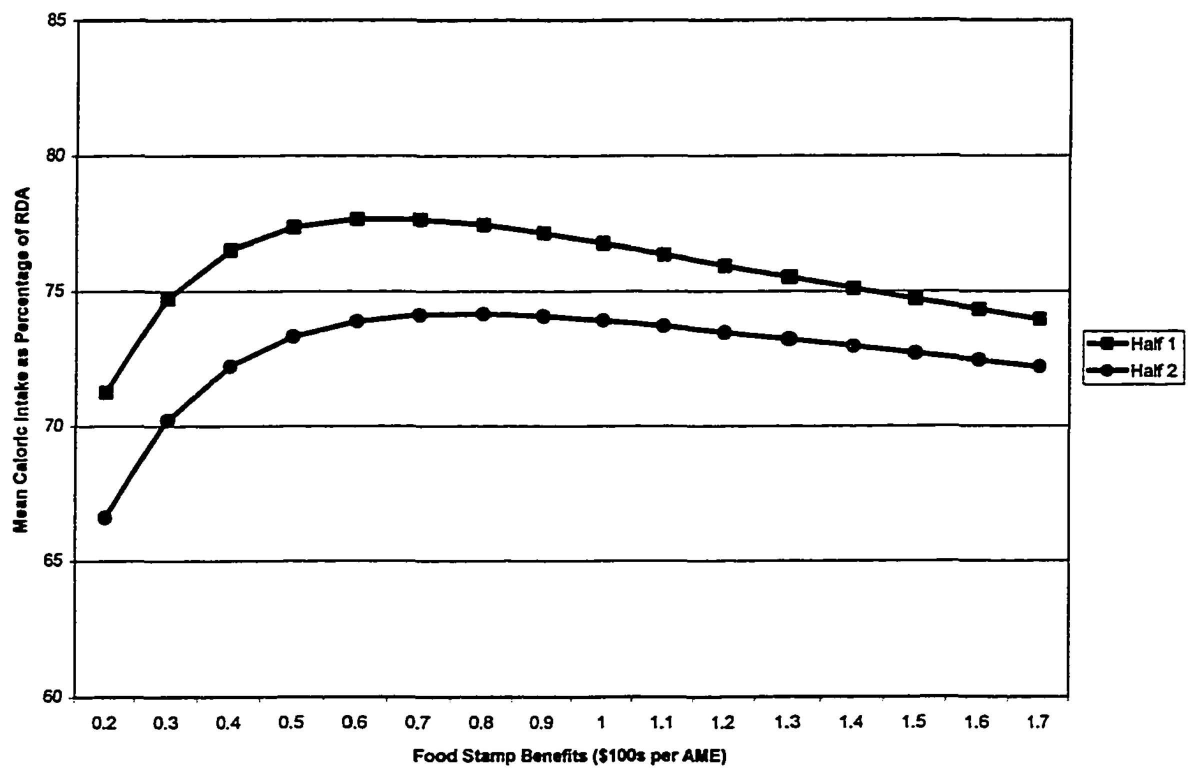


Figure 7.1. Mean Expected Food Intake in Two Halves of the Month as a Function of Food Stamp Benefits, From Computations Using the Full Sample

The unconditional elasticity will be the weighted mean of the conditional elasticities, where the weights are the probabilities of being in each regime:

(7.3) $e_t = P[D=0]e_t^0 + P[D=1]e_t^1$,

where e_t^1 is the elasticity conditional on being in regime 1.

The mean elasticities for the whole sample are reported in table 7.1. Perhaps anticlimactically, given the lengthy description of the calculations, the mean elasticity in each time period is near zero. In this sense, the average impact of additional food stamp benefits on food intake is small. This result agrees with the results from previous research, which has often found insignificant marginal effects of food stamp benefits on food intake (see section 4.5 of the literature review in chapter four).

These small elasticity values for the whole sample are also consistent with figure 7.1 above. Table 7.1 takes the mean elasticity over very disparate observations: for some, food stamp benefits are low and their marginal effect on food intake is positive; for others, food stamp benefits are higher and their marginal effect on food intake is small or even negative. It is not surprising, then, that the mean elasticity for the whole sample is near zero for each time period. These simple mean elasticities are helpful for explaining why previous research might have found small or insignificant marginal effects of food stamps on food intake, but they disguise the diverse patterns in food intake in different time periods, shopping regimes, and levels of food stamp benefits, which are given greater attention in this dissertation.

Table 7.1. Expected Value of Food Intake and the Mean Elasticity of Food Intake with Respect to Food Stamp Benefits, Using the Full Sample

	Time of Month	
	First Half	Second Half
Expected Value of Food Energy Intake, As a Percentage of the RDA:	75.36	72.29
Mean Elasticity of Food Intake With Respect To Monthly Food Stamp Benefits:	-0.0142	0.0096

7.3 The Benefit Formula

As noted above, policy-makers do not in fact assign a single amount of food stamp benefits per AME to all recipient households. The main policy instrument is the benefit formula, which determines the amount of food stamp benefits for which a household is eligible as a function of income, household size, and other factors. First, this section describes the benefit formula. Second, it lays out three possible policies for changing food stamp benefit levels and illustrates these three policies using a simplified version of the actual benefit formula. A simulation using the parameter estimates from chapter six shows that equal-sized program cuts may have different effects on food intake depending on which policy is employed to implement the cuts.

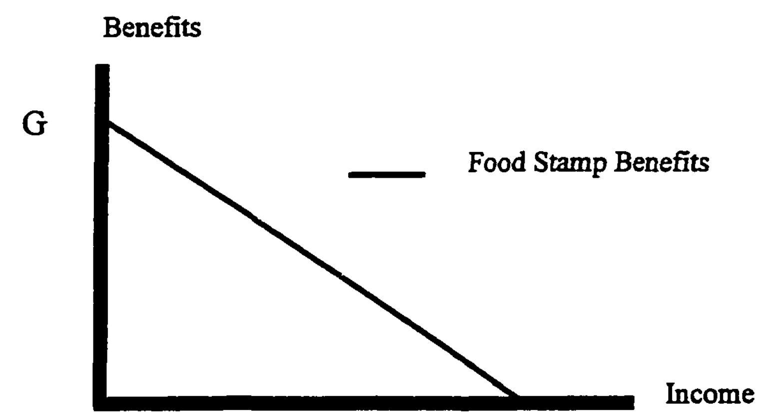
The Benefit Formula in Theory and Practice

The benefit formula is explained in detail in Ohls and Beebout. At it's heart, it contains a simple equation relating food stamp benefits (S) to net income (NY):

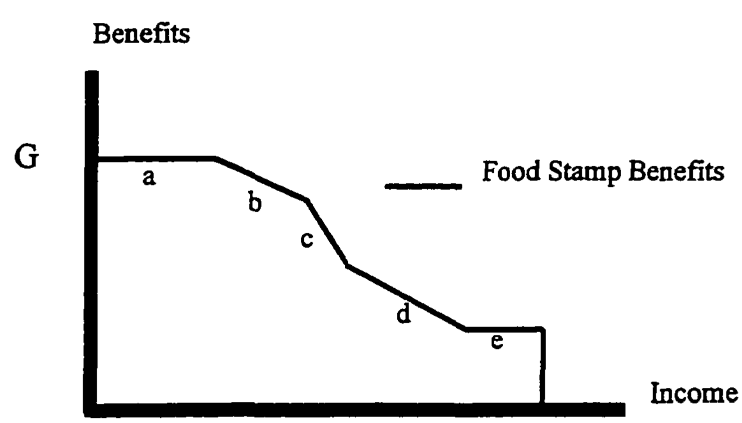
$$(7.4) \quad S = G - 0.3(NY),$$

where G is the maximum benefit level, sometimes called the guarantee level. This equation implies that cash income in the household is effectively taxed at a constant rate of 0.3. Part A of figure 7.2 illustrates this simple equation.

In practice, the benefit formula is more complex. The guarantee level varies with household size. The net income level depends on both gross income, a standard deduction, and a number of deductions for specific medical and housing expenses. Although the tax rate appears at first to be constant, some of the deductions used in calculating net income actually vary with gross income, so the tax rate is also variable.



A) A Simple Food Stamp Benefit Formula



B) A More Realistic Food Stamp Benefit Formula

Figure 7.2. The Food Stamp Benefit Formula

There is an earned income deduction that is 20 percent of income earned in the labor market and a shelter deduction that is calculated as the excess of shelter costs above 50 percent of net income after other deductions are taken. Finally, besides the maximum benefit level, there is also a minimum benefit level, which is received by households that would otherwise be eligible for very few benefits. Part B of figure 7.2 illustrates the various segments of the formula that might describe a particular household's benefits as a function of gross income:

a) Household receives maximum benefit, because net income is less than or equal to zero.
b) Slope reflects deduction for earned income only.
c) Slope reflects deduction for shelter and earned income.
d) Slope reflects deduction, once again, for earned income only.
e) Household is barely eligible and receives minimum food stamp benefit.[2]

Furthermore, in actual survey data such as the CSFII, there may be yet more variation in benefit levels as a function of gross income. For example, not all household income may be reported on food stamp benefit applications. For this reason, the actual tax rate may be even lower than is implied by the official formula explained in the previous paragraph, and it may vary more widely by household. For our sample, figure 7.3 illustrates the mean benefit level by family size for different levels of gross household income. In general, these curves have the downward slope one might expect from figure 7.2 and the preceding discussion, but the slope is flatter than the official formula implies.

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[2] Fraker and Moffitt consider the consequences of the multiple kinks in the food stamp benefit formula for household decisions about labor supply.

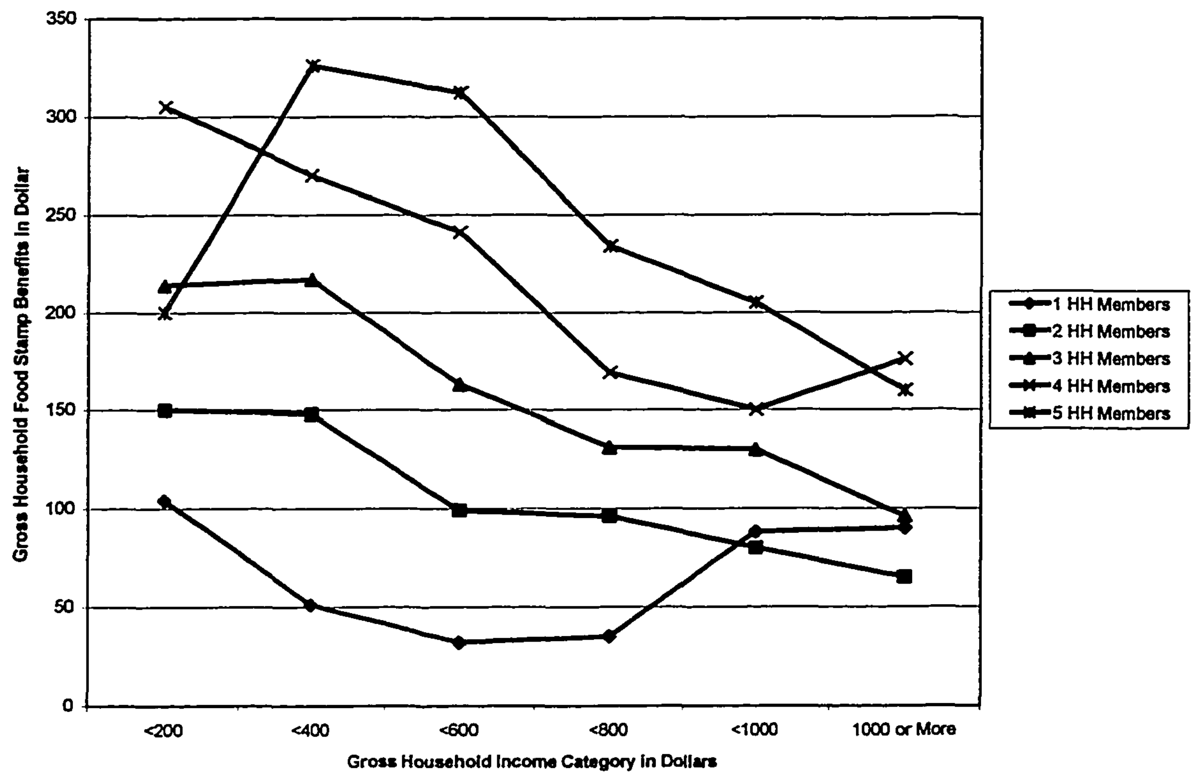


Figure 7.3. The Relationship Between Gross Household Income and Food Stamp Benefits, For Households with One to Five Members

Table 7.2 reports OLS regression results describing gross household food stamp benefits as a linear function of gross cash income and household size. The parameter on cash income is negative and statistically significant, as expected, but still small in absolute value. The R-square of 0.587 implies that in our data, there remains plenty of variation in food stamp benefits that is not explained by variation in gross cash income and household size.

Three Policies for Changes in Food Stamp Benefit Levels

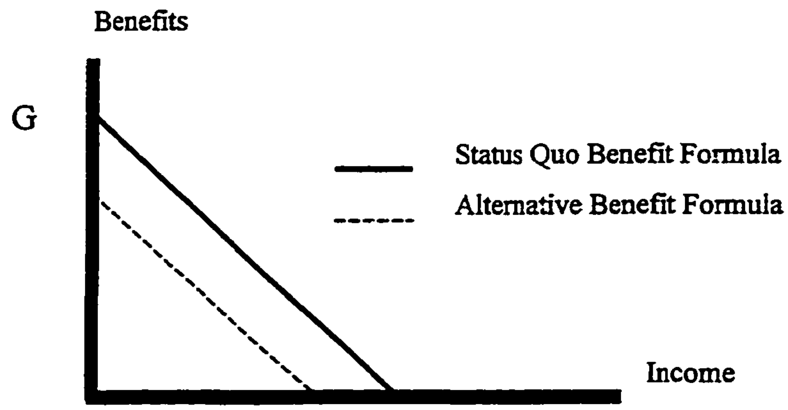
This sub-section conducts a simulation showing how different policies for instituting cuts or increases in food stamp benefits might have different effects on food intake. We want this simulation to be informative about the consequences of different possible changes to the official benefit formula. For this purpose, it might be tempting to assign to each observation the food stamp benefit level that approximates, as well as possible, the level to which the household is eligible under the benefit formula. Then, the effects of changes in the parameters of the benefit formula could be studied directly. However, the regression results in table 7.2 and the preceding discussion suggest that this assignment might be quite different from the benefit levels actually observed.[3] Instead, therefore, this sub-section considers three policies that may be applied to the actual benefits observed in the data. These three policies are interpreted in terms of a simplified version of the benefit formula.

Figure 7.4 illustrates how a cut in food stamp benefits following these three policies would alter the simple benefit formula in part A of figure 7.1. For each policy, the

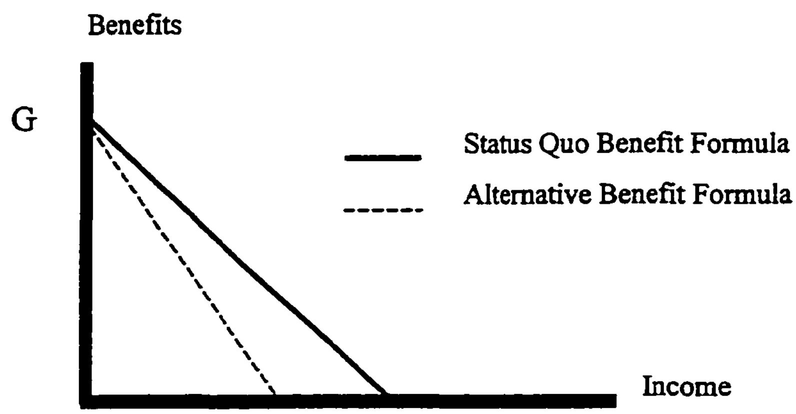
[3] These difficulties often arise in applied research using survey data to study federal social programs. The Survey of Income and Program Participation is the only national survey that comes close to including sufficient information to accurately determine the benefit levels to which a household is entitled under a given benefit formula, but that survey does not include the information that we need about food intake.

Table 7.2. Simple OLS Regression of Gross Household Food Stamp Benefits on Household Size and Gross Household Cash Income

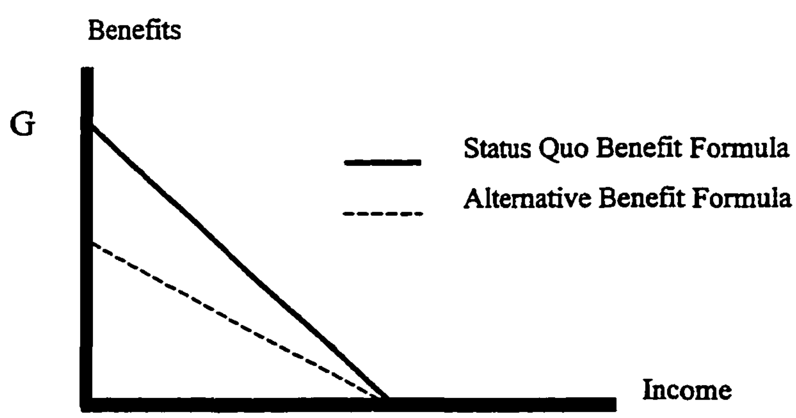
	Parameter Estimate	Standard Error
Intercept	36.542	6.085
Cash Income	-0.058	0.006
Household Size	50.552	1.702
R-Square	0.587	
Adj. *R*-Square	0.588	



***Policy 1:** A "Flat" Reduction in Food Stamp Benefits*



***Policy 2:** A Reduction Proportional to Cash Income*



***Policy 3:** A Reduction Proportional to Food Stamp Benefits*

Figure 7.4. Three Alternative Policies to Guide Changes in the Benefit Formula

solid line segment indicates the status quo funding level, and the dashed line segment illustrates the benefit formula under an alternative lower funding level. The three policies for instituting changes in benefits are:

1. Flat changes. Each household's benefits are reduced or increased by a fixed dollar amount (with the obvious exception that the benefit level cannot be reduced below zero). This change is equivalent to modifying the guarantee level (G) while leaving the tax rate unchanged.
2. Changes proportional to cash income. Each household's benefits are reduced or increased by a fixed proportion of income. This change is equivalent to modifying the tax rate while leaving the guarantee level (G) unchanged.
3. Changes proportional to benefits. This policy is equivalent to changing both the guarantee level (G) and the tax rate such that the level of income where eligibility ends (the horizontal intercept) remains unchanged.

We are interested in the effects of the three policies holding constant their effect on the program budget. Thus, for each policy, the simulation considers the same program budget levels: a) very low benefits, such that program costs are half the status quo, b) low benefits, such that program costs are 25 percent less than the status quo, c) the status quo benefit level, d) high benefits, such that program costs are 25 percent above the status quo, and e) very high benefits, such that program costs are 50 percent above the status quo.

Using the parameter estimates for the final inverse functional form from chapter six, the following simulation is conducted. For each policy option, the amount by which benefits must be changed to reach a particular program funding level is determined. For example, under policy 1, the "flat" amount by which each household's benefits should be reduced to achieve a 25 percent reduction in program funding is determined, while taking account of the restriction that no household's benefits can be reduced below zero. For each observation, the expected value of food intake in each half of the month is then computed using the methods described in section 7.2 above. Finally, for the whole sample, the mean expected food intake is reported for each half of the month under that particular policy option and program funding level. The results appear in table 7.3, and they are illustrated graphically for the three lowest funding levels in figure 7.5.

Under the status quo funding level (c), there is no change in each household's benefits, so the expected food intake is the same under all three policy options. For the higher funding levels (d and e), the three policy options yield similar values for expected food intake (in each case, approximately 75 percent of the RDA in the first half and 72-73 percent of the RDA in the second half of the month). The results concerning program cuts (funding levels a and b) are more interesting. The "flat" reduction in program benefits (policy 1), has the strongest effect on food intake, especially in the second half of the month. At the very low funding level, expected food intake in the second half falls nearly to 60 percent of the RDA under this policy option. By contrast, the reduction proportional to food stamp benefits (policy 3) has little effect on mean expected food intake even at very low funding levels. The benefit reduction proportional to cash income (policy 2) is an intermediate case.

The reason for this difference in effects is that a relatively large portion of the cuts under the "flat" reduction in program benefits (policy 1) falls on people who already receive relatively small benefit levels. For these people, the marginal effect of food stamp benefits on food intake is large, so program cuts lead to substantial reductions in expected food intake. By contrast, a relatively large proportion of the cuts under

Table 7.3. Expected Value of Food Intake in Two Halves of the Month, Under Three Benefit Policy Options and Five Program Funding Levels

Funding Level	Policy for Changes in Benefit Formula: 1. Flat		2. Proportional to Cash Income		3. Proportional to Benefits	
	Half 1	Half 2	Half 1	Half 2	Half 1	Half 2
a. Very Low (-50%)	69.98	60.73	72.63	65.81	75.25	70.44
b. Low (-25%)	73.74	68.19	74.37	69.70	75.58	71.90
c. Status Quo	75.36	72.29	75.36	72.29	75.36	72.29
d. High (+25%)	75.26	73.14	75.49	73.05	74.96	72.24
e. Very High (+50%)	74.59	72.71	75.33	73.16	74.51	72.00

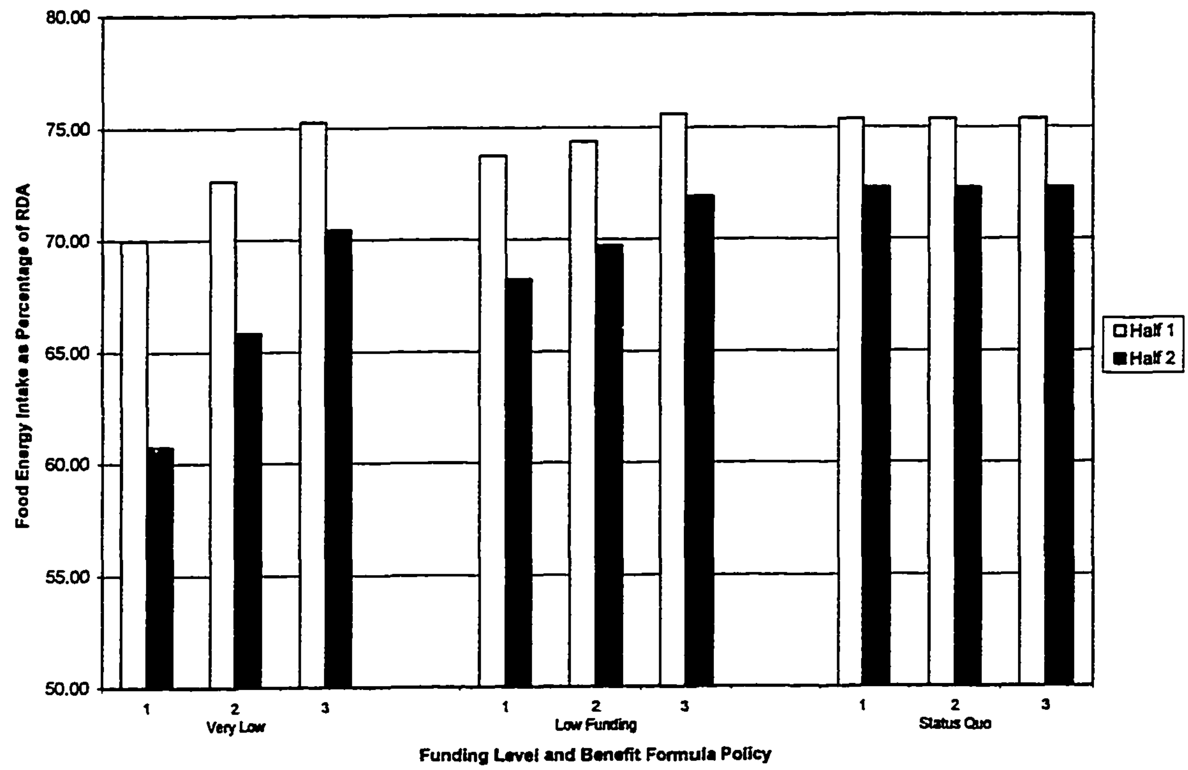


Figure 7.5. Expected Value of Food Intake in Two Halves of the Month, Under Three Benefit Policy Options and Three Program Funding Levels

policy 3 falls on people who receive relatively high benefit levels. For these people, the marginal effect of food stamp benefits on food intake is smaller.

These results imply that if maintaining food intake is an important goal, then any cuts in the program budget should be targeted at households that receive higher levels of food stamp benefits per AME. One cautionary comment on this implication is that, under the benefit formula, households with higher benefit levels would seem to be those with lower cash income levels. So in terms of total household resources, targeting cuts at those who receive more food stamp benefits could be regressive. As noted above in table 7.2, however, the inverse relationship between food stamp benefits and cash income in the data set is not as strong as one might expect from a quick reading of the benefit regulations.

The benefit reductions considered in this section are far from hypothetical. The 1996 welfare reform law cut all food stamp benefits to legal immigrants, although subsequent modifications to this legislation have made it easier for states to contribute their own funding to compensate. According to a Center on Budget and Policy Priorities (CBPP) report on the welfare reform bill as approved by the House-Senate conference committee, the bill also would lead to general benefit reductions of almost 20 percent in 2002. A substantial portion of these cuts take the form of "across-the-board benefit reductions that would affect nearly all recipient households, including families with children, the working poor, the elderly, and the disabled." The Center's projections suggested that "half of the food stamp cuts in the bill would be absorbed by the more than three million food stamp households with incomes below half the federal poverty line." Cuts that fall most heavily on those with low cash income would be most similar to policy 3 above. Although this form of cuts might tend to have the smallest effect in reducing expected food intake, it is more regressive in economic terms.

7.4 Changes in the Propensity to Shop Frequently

This final section of the chapter considers what happens if a new policy alters the incentive or propensity to shop frequently. The descriptive results (chapter three) found that infrequent shopping is associated with a drop in food intake at the end of the food stamp month, so this section focuses on how shopping frequency affects the difference between food intake in the first and second halves of the month.

Some government policies could affect the independent variables in the switching equation for choice of shopping regime. For example, many municipalities struggle to keep supermarkets in downtown neighborhoods. If a downtown supermarket closes, and local shoppers must travel further to a store where they can make major grocery purchases, the empirical illustration in table 6.7 of the previous chapter indicates the small reduction in the probability of shopping frequently that might result.

Other government policies, which were not in place at the time the CSFII survey data were collected, might potentially have even stronger effects on the propensity to shop frequently. One policy change that has received a great amount of attention is the introduction of electronic benefit transfer (EBT), which replaces food stamp coupons with electronic debit cards. Twenty-three states are already using EBT in some form, and eight operate such systems state-wide. The Food and Consumer Service lists several advantages to the new technology, including that recipients "can draw their benefits as needed instead of receiving a month's allotment at one time." Also, "many recipients have said that EBT reduces the stigma associated with food stamp use"

(Food and Consumer Service 1997). If EBT leads to the distribution of benefits more steadily over the course of the food stamp month, or if it reduces the stigma from shopping frequently, it could increase the propensity for recipients to shop more frequently.

The following simulation aims to take account of these effects indirectly. Because use of EBT is not one of the independent variables in the data set, the simulation considers the effect of a policy that increases or decreases the propensity to shop frequently by shifting the intercept of the regime choice equation in the endogenous switching regression model. Five levels of this intercept are considered:

a) Very low (0.8 units below MLE)

b) Low (0.4 units below MLE)

c) Status quo (the maximum likilihood estimate itself)

d) High (0.4 units above MLE)

e) Very high (0.8 units above MLE).

These changes are measured in the same units as the *z*-score for the probability of being a frequent shopper. The size of these shifts was chosen so that the change in the probability of being a frequent shopper in the "low" or "high" cases is about as large as the largest change seen in response to variation in the actual independent variables that appear in the switching equation. The "very low" or "very high" cases suggest the potential impact of hypothetical policies that affect this probability yet more strongly.

Preliminary consideration of the main results from chapter six suggests that these five cases may have different effects, depending on the level of food stamp benefits. In figure 6.1, the difference in the expected value of latent food intake in the two halves of the month may be seen by comparing the curve marked with squares to the corresponding curve marked with circles, for a particular shopping regime. This figure shows that at very low benefit levels, there is a substantial difference in the two halves of the month for frequent shoppers and a smaller difference for infrequent shoppers. This pattern reverses for benefit levels between about 0.5 and about 1.4, where there is a smaller difference between the two periods for frequent shoppers and a larger difference for infrequent shoppers. Finally, at very high benefit levels, the pattern reverses once again, and we see a larger difference between the two period for frequent shoppers. These patterns in the expected value of latent food intake suggest that our simulation should consider different levels of program benefits separately.

In the simulation, the sample is divided into four quartiles according to the level of food stamp benefits per AME, and results are reported separately for each quartile. The simulation uses the same method for computing each observation's expected value of food intake that was used in section 7.2 and 7.3 above. This simulation differs from the results described in the previous chapter, and reviewed in the preceding paragraph, because here expected food intake levels are calculated for each observation, and then the mean is taken for the full sample. The previous discussion in chapter six applied to a recipient with mean values of the independent variables.

For the five policy scenarios, the second column of table 7.4 reports the mean probability of shopping frequently, which ranges from 28 percent in scenario (a) to 83 percent in scenario (e). The remaining columns report the mean difference in expected food intake in the two halves of the month for each quartile.

The results correspond to what one might expect from the discussion of figure 6.1. For the first quartile (low levels of food stamp benefits) and the fourth quartile (high levels of food stamp benefits), the mean difference in food intake between the two

Table 7.4. Mean Difference Between Food Intake as a Percentage of RDA In the Two Halves of the Month, Under Varying Propensities to Shop Frequently

Propensity to Shop Frequently	Mean Prob. Of Shopping Freq'tly.	Quartile of Food Stamp Benefits per AME: Q1	Q2	Q3	Q4
		*(Intake in first half minus intake in second half)**			
a. Very Low (-0.8)	28%	3.96	4.66	3.75	1.42
b. Low (-0.4)	42%	4.96	3.55	2.91	1.69
c. Status Quo	58%	5.96	2.37	1.99	1.99
d. High (+0.4)	72%	6.82	1.28	1.14	2.27
e. Very High (+0.8)	83%	7.46	0.41	0.44	2.51

* Each entry is the difference in mean expected food intake between the two halves of the month, given a particular level of the propensity to shop frequently. The calculations are conducted separately for households in each quartile of food stamp benefits per AME: Q1 indicates the lowest level of food stamp benefits, and Q4 indicates the highest level.

periods is greatest when the propensity to shop frequently is highest. For the middle two quartiles, the results follow a more intuitive pattern: the mean difference in food intake between the two periods is high when the propensity to shop frequently is low, but this difference falls nearly to zero when the propensity to shop frequently is high. In sum, for recipients who receive "typical" levels of food stamp benefits (in the middle two quartiles), a policy that substantially increases the propensity to shop frequently could essentially eliminate the monthly cycle in food intake.

The two main simulations in sections 7.3 and 7.4 suggest how different policies about food stamp benefit levels and distribution methods, respectively, could affect food intake differently in the two halves of the food stamp month. These two simulations inform our central conclusions about policy implications, described in the next chapter.

CHAPTER EIGHT

SUMMARY, POLICY IMPLICATIONS, AND SUGGESTIONS FOR FUTURE RESEARCH

8.1 Summary

This dissertation contributes to two areas of research: 1) research in public health and public policy about hunger and food insecurity, and 2) research in the applied economic literature about the effects of food stamp benefits on food expenditure and consumption. These fields have influenced each other to some extent, but they generally have addressed distinct research questions and employed different methods. In both research areas, there is good reason to want to know more about monthly cycles in food expenditure and food intake.

Before this dissertation, journalists and policy-makers had already discussed monthly food stamp cycles, and the nutrition literature had already reported some empirical results using small data sets for particular localities. However, there was no study of these cycles in the peer-reviewed literature in economics, and nobody had measured these cycles using nationally representative data (chapter two).

The empirical description of monthly patterns in food expenditure and food intake is the most important contribution of this dissertation to research about hunger and food insecurity (chapter three). There is a sharp peak in mean food expenditure in the first three days of the food stamp month, and a more moderate drop in mean food intake in the last week of the month. The expenditure peak is exhibited by households of all the demographic and economic types, but only certain households exhibit the monthly cycle in food intake. In particular, households that conduct major grocery shopping trips infrequently (once a month or more seldom) exhibit a significant cycle in food intake, but households that shop more frequently exhibit a smoother food intake pattern over the month.

The applied economic literature has focused on estimating demand functions for food expenditure or food intake, using models inspired by the economic theory of choice (chapter four). The most popular family of models includes various forms of endogenous regime choice, where each recipient simultaneously chooses between two regimes and also chooses food expenditure or intake conditional on that choice of regime. While this family of models is promising for empirical work, the descriptive results above motivate a new model, where the regime choice concerns how frequently a household conducts major grocery trips.

In this dissertation's theoretical model, the recipient chooses whether to shop frequently or infrequently, as defined above, and he or she simultaneously chooses a level of food energy intake in each half of the month (chapter five). A corresponding empirical model takes account of the endogeneity of the shopping frequency decision. The main features of this model are a regime choice function that determines shopping frequency and functions describing food intake in each time period under each potential shopping regime.

Empirical estimation with this model finds that food stamps probably have a distinct effect on food intake for frequent and infrequent shoppers, but unobserved correlation between the disturbances of the shopping regime equation and the food intake equations is insignificant (chapter six). For the majority of recipient households, who receive a monthly benefit level higher than $50 per adult male equivalent (AME), food energy intake appears to reach a "satiation" level, where additional food stamp benefits have a small or even slightly negative effect on food energy intake. The exception is that, in the second half of the month only, infrequent shoppers fail to achieve this relatively high level of food energy intake. For the minority of food stamp recipient households who receive a benefit level lower than $50 per AME, food energy intake appears to be lower and more strongly affected by additional food stamp benefits. Again there is an exception: in the first half of the month only, frequent shoppers have a high level of food intake even when their benefit levels are in this low region.

In general, these results corroborate previous evidence that, on average, food stamp benefits do not have a strong positive effect on food energy intake, even though food stamps are known to have a strong effect on food expenditure. However, these results also indicate that the general pattern of insignificant food intake effects may obscure interesting exceptions for households with particular food stamp benefit levels, shopping patterns, or at particular times of month.

8.2 Policy Implications

Simulations using the econometric results (chapter 7) shed light on some policy options, such as changes in food stamp benefit levels, that have already received substantial attention in the previous economic literature. They also illuminate policy options that affect food intake through their effect on shopping frequency, which previous economic models have not been well-equipped to address. In this section, we consider in turn policies for changing benefit levels and policies that might affect the propensity to shop frequently.

The first main policy simulation (section 7.3) finds that equal-sized changes in food stamp program funding levels could have different effects on mean expected food intake, depending on how the program changes are implemented. Program cuts that fall more heavily on people with relatively low amounts of benefits have a comparatively large effect in reducing mean food intake, especially in the second half of the month. By contrast, program cuts that fall more heavily on people with high amounts of benefits have a much smaller effect on food intake.

All else equal, this finding might lead us to recommend that any program cuts should fall most heavily on those who receive the highest benefit levels. However, because the official benefit formula implies a negative relationship between cash income and food stamp benefits, such a policy might unduly penalize the recipients who are most poor in economic terms. In the CSFII data, the negative relationship between cash income and food stamp benefits is not as pronounced as one might expect, for reasons discussed in chapter seven. Nevertheless, the optimal policy for imposing program cuts may depend on a tradeoff between serving the program's goals for supplementing food intake and for alleviating poverty.

The second policy simulation investigates the effect of changes in the incentive or propensity to conduct major grocery trips frequently (section 7.4). A policy that increases the incentive to shop frequently has the greatest effect for households that receive "typical" amounts of food stamp benefits (in the second and third quartiles of food stamp benefits per AME). For these households, if the propensity to shop frequently is very low (leading to a 28 percent probability of shopping frequently), there is a substantial difference of about four percentage points of the RDA in expected food energy intake in the two halves of the month. However, if the propensity to shop frequently is very high (leading to an 83 percent probability of shopping frequently), the difference in food intake in the two halves of the month drops almost to zero.

A number of real-world policies could imitate the effects of this simulated policy change. For example, efforts by municipal governments to attract and retain supermarkets in low-income urban areas may reduce (or prevent from increasing) the distance that food stamp recipients must travel for their grocery shopping trips. Section 6.4 indicates that reduced distance to the grocery store would have a small but statistically significant effect in increasing the probability of shopping frequently.

As another example, nutrition education efforts could focus on encouraging households to make major grocery trips more than once per month. One emphasis of current nutrition education efforts is the importance of purchasing fruits and vegetables, which include some particularly perishable foods. Encouraging more frequent major grocery trips might be an easier "sell" with consumers than direct admonitions to purchase fruits and vegetables, but increased purchases of fresh fruits and vegetables could result nonetheless. This possibility merits further investigation.

The most important and imminent policy change of this type, however, is the introduction of electronic benefit transfer (EBT) in the Food Stamp Program. Most states are now investigating some type of EBT or "debit card" system for use in the grocery store checkout line, and several states have instituted such programs state-wide. In previous models of consumer choice, there is little to distinguish these electronic benefits from traditional food stamp coupons, if the dollar amount and the legal restriction on how benefits are used remain unchanged. However, EBT could reduce the amount of stigma associated with using food stamps in grocery stores, and it could also allow program administrators inexpensively to begin distributing food stamp benefits twice monthly rather than just once. In terms of the model in this dissertation, either change could encourage more recipients to shop more than once monthly, and that in turn could reduce the monthly cycle in food intake. With little change in program costs, this policy change could improve the Food Stamp Program's effectiveness in increasing food intake during those times of month when food intake is lowest.

Of course, such policy changes cannot be instituted solely on the basis of our analysis of food intake survey data from the late 1980s and early 1990s. Rather, our main recommendation here is for the establishment of a demonstration project, where EBT benefits are updated more than once monthly. We suggest a particular criterion by which the demonstration should be evaluated: its effect in raising the lowest monthly trough in food intake.

8.3 Suggestions for Future Research

As discussed at the start of chapter five, the direction of causation linking the shopping frequency and food intake cycles is not obvious. The approach in the second half of this dissertation is based on the observation that some households may have a greater propensity to shop infrequently, and as a result of shopping infrequently they may face a higher "effective" price of food intake by the end of the month. Alternatively, one could hypothesize that some recipients are too "impatient" to save resources for the end of the month, and as a consequence they have little reason to conduct a late-month major shopping trip. A theory of choice based on "impatience" is described in Wilde and Ranney (1997), with the feature that it could explain why even inframarginal recipients spend coupons and cash differently. Empirical work along those lines remains to be explored.

Accepting the basic relationship between shopping frequency and food intake described in this dissertation, further improvement may yet be possible in the empirical estimation. Chapters five and six employed an endogenous switching regression model with relatively modest modifications from what was available in the earlier applied literature on the Food Stamp Program. One contribution of this model is that we rationalize it in terms of an explicit theory of choice. Another contribution is that we attempt to account for specification problems such as heteroskedasticity that complicate estimation of limited dependent variable models. However, we suspect that by straying further afield from the switching regression approach that has been popular in the recent literature, future models could improve the empirical methodology for studying the effects of food stamp benefits on food intake over time.

The second half of this dissertation developed a model and empirical specification suited for estimation with the food intake data from the CSFII, even though the food intake cycle is in some sense the more humble of the two food stamp cycles. We passed over the more striking cycle in food expenditure, because without a corresponding impact on food intake, its policy implications seemed dubious: nobody cares if food stamp recipients have eccentric shopping practices unless these practices influence the program's effectiveness in improving food security. There are econometric techniques for studying household spending on goods that are purchased sporadically, while recognizing that actual consumption may follow a smoother pattern than expenditures (see Meghir and Robin 1992 for an application with food goods). However, these techniques generally require the assumption that actual consumption is perfectly smooth. This assumption is unattractive for food stamp applications, because the potential for reduced food intake at the end of the month is one of the most important phenomena under study. Again, however, improved models may better capture the relationship between food expenditure, storage, and intake over the course of the month. Such developments could provide a basis for modeling cycles in food consumption using the excellent expenditure data (and larger sample size) in the CEX, or using a combination of the CEX and CSFII.

This observation leads to a discussion of future data needs. Not all major national surveys include the key question that makes this research possible, identifying the day on which food stamp benefits were received. Indeed, the public data files for the newer version of the CSFII (for 1994-1996), which has only recently been released, appears to report the month and year that food stamp benefits were received, but not the date of the month. This omission is surprising, because the survey instrument appears to ask for the exact date. Furthermore, no major nationally representative survey includes similarly detailed timing questions for household resources other than food stamp benefits. Administrators of major surveys are sensibly cautious about taking suggestions for further questions to add, but it appears that a small number of detailed questions on the timing of various household resources could greatly improve the ability of cross-sectional surveys to reveal what is happening over time.

Finally, this dissertation's research on the food stamp cycle may address merely the most accessible example of a more general economic issue. Anecdotal evidence suggests that low-income households go through periodic or occasional economic crises, during which the welfare consequences of poverty are far worse than one might think by measuring, say, annual income and expenditures. Such crises are difficult for economists to study, partly because of insufficient data and partly because most economic theories allow for rational saving and dissaving that should eliminate such crises. The monthly cycle in food intake for food stamp recipients is particularly accessible, because it is periodic and because the same temporary resource shortages appear to hit many families in a similar pattern. Nevertheless, the welfare effects of other occasional and less predictable economic crises in low-income families may be severe, and deserving of further study.

APPENDIX A

LIKELIHOOD FUNCTION AND GRADIENTS

A.1 Introduction

This appendix derives the likelihood function for the econometric model in chapter five. The notation in this appendix is the standard notation for this literature, for reasons of generality and ease of comparability with other published work, such as Maddala (pp. 283-284). Thus, while the dependent variable in chapter five is F (for food intake), it is y in this appendix. The independent variables for the conditional equations in chapter five (S, M, Z_F, and so forth), will be denoted by the matrices X_0 and X_1 for the two regimes here, even though in chapter five the same variables appear under each regime and the regime subscripts are therefore not necessary. The independent variables in the switching equation will be denoted by the matrix Z in this appendix. The index for regime is D in chapter five (and in appendix B), but I in this appendix as in Maddala. We believed it would be easier for the reader to make these substitutions between chapter five and this appendix, rather than between this appendix and the rest of the econometric literature.

A.2 Homoskedastic Case

The endogenous switching regression model for dependent variable y_i for individual i is written:

(A.1) $$y_{0i} = X_{0i}\beta_0 + u_{0i},$$
$$y_{1i} = X_{1i}\beta_1 + u_{1i},$$
$$I_i^* = Z_i\gamma + \varepsilon_i,$$

where $I_i = 0$ if $I_i^* \le 0$,

$I_i = 1$ if $I_i^* > 0$,

and $y_i = y_{0i}$ iff $I_i = 0$,

$y_i = y_{1i}$ iff $I_i = 1$.

At first we consider the homoskedastic structure for the three disturbances (and we consider the subscript i to be understood in what follows):

(A.2) $(u_0, u_1, \varepsilon) \sim N(0, \Sigma)$, where $\Sigma = \begin{bmatrix} \sigma_{00} & \sigma_{01} & \sigma_{0\varepsilon} \\ & \sigma_{11} & \sigma_{1\varepsilon} \\ & & 1 \end{bmatrix}$.

To derive the likelihood function, it is convenient to begin by supposing hypothetically that we know the values of the estimable parameters ($\beta_0, \beta_1, \gamma, \Sigma$) and need to calculate the probability density for the dependent variable $f(y|\beta_0, \beta_1, \gamma, \Sigma)$, which we denote more briefly $f(y)$. This density is:

(A.3) $f(y) = P(I = 0) f(u_0 \mid I = 0)$, if $I = 0$, and

$f(y) = P(I = 1) f(u_1 \mid I = 1)$, if $I = 1$

where $u_0 = y - X_0\beta_0$ and $u_1 = y - X_1\beta_1$. The probabilities of participation are:

(A.4) $P(I = 0) = P(\varepsilon \le -Z\gamma) = 1 - \Phi(Z\gamma)$, and

$P(I = 1) = P(\varepsilon > -Z\gamma) = P(\varepsilon < Z\gamma) = \Phi(Z\gamma)$,

where Φ is the standard normal distribution function. The conditional densities for u_0 and u_1 in equation (A.3) are a bit more involved, in that they involve integrating out ε (which is of course never actually observed) from the joint densities $f(u_0,\varepsilon|I=0)$ and $f(u_1,\varepsilon|I=1)$:

(A.5) $$f(u_0\,|\,I=0)=\int_{Z\gamma}^{\infty} f(u_0,\varepsilon\,|\,I=0)d\varepsilon=\int_{Z\gamma}^{\infty} f(u_0,\varepsilon)d\varepsilon/(1-\Phi(Z\gamma)),\text{ and}$$

$$f(u_1|I=1)=\int_{-\infty}^{Z\gamma} f(u_1,\varepsilon|I=1)d\varepsilon=\int_{-\infty}^{Z\gamma} f(u_1,\varepsilon)d\varepsilon\,/\,\Phi(Z\gamma).$$

To understand the second equality in the second line of equation (A.5), which appears with minimal comment in Maddala [1983, p. 284], notice that the denominator adjusts the density $f(u_1,\varepsilon)$ so that this density integrates properly to unity when conditioned on $I=1$ (and similarly for the first line of this equation).

Now, our calculation of the density $f(y)$ depends on the densities $f(u_0,\varepsilon)$ and $f(u_1,\varepsilon)$, which are bivariate normal densities. The decomposition of these densities into a normal marginal density and a normal conditional density is straightforward (the formulas are in Greene [1993, pp. 72-73], for example):

(A.6) $$f(u_0,\varepsilon)=f(u_0)f(\varepsilon|u_0)$$

$$=\left(1/\sqrt{\sigma_{00}}\right)\phi\!\left(u_0/\sqrt{\sigma_{00}}\right)\left(1/\sqrt{1-\sigma_{0\varepsilon}{}^2/\sigma_{00}}\right)\phi\!\left(\frac{\varepsilon+(\sigma_{0\varepsilon}/\sigma_{00})u_0}{\sqrt{1-\sigma_{0\varepsilon}{}^2/\sigma_{00}}}\right),\text{ and}$$

$$f(u_1,\varepsilon)=f(u_1)f(\varepsilon|u_1)$$

$$=\left(1/\sqrt{\sigma_{11}}\right)\phi\!\left(u_1/\sqrt{\sigma_{11}}\right)\left(1/\sqrt{1-\sigma_{1\varepsilon}{}^2/\sigma_{11}}\right)\phi\!\left(\frac{\varepsilon+(\sigma_{1\varepsilon}/\sigma_{11})u_1}{\sqrt{1-\sigma_{1\varepsilon}{}^2/\sigma_{11}}}\right),$$

where ϕ is the standard normal density function. The advantage of this decomposition appears if we look back at equation (A.5) and recall that we will be integrating out ε. In equation (A.6), ε conveniently appears only in the final density.

Substituting equation (A.6) into equation (A.5) and integrating we get:

(A.7) $f(u_0|I=0)=\left(1/\sqrt{\sigma_{00}}\right)\phi\left(u_0/\sqrt{\sigma_{00}}\right)(1-\Phi(Q_0))/(1-\Phi(Z\gamma))$, and
$f(u_1|I=1)=\left(1/\sqrt{\sigma_{11}}\right)\phi\left(u_1/\sqrt{\sigma_{11}}\right)\Phi(Q_1)/\Phi(Z\gamma)$,
where $Q_0=\dfrac{Z\gamma+(\sigma_{0\varepsilon}/\sigma_{00})u_0}{R_0}$, $Q_1=\dfrac{Z\gamma+(\sigma_{1\varepsilon}/\sigma_{11})u_1}{R_1}$,
$R_0=\sqrt{1-\sigma_{0\varepsilon}{}^2/\sigma_{00}}$, and $R_1=\sqrt{1-\sigma_{1\varepsilon}{}^2/\sigma_{11}}$.

Substituting (A.7) and (A.4) into (A.3), we get:

(A.8) $f(y)=\left(1/\sqrt{\sigma_{00}}\right)\phi\left((y-X_0\beta_0)/\sqrt{\sigma_{00}}\right)(1-\Phi(Q_0))$ if $I=0$,
$f(y)=\left(1/\sqrt{\sigma_{11}}\right)\phi\left((y-X_1\beta_1)/\sqrt{\sigma_{11}}\right)\Phi(Q_1)$ if $I=1$.

Because the error terms are i.i.d. across observations, the probability density for the full vector of observations on the dependent variable is the product of individual probability densities of the forms in equation (A.8). The likelihood function is equivalent to this density, except that the likelihood is interpreted as a function of the parameters conditional on the observations, rather than vice versa. Taking logarithms, we get the log-likelihood function:

(A.9) $L(\beta_1,\beta_0,\gamma,\Sigma|y,I,X_0,X_1,Z)=$
$\Sigma\{[-\ln(\sqrt{\sigma_{00}})+\ln\phi\left((y-X_0\beta_0)/\sqrt{\sigma_{00}}\right)+\ln(1-\Phi(Q_0))](1-I)+$
$[-\ln(\sqrt{\sigma_{11}})+\ln\phi\left((y-X_1\beta_1)/\sqrt{\sigma_{11}}\right)+\ln\Phi(Q_0)](I)\}$,

where the summation is over all observations (the regime indicator I picks out the appropriate term for each regime). The maximum likelihood estimates are the values of the parameters that maximize this log-likelihood function.

The log-likelihood function (A.9) agrees with Maddala's equation (9.65) (p. 284), except for the final plus sign in the last term of his equation. Interestingly, the LIMDEP statistical package appears to give the wrong sign on its covariance estimate "Rho(0,2)" in its endogenous switching regression routine, an error that would result if one used Maddala's equation (9.65) as is. We have double-checked this claim using simulated data with known covariance parameters, confirming that our own log-likelihood function gives the correct sign and LIMDEP gives the reverse. In September 1997, we posted a brief note raising this issue on the LIMDEP e-mail discussion list, but no authoritative corroboration has yet been received.

To maximize this log-likelihood function, we need the gradient of the log-likelihood function with respect to the parameters to be estimated:

$$\text{(A.10)}\quad \frac{\partial L}{\partial \beta_0} = (1-I)\{\frac{u_0 X_0}{\sigma_{00}} + \lambda_0(Q_0)\frac{\partial Q_0}{\partial \beta_0}\},$$

$$\frac{\partial L}{\partial \beta_0} = (I)\{\frac{u_1 X_1}{\sigma_{11}} + \lambda_1(Q_1)\frac{\partial Q_1}{\partial \beta_1}\},$$

$$\frac{\partial L}{\partial \gamma} = (1-I)\{\lambda_0(Q_0)\frac{\partial Q_0}{\partial \gamma}\} + (I)\{\lambda_1(Q_1)\frac{\partial Q_1}{\partial \gamma}\},$$

$$\frac{\partial L}{\partial \sigma_0} = (1-I)\{\frac{-1}{\sigma_0} + \frac{u_0^2}{\sigma_0^3} + \lambda_0(Q_0)\frac{\partial Q_0}{\partial \sigma_0}\},$$

$$\frac{\partial L}{\partial \sigma_1} = (I)\{\frac{-1}{\sigma_1} + \frac{u_1^2}{\sigma_1^3} + \lambda_1(Q_1)\frac{\partial Q_1}{\partial \sigma_1}\},$$

$$\frac{\partial L}{\partial \sigma_{0e}} = (1-I)\{\lambda_0(Q_0)\frac{\partial Q_0}{\partial \sigma_{0e}}\},$$

$$\frac{\partial L}{\partial \sigma_{1e}} = (I)\{\lambda_1(Q_1)\frac{\partial Q_1}{\partial \sigma_{1e}}\},$$

where $\lambda_0(Q_0) = \dfrac{-\phi(Q_0)}{1-\Phi(Q_0)}$, $\lambda_1(Q_1) = \dfrac{\phi(Q_1)}{\Phi(Q_1)}$, $\sigma_0 = \sqrt{\sigma_{00}}$, and $\sigma_1 = \sqrt{\sigma_{11}}$.

The partial derivatives of Q_I for regime I in equation (A.10) are:

(A.11)
$$\frac{\partial Q_I}{\partial \beta_I} = \frac{-\sigma_{Ie} X}{R_I \sigma_{II}},$$
$$\frac{\partial Q_I}{\partial \gamma} = \frac{Z}{R_I},$$
$$\frac{\partial Q_I}{\partial \sigma_{Ie}} = \frac{u_I R_I + Q_I \sigma_{Ie}}{R_I^{\,2} \sigma_{II}},$$
$$\frac{\partial Q_I}{\partial \sigma_I} = \frac{-2\sigma_{Ie} u_I R_I - Q_I \sigma_{Ie}^{\,2}}{R_I^{\,2} \sigma_I^{\,3}}.$$

The log-likelihood function and the corresponding gradients above may be compared to the code for the GAUSS routine "Switch" described in appendix B.

Heteroskedastic Case

Now, suppose the disturbances for the conditional regression disturbances take the following heteroskedastic parametric form:

(A.12) $u_I = u_I * e^{\delta_I W}$,

where δ_I is a vector of parameters to be estimated, W_I is a vector of variables that affect the standard deviation of the disturbance, and u_I * is an "underlying" homoskedastic normal disturbance. The homoskedastic case is equivalent to the restriction $\delta_I = 0$. The stochastic model of the underlying disturbances is:

(A.13) $(u_0^*, u_1^*, \varepsilon) \sim N(0, \Sigma)$, where $\Sigma = \begin{bmatrix} \sigma_{00}^* & \sigma_{01}^* & \sigma_{0\varepsilon}^* \\ & \sigma_{11}^* & \sigma_{1\varepsilon}^* \\ & & 1 \end{bmatrix}$.

In the heteroskedastic case, the only modification to the log-likelihood function in equation (A.9) is to substitute for the standard deviation using:

(A.14) $\sigma_I = \sigma_I^* e^{\delta_I W_I}$, where $\sigma_I^* = \sqrt{\sigma_{II}^*}$.

The only modifications to the gradients in equation (A.10) are:

(A.15) $$\frac{\partial L}{\partial \sigma_I^*} = \frac{\partial L}{\partial \sigma_I} e^{\delta W_I}, \text{ and}$$
$$\frac{\partial L}{\partial \delta_I^*} = \frac{\partial L}{\partial \sigma_I} \sigma_I^* e^{\delta_I W_I} W_I .$$

The log-likelihood function and the corresponding gradients for the heteroskedastic case may be compared to the code for the GAUSS routine "Het," described in appendix B.

APPENDIX B

GAUSS PROGRAMS AND DOCUMENTATION

B.1 Introduction

This appendix documents the programs used to estimate the endogenous switching regression models, with and without heteroskedasitity, and also several programs used in support to generate starting values and check the routines using simulated data. A detailed reading of this appendix requires knowledge of GAUSS (Aptech Systems 1996a) and the MAXLIK add-on routines (Aptech Systems 1996b). However, a nice feature of GAUSS is that it uses matrices as its fundamental expressions, so that at least parts of the programs appear similar to notation used in the econometric literature. Wherever possible, we have chosen variable names and program organization so that the reader may compare the program details to the corresponding equations in appendix A.

In this appendix, section B.2 describes the program files used, and section B.3 explains key variables. Section B.4 contains the program files themselves.

B.2 Program File Description

The .prg files are the main programs to set up the estimation. They define variables, read or create data, and call estimation routines. Two examples are included in this appendix:

switsim.prg — Creates simulated data without heteroskedasticity and calls the routine "switch" to estimate an endogenous switching regression model with a linear functional form.

spline.prg — Reads food stamp data and calls the routine "het" to estimate the model with heteroskedasticity for the spline functional form.

The .src files are routines that either estimate the models or perform other functions, such as arranging data and defining global variables or creating simulated data. The programs in this appendix are:

pwutil.src — Contains the procedure "setup," which converts user-supplied variable names into index vectors telling other programs where to find the variables in the main data set.

sim.src — Contains the procedure "hetsim," which converts user-supplied "true" parameters into a simulated data set with desired properties.

probit.src — Contains the procedure "probit," which uses analytic gradients and hessians to quickly estimate probit problems.

heck.src — Contains the procedure "heck," which uses a Heckman-Lee two-step consistent estimator to solve endogenous switching regression problems. Calls "probit" for the first step.

switch.src — Contains the procedure "switch," which estimates an endogenous switching regression problem without heteroskedasticity by maximum likelihood. Calls "heck" to generate starting values. Also contains the routines "liksw" and "swgrad," for the log-likelihood function and gradient.

het.src — Contains the procedure "het," which estimates the same problem as "switch" in the presence of heteroskedasticity. Also contains the routines "likhet" and a distinct version of "swgrad," for the log-likelihood function and gradient.

Although this appendix is not intended as a user's manual, this guide and the program files should suffice for programmers. Comments are provided in switsim.prg and hetsim.prg to allow the user to employ these programs as templates by replacing the names of variables, data set names, and so forth.

B.3 Variable Description

Local variables are declared at the start of each procedure, and the names are chosen to aid interpretation. The following types of global variables are accessed by multiple procedures:

*name — Variables xname, zname, yname, and so forth are strings containing the names of variables in vector x, z, and y, respectively.

*v — Variables xv, zv, yv, and so forth are vectors containing index numbers showing the locations of x, z, and y, respectively, in the main data set.

b*	Variables bx0, bx1, bz, and so forth are vectors containing index numbers showing the locations of β_0, β_1, γ, respectively, in the vectors of estimated parameters.
hetstrt*	Variables hetstrt0 and hetsrt1 contain user-supplied starting values for the heteroskedasticity parameters, which are not produced by "heck."
sw_alg	A user-supplied global variable that instructs MAXLIK on what maximization algorithm to use ("3" indicates DFP, "4" indicates Newton).

B.4 Program Files

This section contains the program files used for estimation of the maximum likelihood models.

Switsim.prg

```
/* File switsim.prg */
/* Test switch routine using sim data. */
/* Parke Wilde 9-11-97 */
/* Modified 11-3-97 */

new;
output file=switsim.out reset;
library maxlik limdep;
#include maxlik.ext ;
#include limdep.ext ;
maxset;

/* Choose what variables, starting values, and algorithm to use */
let xname= intcept x1;       /* use "intcept" for intercept */
let zname= intcept x1 x2;
let hname= none ;            /* may be 'none' */
let wname= none;             /* may be 'none' */
let yname= Y ;               /* may be Y */
let dname= D ;               /* may be D */
let hetstrt0=0;
let hetstrt1=0;
let any_het=0;
let any_share=0;
sw_alg=4;
/*
/* Make Simulated Data */
trueb0={10,20};
trueb1={15,25};
truebz={5,-5,-5};
truesig = {1 0 .3, 0 1 .1, .3 .1 1};
truedel0=0.00;
truedel1=0.00;
nobs=1000;
{alldat,allname}=
  hetsim(trueb0,trueb1,truebz,truesig,truedel0,truedel1,nobs);
save alldat;
save allname;
*/
load alldat;
load allname;

/* Redefine Analysis Variables and Set Globals */
{alldat,allname}=setup(alldat,allname);
/*
print alldat;
*/
```

```
{new1,new2,new3,new4,new5}=switch(alldat);
call maxprt(new1,new2,new3,new4,new5);
```

Spline.prg

```
/* spline.prg */
/*  Estimates spline functional form using het */
/*  Parke Wilde 11-4-97 */

new;
output file=spline.out reset;
library maxlik limdep;
#include maxlik.ext;
#include limdep.ext;
maxset;

print "Program: spline.prg";
/* Choose what data file, variables, and algorithm to use */
let xname= half1 half2 stampsh1 stampsh2 spline1 spline2 cash1 cash2
           ametot welf fhead wicfood urban soutgeo;
let zname= intcept stamps spline cashinc ametot
           welf fhead wicfood urban soutgeo dist ;
let hname= ametot stamps;
let yname=rda1;
let dname=oft;
let wname=none;
let hetstrt0= -.01 0;
print "hetstrt0" hetstrt0;
let hetstrt1= -.01 0;
fsdat="d:/gauss/parke/switch/fspline";
any_het=1;
any_share=0;
sw_alg=4;

/* Read Data */
open f=^fsdat for read;
alldat=readr(f,100);
do until eof(f);
alldat=alldat|readr(f,100);
endo;
f=close(f);
startdat=alldat;
startname=getname(fsdat);
{alldat,allname}=setup(startdat,startname);

{bout,f,g,cov,retc}=het(alldat);
call maxprt(bout,f,g,cov,retc);
/* Save results for later calculations */
bspln=bout;
namspln=startname;
covspln=cov;
save bspln;
save namspln;
save covspln;
```

Pwutil.src

```
/* PROC SETUP */

proc (2) = setup(alldat,allname);
/* matrices " *a " indicate original data  */
local xa, za, ha, wa, ya, da, userdat, username, uservars,
      means,  mask, userindx, count ;

username=allname ;
userdat=alldat;

xa=indcv(xname,username);
/* print "xa" xa; */
za=indcv(zname,username);
/* print "za" za; */
if any_het==1;
  ha=indcv(hname,username);
endif;
if any_share==1;
  wa=indcv(wname,username);
endif;
ya=indcv(yname,username);
da=indcv(dname,username);

uservars=xa|za|ya|da;
if any_het==1;
  uservars=uservars|ha;
endif;
if any_share==1;
  uservars=uservars|wa;
endif;
userindx=unique(uservars,1);
/* print "userindx" userindx; */
username=username[userindx];
userdat=userdat[.,userindx];
means=meanc(userdat);

xv=indnv(xa,userindx);
zv=indnv(za,userindx);
if any_het==1;
  hv=indnv(ha,userindx);
endif;
if any_share==1;
  wv=indnv(wa,userindx);
endif;
yv=indnv(ya,userindx);
dv=indnv(da,userindx);

/*  Printout  */
mask={1 0 1};
print "xv: ";

call printfmt(xv~username[xv]~means[xv],mask);
print "zv: ";
```

```
call printfmt(zv~username[zv]~means[zv],mask);
if any_het==1;
  print;
  print "hv: ";
  call printfmt(hv~username[hv]~means[hv],mask);
endif;
if any_share==1;
  print;
  print "wv: ";
  call printfmt(wv~username[wv]~means[wv],mask);
endif;
print;
print "yv: ";
call printfmt(yv~username[yv]~means[yv],mask);
print;
print "dv: ";
call printfmt(dv~username[dv]~means[dv],mask);
print;

/* Set global variables in b matrix */
bx0=seqa(1,          1  ,rows(xv));
  count=rows(xv);
/*  print "bx0 count" count;*/
bx1=seqa(count+1, 1  ,rows(xv));
  count=count+rows(xv);
/*  print "bx1 count" count;*/
bz= seqa(count+1, 1  ,rows(zv));
  count=count+rows(zv);
/*  print "bz count" count;*/
bs0=count+1;
bs1=count+2;
bc0=count+3;
bc1=count+4;
  count=count+4;
/*  print "bc1 count" count;*/
if any_het==1;
  bh0=seqa(bc1+1,      1  ,rows(hv));
  bh1=seqa(maxc(bh0)+1,1  ,rows(hv));
  count=count+2*rows(hv);
/*  print "bh1 count" count;*/
endif;
if any_share==1;
  bw=seqa(maxc(bh1)+1,1,rows(wv));
  count=count+rows(wv);
/*  print "bw count" count;*/
endif;

retp(userdat,username);
endp;
```

Sim.src

```
/* Make Simulated Data */
/* Parke Wilde 9/97 */
/* Inputs: parameter values and nobs */
/* Outputs: Vector of data and vector of names -- */
/*          intcept x1 x2 Y D   */

proc (2) =
hetsim(trueb0,trueb1,truebz,truesig,truedel0,truedel1,nobs);
local err, x, ystar0, ystar1, ystar, d, y, alldat, allname, intcept;
err=rndn(nobs,3)*chol(truesig);
x=rndu(nobs,2);
intcept=ones(nobs,1);
err[.,1]=err[.,1].*exp(x[.,1]*truedel0);
err[.,2]=err[.,2].*exp(x[.,1]*truedel1);
ystar0=(intcept~x[.,1])*trueb0+err[.,1];
ystar1=(intcept~x[.,1])*trueb1+err[.,2];
ystar=(intcept~x)*truebz+err[.,3];
print "cov" (err'*err)/rows(err);
print "corr" corrx(err);
d=ystar .> 0;
y=(1-d).*ystar0+d.*ystar1;
alldat=intcept~x~y~d;
let allname="intcept" x1 x2 Y D;
retp(alldat,allname);
endp;
```

Probit.src

```
/*  Probit.src */
/*  A Simple Probit Estimator,
    With any number of columns.
    Generates starting values by OLS.
    Uses analytic gradient and hessian.
    Assumes data matrix has bin var
    in the last column.
    Input: data matrix
    Output: maxlik format output
    Globals: none.
**  Parke Wilde 8/18/97  Mod. 8/29/97
**
*/

proc lambda(d,m);
    /* gives correct lambda under each regime */
    local pdf,cdf;
    pdf=pdfn(m);
    cdf=cdfn(m);
    retp(d.*(pdf./cdf)-(1-d).*(pdf./(1-cdf)));
endp;
```

```
proc likprob(b,z);
    /* Returns the log-likelihood */
    /* The last column of matrix z is the binary dep. variable */
    local d, cdf;
    d=z[.,cols(z)];
    cdf = cdfn(z[.,1:(cols(z)-1)]*b);
    retp(d.*ln(cdf) + (1-d).*ln(1-cdf));
endp;

proc gradprob(b,z);
   /* Returns the gradient */
   /* See Greene p. 644 eq. 21-21 */
   local x;
    x=z[.,1:(cols(z)-1)];
    retp(lambda(z[.,cols(z)],x*b).*x);
endp;

proc hessprob(b,z);
   /* Returns the hessian. */
   /* See Greene p. 645 eq. 21-23 */
   local m,d,x;
    d=z[.,cols(z)];
    x=z[.,1:(cols(z)-1)];
    m = x*b;
    retp(-(x.*lambda(d,m).*(lambda(d,m)+m))'x);
endp;

proc (5) = probit(dat);
local x,bstart;
/* The probit procedure takes a data matrix z as input
   and returns the maxlik output.  It uses zv as
   the indices of the columns with the independent
   vars and dv as the index for the binary dependent. */
/* Get starting values using OLS */
 x=dat[.,zv];
 bstart=inv(x'*x)*x'*dat[.,dv];
/* Call Maxlik */
__output = 5;
_max_GradProc = &gradprob;
_max_HessProc=&hessprob;
print "default probit algorithm " _max_Algorithm;
_max_Algorithm = 4;
print "probit algorithm " _max_Algorithm;
/* _max_GradCheckTol = 1e-3;   */
/* Delete _max_ParNames if not defined */
_max_ParNames=allname[zv];
retp( maxlik(dat[.,zv]~dat[.,dv],0,&likprob,bstart));
endp;
```

Heck.src

```
/* Heck.src */
/* A Two-Step Heckman Lee Switching Regression
** Parke Wilde 9/4/97
*/

/* Heck2(dat)
** Calculates selection bias correction in regression.
** Uses global variables:
**    xv, zv,  yv, dv
** Inputs: data matrix dat with xv~zv~yv~dv
** Outputs: parameter vector b with bx0|bx1|bz|sig|rho
*/

proc heck2(dat);
  local d, pstart, f, g, cov, retcode,
           alpha, mills0, mills1,x0,y0,x1,y1,
           b0,b1,var0,var1,dbar0,dbar1,sig0,sig1,c0,c1, b;
  d=dat[.,dv];
  {pstart,f,g,cov,retcode}=probit(dat);
  print "probit results" pstart;
  /* Get mills from probit for two-step */
  alpha=dat[.,zv]*pstart;
  mills0 = - (1-d).*pdfn(alpha)./cdfnc(alpha);
  mills1=          d.*pdfn(alpha)./  cdfn(alpha);
  /* Estimate regression for selected obs only */
  x0 = delif((dat[.,xv]~mills0),d);
  y0 = delif( dat[.,yv]          ,d);
  x1 = selif((dat[.,xv]~mills1),d);
  y1 = selif( dat[.,yv]          ,d);
  b0 = inv(x0'*x0)*x0'*y0;
  b1 = inv(x1'*x1)*x1'*y1;
  print "number and proportion in regime 1: " rows(y1)
rows(y1)/rows(dat);
  print "rows b0" rows(b0);
  print "rows b1" rows(b1);
  print "Heckman results (b0, b1): " b0~b1;
  var0=((y0-x0*b0)'*(y0-x0*b0)) /rows(y0);
  var1=((y1-x1*b1)'*(y1-x1*b1)) /rows(y1);
  print "Heckman simple variances (var0, var1): " var0~var1;
   /* correct standard deviations for selection */
  dbar0=meanc(   -(mills0.*(alpha+mills0))   );
  dbar1=meanc(   -(mills1.*(alpha+mills1))   );
  sig0=sqrt(var0-(b0[rows(b0)]^2)*dbar0);
  sig1=sqrt(var1-(b1[rows(b1)]^2)*dbar1);
  print "Heckman corrected standard errors (sig0, sig1): " sig0~sig1;
  c0=b0[rows(b0)];
  c1=b1[rows(b1)];
  print "Heckman covariances (c0, c1): " c0~c1;
  b=b0[1:rows(b0)-1] | b1[1:rows(b0)-1] | pstart | sig0 | sig1 | c0 |
c1 ;
retp(b);
endp;
```

Switch.src

```
/*  The maximum likelihood routine switch
**  without heteroskedasticity
**  Parke Wilde 9/7/97
**  Modified  11/3/97 to correspond to dissertation
**  Input: data matrix.
**  Uses global index vectors:
**    xv, zv, yv, dv
**    bx0,bx1,bxz, brho0,brho1
**  Output: maxlik format results
*/

proc liksw(b,dat);
    /* Calculates Log-likelihood function.  */
    /* See Appendix A.  See Maddala p. 224 and p. 284. */

    local d,b0,b1,gam,sig0,sig0e,sig1,sig1e,
          u0,u1,q0,q1,r0,r1;

    d=dat[.,dv];
    b0=b[bx0];
    b1=b[bx1];
    gam=b[bz];
    sig0=b[bs0]*ones(rows(dat),1);
    sig0e=b[bc0];
    sig1=b[bs1]*ones(rows(dat),1);
    sig1e=b[bc1];

    u0=(dat[.,yv]-dat[.,xv]*b0) ;
    u1=(dat[.,yv]-dat[.,xv]*b1) ;
    r0=sqrt(1-sig0e^2./sig0^2) ;
    r1=sqrt(1-sig1e^2./sig1^2) ;
    q0=(( dat[.,zv]*gam+sig0e*u0./sig0^2)./r0);
    q1=(( dat[.,zv]*gam+sig1e*u1./sig1^2)./r1);

    retp( (1-d).*(-ln(sig0)+lnpdfn(u0./sig0)+ln(cdfnc(q0))) +
              d .*(-ln(sig1)+lnpdfn(u1./sig1)+ln(cdfn(q1))) );
endp;


proc swgrad(b,dat);
    /* Calculates Gradient */
    local d,b0,b1,gam,sig0,sig0e,sig1,sig1e,
          u0,u1,q0,q1,r0,r1,lam0,lam1,
          dq0db0,dq1db1,dq0dgam,dq1dgam,dq0ds0e,dq1ds1e,
          dq0ds0,dq1ds1;

    d=dat[.,dv];
    b0=b[bx0];
    b1=b[bx1];
    gam=b[bz];
    sig0=b[bs0]*ones(rows(dat),1);
    sig0e=b[bc0];
```

```
        sig1=b[bs1]*ones(rows(dat),1);
        sig1e=b[bc1];

        u0= (dat[.,yv]-dat[.,xv]*b0) ;  ,
        u1= (dat[.,yv]-dat[.,xv]*b1) ;
        r0= sqrt(1-sig0e^2./sig0^2) ;
        r1= sqrt(1-sig1e^2./sig1^2) ;
        q0= (( dat[.,zv]*gam+sig0e*u0./sig0^2)./r0);
        q1= (( dat[.,zv]*gam+sig1e*u1./sig1^2)./r1);
        lam0=(-pdfn(q0))./cdfnc(q0);
        lam1=( pdfn(q1))./ cdfn(q1);

        /* Derivatives of Q0 and Q1 */
        dq0db0 =(1-d).*(-(sig0e*dat[.,xv])./(r0.*sig0^2));
        dq1db1 =    d.*(-(sig1e*dat[.,xv])./(r1.*sig1^2));
        dq0dgam=(1-d).*(( dat[.,zv])./r0);
        dq1dgam=    d.*(( dat[.,zv])./r1);
        dq0ds0 =(1-d).*((-2*sig0e*u0.*r0-
          q0*sig0e^2)./((r0^2).*(sig0^3)));
        dq1ds1 =    d.*((-2*sig1e*u1.*r1-
          q1*sig1e^2)./((r1^2).*(sig1^3)));
        dq0ds0e=(1-d).*(( u0.*r0+q0*sig0e)./((r0^2).*(sig0^2)));
        dq1ds1e=    d.*(( u1.*r1+q1*sig1e)./((r1^2).*(sig1^2)));

        /* Gradients: b0,b1,gam,sig0,sig1,sig0e,sig1e    */
        retp((1-d).*((u0.*dat[.,xv]./(sig0^2)) + (lam0.*dq0db0))   ~
                 d.*((u1.*dat[.,xv]./(sig1^2)) + (lam1.*dq1db1))   ~
             (1-d).*(lam0.*dq0dgam) + d.*(lam1.*dq1dgam) ~
             (1-d).*(-1/sig0+(u0^2)./sig0^3+lam0.*dq0ds0) ~
                 d.*(-1/sig1+(u1^2)./sig1^3+lam1.*dq1ds1) ~
             (1-d).*(lam0.*dq0ds0e) ~
                 d.*(lam1.*dq1ds1e)  );
endp;

proc (5) = switch(dat);
local startvec;
startvec=heck2(dat);
print "startvec" startvec;
print "rows startvec" rows(startvec);
maxset;
__title = "Switch Procedure Output";
__output = 20;

 _max_GradCheckTol=1e-1;
print "Maxlik checking analytic gradient against numerical.";
 _max_GradProc=&swgrad;
print "Maxlik using gradients in swgrad.";

_max_Algorithm=sw_alg;    /* (a user-supplied global) */
print "max algorithm" _max_Algorithm;
_max_ParNames=allname[xv]|allname[xv]|allname[zv]|"s0    "
              |"s1    "|"c0    "|"c1    ";
retp(maxlik(dat,0,&liksw,startvec));
endp;
```

Het.src

```
/*  The maximum likelihood routine het
**  Parke Wilde 9/7/97
**  Modified  11/3/97 to correspond to dissertation
**  Input: data matrix.
**  Uses global index vectors:
**    xv, zv, yv, dv
**    bx0,bx1,bxz, brho0,brho1
**  Output: maxlik format results
**  Differences from switch are noted by /**/
*/

proc likhet(b,dat);
    /* Calculates Log-likelihood function.  */
    /* See Appendix A.  See Maddala p. 224 and p. 284. */

    local d,b0,b1,gam,sig0,sig0e,sig1,sig1e,
          u0,u1,q0,q1,r0,r1,
          del0,del1,sigstr0,sigstr1;                    /**/

    d=dat[.,dv];
    b0=b[bx0];
    b1=b[bx1];
    gam=b[bz];
    sigstr0=b[bs0];                                     /**/
    sigstr1=b[bs1];                                     /**/
    sig0e=b[bc0];
    sig1e=b[bc1];
    del0=b[bh0];                                        /**/
    del1=b[bh1];                                        /**/
    sig0=sigstr0*exp(dat[.,hv]*del0);                   /**/
    sig1=sigstr1*exp(dat[.,hv]*del1);                   /**/

    u0=(dat[.,yv]-dat[.,xv]*b0) ;
    u1=(dat[.,yv]-dat[.,xv]*b1) ;

    r0=sqrt(1-sig0e^2/sig0^2) ;                         /**/
    r1=sqrt(1-sig1e^2/sig1^2) ;                         /**/

    q0=(( dat[.,zv]*gam+sig0e*u0./sig0^2)./r0);         /**/
    q1=(( dat[.,zv]*gam+sig1e*u1./sig1^2)./r1);         /**/

    retp( (1-d).*(-ln(sig0)+lnpdfn(u0./sig0)+ln(cdfnc(q0))) +
              d .*(-ln(sig1)+lnpdfn(u1./sig1)+ln(cdfn(q1))) );
endp;


proc swgrad(b,dat);
    /* Calculates Gradient */
    local d,b0,b1,gam,sig0,sig0e,sig1,sig1e,
          u0,u1,q0,q1,r0,r1,lam0,lam1,
          del0,del1,sigstr0,sigstr1,                        /**/
          dq0db0,dq1db1,dq0dgam,dq1dgam,dq0ds0e,dq1ds1e,
          dq0ds0,dq1ds1,
```

```
        db0,db1,dgam,dsigstr0,dsigstr1,dsig0e,dsig1e,ddel0,ddel1;

    d=dat[.,dv];
    b0=b[bx0];
    b1=b[bx1];
    gam=b[bz];
    sigstr0=b[bs0];                                    /**/
    sigstr1=b[bs1];                                    /**/
    sig0e=b[bc0];
    sig1e=b[bc1];
    del0=b[bh0];                                       /**/
    del1=b[bh1];                                       /**/
    sig0=sigstr0*exp(dat[.,hv]*del0);                  /**/
    sig1=sigstr1*exp(dat[.,hv]*del1);                  /**/

    u0= (dat[.,yv]-dat[.,xv]*b0) ;
    u1= (dat[.,yv]-dat[.,xv]*b1) ;
    r0= sqrt(1-sig0e^2/sig0^2) ;
    r1= sqrt(1-sig1e^2/sig1^2) ;
    q0= (( dat[.,zv]*gam+sig0e*u0./sig0^2)./r0);
    q1= (( dat[.,zv]*gam+sig1e*u1./sig1^2)./r1);
    lam0=(-pdfn(q0))./cdfnc(q0);
    lam1=( pdfn(q1))./ cdfn(q1);

    /* Derivatives of Q0 and Q1 */
    dq0db0 =(1-d).*(-(sig0e*dat[.,xv])./(r0.*(sig0^2)));
    dq1db1 =    d.*(-(sig1e*dat[.,xv])./(r1.*(sig1^2)));
    dq0dgam=(1-d).*(( dat[.,zv])./r0);
    dq1dgam=    d.*(( dat[.,zv])./r1);

    dq0ds0 =(1-d).*((-2*sig0e*u0.*r0-
     q0*(sig0e^2))./((r0^2).*(sig0^3)));
    dq1ds1 =    d.*((-2*sig1e*u1.*r1-
     q1*(sig1e^2))./((r1^2).*(sig1^3)));
    dq0ds0e=(1-d).*(( u0.*r0+q0*sig0e)./((r0^2).*(sig0^2)));
    dq1ds1e=    d.*(( u1.*r1+q1*sig1e)./((r1^2).*(sig1^2)));

    /* Gradients: b0,b1,gam,sig0,sig1,sig0e,sig1e   */
    db0=(1-d).*((u0./(sig0^2)).*dat[.,xv] + lam0.*dq0db0);
    db1=    d.*((u1./(sig1^2)).*dat[.,xv] + lam1.*dq1db1);
    dgam=(1-d).*(lam0.*dq0dgam) + d.*(lam1.*dq1dgam);
    dsigstr0=(1-d).*(-1/sig0+(u0^2)./sig0^3+lam0.*dq0ds0).*
                   exp(dat[.,hv]*del0);
    dsigstr1=    d.*(-1/sig1+(u1^2)./sig1^3+lam1.*dq1ds1).*
                   exp(dat[.,hv]*del1);
    dsig0e= (1-d).*(lam0.*dq0ds0e);
    dsig1e=     d.*(lam1.*dq1ds1e)  ;
    ddel0=(1-d).*((-1/sig0)+(u0^2)./sig0^3+lam0.*dq0ds0).*
                   (exp(dat[.,hv]*del0).*dat[.,hv]*sigstr0);
    ddel1=    d.*((-1/sig1)+(u1^2)./sig1^3+lam1.*dq1ds1).*
                   (exp(dat[.,hv]*del1).*dat[.,hv]*sigstr1);

retp(db0~db1~dgam~dsigstr0~dsigstr1~dsig0e~dsig1e~ddel0~ddel1);
endp;

proc (5) = het(dat);
local startvec;
```

```
startvec=heck2(dat);
print "hetstrt";
print hetstrt0 hetstrt1;
startvec=startvec|hetstrt0|hetstrt1;                    /**/
print "startvec" startvec;
print "rows startvec" rows(startvec);
maxset;
__title = "Switch Procedure Output";
__output = 20;

 _max_GradCheckTol=1e-1;
print "Maxlik checking analytic gradient against numerical.";
 _max_GradProc=&swgrad;
print "Maxlik using gradients in swgrad.";

_max_Algorithm=sw_alg;    /* (a user-supplied global) */
print "max algorithm" _max_Algorithm;
_max_ParNames=allname[xv]|allname[xv]|allname[zv]|"s0    "
              |"s1   "|"c0   "|"c1   "|allname[hv|hv];  /**/
retp(maxlik(dat,0,&likhet,startvec));
endp;
```

APPENDIX C

ALTERNATE FUNCTIONAL FORMS

The two final functional forms in chapters five and six each contain, for different reasons, a special parameter that must be estimated by an initial grid search. The maximum likelihood estimates for the remaining parameters are reported conditional on the estimated special parameters being the true values. In this appendix we consider two alternate functional forms, where reasonable values of the special parameters are chosen *a priori* rather than by grid search. These alternative functional forms therefore avoid the statistical problems associated with the grid search, but they fit the data less well.

For the inverse form, the special parameter α in equation 5.15 is essentially a horizontal shifter. In the "alternate inverse" form, this equation is simplified by the assumption simply that $\alpha = 0$. Thus, this alternate functional form may be estimated directly by maximum likelihood. Table C.1 reports the parameter estimates, and figure C.1 illustrates the main effects of food stamps on food intake.

For the spline form, the special parameter μ in equation 5.16 represents the amount of food stamp benefits (in $100s per AME) at the kink in the food intake functions. The "alternate spline" form simply assumes that the kink point occurs at approximately the median food stamp benefit level: $\mu = 0.8$. Table C.2 reports the parameter estimates, and figure C.2 illustrates the main effects of food stamps on food intake.

Goodness-of-fit measures for both the final and alternate functional forms are reported in chapter six (table 6.5). As noted there, the final forms appear to perform as well as or better than the alternate functional forms by all measures. Because the mechanics of our estimation procedure for the initial grid searches did not generate a measure of dispersion for the parameter estimates for α and μ, we did not formally test the alternate functional forms as restrictions on the final functional forms

The estimated results for the alternate forms differ from the final forms in several respects. The standard errors for many parameter estimates in the food intake equations are larger under the alternate forms. The alternate and final forms agree more closely on the switching equation parameters and the distributional parameters, which appear similarly in all functional forms. The figures describing the alternate and final spline forms generally agree on the main effects of food stamps benefits on food intake, with the obvious difference that the "kink" point occurs at a different level of food stamp benefits (figures 6.1 and C.1). The main implications differ more strongly between the alternate and final inverse forms (figures 6.2 and C.2). The alternate inverse form suggests, oddly, that for infrequent shoppers in the second half of the month, food intake generally declines slightly as food stamp benefits increase. This negative slope is not corroborated by estimated results under any of the other functional forms.

Table C.1. Endogenous Switching Regression Model with Alternate Inverse Form

Engel Functions:		Regime 0 Estimates	Regime 0 Std. err.	Regime 1 Estimates	Regime 1 Std. err.
INTCEPT1	*beta01*	66.751	18.863	72.788	6.252
INTCEPT2	*beta02*	60.137	17.499	76.861	6.777
INVERSE1	*beta11*	3.283	6.080	1.546	1.338
INVERSE2	*beta12*	3.374	3.863	-1.774	1.635
INV-SQUARE1	*beta21*	-0.898	0.886	-0.050	0.069
INV-SQUARE2	*beta22*	-0.616 *	0.414	0.068	0.098
CASH1	*beta31*	-0.282	0.892	0.021	0.424
CASH2	*beta32*	0.198	0.300	0.125	0.604
AMETOT	*beta4[1]*	2.541 *	1.462	0.750	1.215
WELF	*beta4[2]*	0.155	4.154	3.810 *	2.964
FHEAD	*beta4[3]*	0.327	3.808	1.395	2.784
WICFOOD	*beta4[4]*	6.794 *	3.569	5.067 *	3.088
URBAN	*beta4[5]*	-0.350	2.969	-5.034 **	2.465
SOUTGEO	*beta4[6]*	0.506	3.665	-3.365	2.817

Switching Function:		Estimates	Std. err.
INTCEPT	*gamma0*	0.7764	0.2124
STAMPS	*gamma1*	-0.0158	0.0736
CASHINC	*gamma3*	0.0004	0.0118
AMETOT	*gamma4[1]*	0.0069	0.0574
WELF	*gamma4[2]*	-0.2664 **	0.1245
FHEAD	*gamma4[3]*	-0.2184 **	0.1191
WICFOOD	*gamma4[4]*	-0.0926	0.1342
URBAN	*gamma4[5]*	-0.1486 *	0.1091
SOUTGEO	*gamma4[6]*	-0.2788 **	0.1103
DIST	*gamma5[1]*	-0.0205 **	0.0078

Distributional Parameters:		Estimates	Std. err.
std. dev. 0	*sig0*	25.8790	3.1110
std. dev. 1	*sig1*	24.6123	2.3986
cov. (0,R)	*sig0R*	-3.0370	13.1228
cov. (1,R)	*sig1R*	-3.9100	7.0247
AMETOT-R0	*delta0[1]*	-0.1029 **	0.0420
STAMPS-R0	*delta0[2]*	0.0476	0.0525
AMETOT-R1	*delta1[1]*	-0.0651 **	0.0346
STAMPS-R1	*delta1[2]*	0.0008	0.0497

* Indicates significant at alpha=.10, one-tailed test. ** Indicates significant at alpha=.05.

Table C.2. Endogenous Switching Regression Model with Alternate Spline Form

Engel Functions:		Regime 0 Estimates	Regime 0 Std. err.	Regime 1 Estimates	Regime 1 Std. err.
INTCEPT1	*beta01*	55.613	19.095	80.646	7.021
INTCEPT2	*beta02*	53.751	19.750	65.034	8.260
STAMPS1	*beta11*	17.498 *	11.515	-6.204	7.888
STAMPS2	*beta12*	11.221	11.348	16.553 **	8.357
SPLINE1	*beta21*	-19.900 *	13.935	5.182	9.937
SPLINE2	*beta22*	-9.336	13.039	-20.959 **	9.660
CASH1	*beta31*	-0.003	1.057	0.026	0.427
CASH2	*beta32*	0.231	0.304	0.360	0.620
AMETOT	*beta4[1]*	3.365 **	1.508	0.394	1.235
WELF	*beta4[2]*	-1.054	4.252	3.749	2.975
FHEAD	*beta4[3]*	0.766	3.889	0.749	2.772
WICFOOD	*beta4[4]*	7.022 **	3.600	4.943 *	3.079
URBAN	*beta4[5]*	-0.559	3.009	-5.427 **	2.470
SOUTGEO	*beta4[6]*	0.209	3.762	-3.261	2.818

Switching Function:		Estimates	Std. err.
INTCEPT	*gamma0*	0.7716	0.2121
STAMPS	*gamma1*	-0.0103	0.0712
CASHINC	*gamma3*	0.0003	0.0118
AMETOT	*gamma4[1]*	0.0077	0.0573
WELF	*gamma4[2]*	-0.2692 **	0.1241
FHEAD	*gamma4[3]*	-0.2183 **	0.1191
WICFOOD	*gamma4[4]*	-0.0933	0.1341
URBAN	*gamma4[5]*	-0.1479 *	0.1091
SOUTGEO	*gamma4[6]*	-0.2802 **	0.1103
DIST	*gamma5[1]*	-0.0204 **	0.0078

Distributional Parameters:		Estimates	Std. err.
std. dev. 0	*sig0*	27.0671	3.2606
std. dev. 1	*sig1*	24.5266	2.3973
cov. (0,R)	*sig0R*	-2.1822	13.9566
cov. (1,R)	*sig1R*	-3.5770	7.1316
AMETOT-R0	*delta0[1]*	-0.1091 **	0.0423
STAMPS-R0	*delta0[2]*	0.0216	0.0570
AMETOT-R1	*delta1[1]*	-0.0673 **	0.0348
STAMPS-R1	*delta1[2]*	0.0033	0.0499

* Indicates significant at alpha=.10, one-tailed test. ** Indicates significant at alpha=.05.

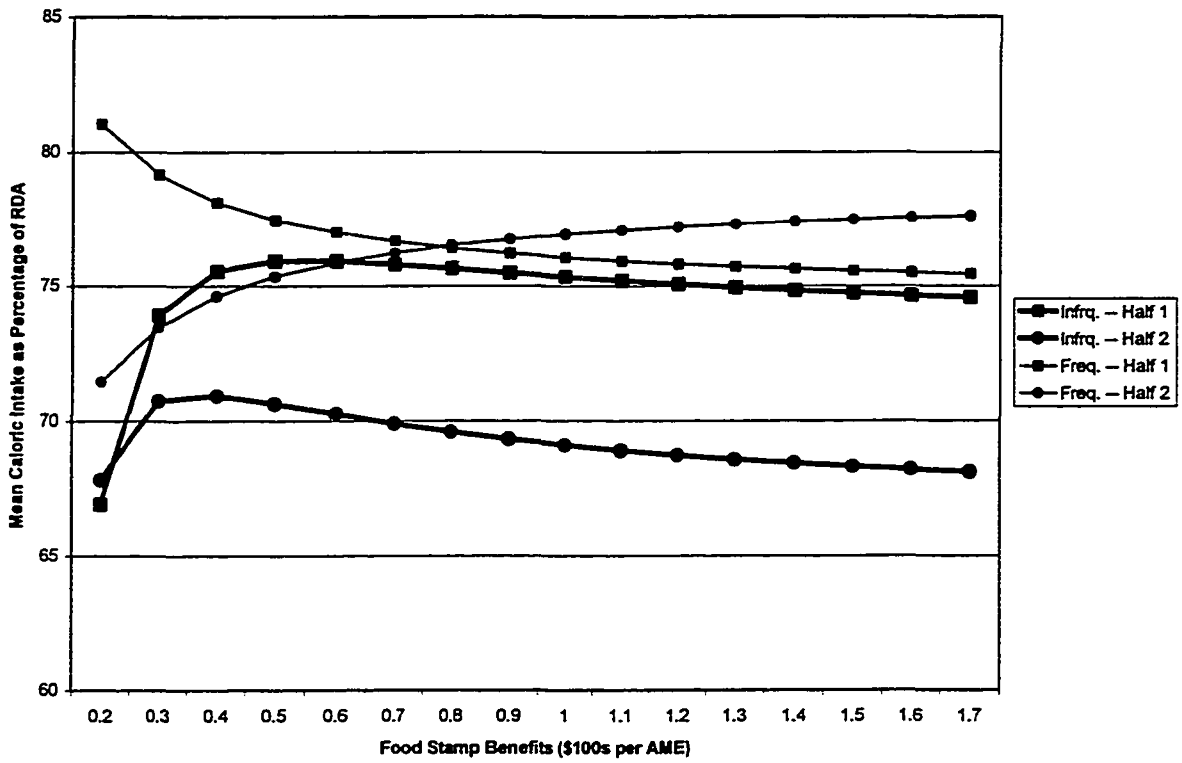


Figure C.1. Expected Value of Latent Food Intake in Each Time Period and Shopping Regime, With the Alternate Inverse Functional Form

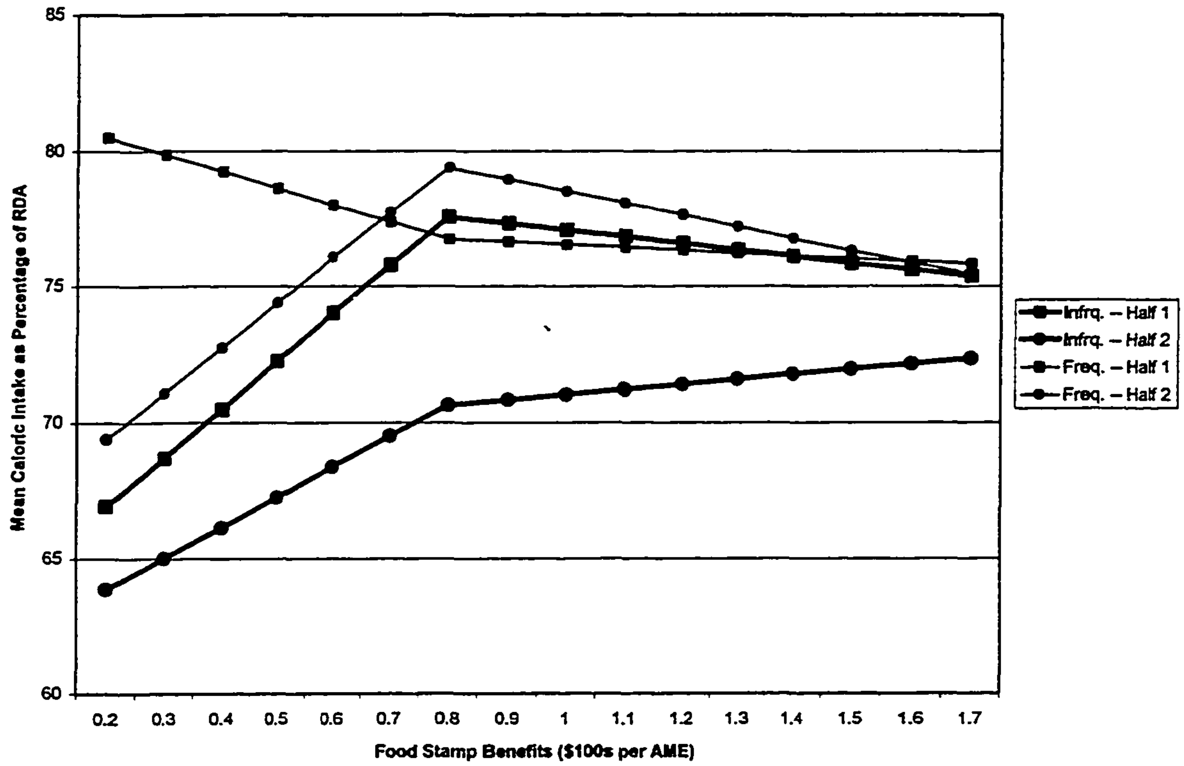


Figure C.2. Expected Value of Latent Food Intake in Each Time Period and Shopping Regime, With the Alternate Spline Functional Form

APPENDIX D

THEORETICAL CROSS-PRICE EFFECTS

In this appendix, we consider a somewhat simpler consumer choice problem, where utility, defined over food and non-food in the two time periods, is maximized subject to an ordinary budget constraint. We describe the equivalence between the food demand functions that solve this simpler problem and the food intake functions in equation 5.4 of chapter five. We consider the own-price and cross-price effects, which decribe how the price of food in period 2 affects the quantity of food demanded in period 2 and period 1, respectively. The main observations are that the own-price effect is negative, but the cross-price effect may be negative or positive. Finally, we consider some additional assumptions on preferences under which the cross-price effect must be negative.

Consider first a re-statement of the consumer's problem from equation 5.3, where we do not impose the particular structure on effective prices and shopping regimes discussed in section 5.2. Instead we will allow any positive prices of food (F) and non-food (X) in the two periods: p_{F1}, p_{X1}, p_{F2} and p_{X2}, respectively. We consider the consumer's problem of maximizing the utility function *U* from equation 5.1 with respect to an ordinary budget constraint:

$$\text{(D.1)} \quad \underset{F_1, X_1, F_2, X_2}{Max} \quad U(F_1, X_1, F_2, X_2; \theta), \text{ s.t.}$$

$$p_{F1}F_1 + p_{X1}X_1 + p_{F2}F_2 + p_{X2}X_2 = \overline{M}.$$

The food demand functions in each period *t*, which solve this consumer's problem, may be denoted:

(D.2) $F_t = F_t(p_{F1}, p_{X1}, p_{F2}, p_{X2}, \overline{M}; \theta)$.

These demand functions are not as irrelevant to the discussion in chapter five as they might seem in first glance. There, we specified that preferences over food and non-food are strongly separable from preferences over shopping regime. In that case, under either shopping regime, demand for food may be expressed as a function of the prices for food and non-food in the two periods and the total expenditure on these four "goods." A particular feature of the model in chapter five is that total spending on food and non-food is equal to total income $\overline{M}$, because the choice of shopping regime does not involve pecuniary costs that are subtracted from income. For this reason, the food intake functions for the two regimes given in equation 5.4 can each be described as solutions to the problem in D.1, where the prices in D.1 are replaced by the appropriately restricted prices for the two regimes (p_F, q_F, and p_X). Likewise, if the prices in D.2 are replaced by the appropriately restricted prices for the two regimes, we will get exactly the food intake functions that appear in equation 5.4 for the two regimes. The purpose of noting this equivalence is so that we can use some observations about the own-price and cross-price effects of an increase in p_{F2} in equation D.2 to demonstrate the claims in equations 5.5 and 5.6 of the chapter text.

If we rule out Giffen goods, then the own-price effect of food in the second period will be negative:

(D.3) $\partial F_2(p_{F1}, p_{X1}, p_{F2}, p_{X2}, \overline{M}; \theta) / \partial p_{F2} < 0$.

If we replace p_{F2} with p_F under regime 1 and with q_F under regime 0, then equation D.3 shows that the conditional food intake function for the second period under regime 0 will lie below the corresponding food intake function under regime 1, as equation 5.5 claims.

By contrast, the cross-price effect of p_{F2} on F_1 in equation D.2 may take either sign, depending on whether food in the first and second periods are gross substitutes or gross complements:

(D.4) $\partial F_1(p_{F1}, p_{X1}, p_{F2}, p_{X2}, \overline{M};\theta) / \partial p_{F2} > 0$ or
$\partial F_1(p_{F1}, p_{X1}, p_{F2}, p_{X2}, \overline{M};\theta) / \partial p_{F2} \leq 0$.

However, under some additional assumptions, we may determine the direction of the inequality in D.4. In particular, if we assume preferences are strongly separable between the two time periods, and we make an assumption about the elasticity of expenditure in period 2 with respect to the price of food in period 2, we may conclude that only the last inequality in D.4 is true.

Suppose the utility function U represents preferences that are strongly separable over time, in which case it may be written in the following form:

(D.5) $U(F_1, X_1, F_2, X_2;\theta) = u^1(F_1, X_1;\theta) + u^2(F_2, X_2;\theta)$.

From this separability assumption, we can write the demand function for food intake in the first period as a function of first period prices and total first period expenditures (M_1). These first period expenditures, in turn, are a function of all prices and income:

(D.6) $F_1(p_{F1}, p_{X1}, p_{F2}, p_{X2}, \overline{M}) = F_1{}^*(p_{F1}, p_{X1}, M_1(p_{F1}, p_{X1}, p_{F2}, p_{X2}, \overline{M}))$,

where for convenience we drop demographic variables from the notation. Taking the derivative of this function with respect to the price of food in the second period, we have:

(D.7) $\partial F_1 / \partial p_{F2} = (\partial F_1{}^* / \partial M_1)(\partial M_1 / \partial p_{F2})$.

Because we continue to assume food is a normal good, the first partial derivative on the right-hand side is positive, but, perhaps surprisingly, the second derivative may be negative or positive. From the budget constraint, we can re-write the second partial derivative:

(D.8) $(\partial M_1 / \partial p_{F2}) = -(\partial M_2 / \partial p_{F2}) = -F_2 - p_{F2}(\partial F_2 / \partial p_{F2}) - p_{X2}(\partial X_2 / \partial p_{F2})$.

Dividing both sides by F_2, we have:

(D.9) $(1/F_2)(\partial M_1 / \partial p_{F2}) = -(1 + e_{F2}) - (m_{X2} / m_{F2}) e_{X2F2}$,

where e_{F2} is the marshallian own-price elasticity of food in the second period, e_{X2F2} is the marshallian cross-price elasticity of non-food with respect to food in the second period, and the m's are expenditures on non-food and food, respectively. If food in the second period is own-price inelastic and the food and non-food goods in the second period are gross substitutes, then the right-hand sides of equation D.8 and D.9 will be negative. Even if the goods in the second period are gross complements, the right-hand side will be negative if food in the second period is "sufficiently" own-price inelastic. These conditions may be expected to hold in practice, because we may expect the own-price elasticity of food in the second period to be quite small in absolute value.

Under these additional conditions the inequality in equation D.4 is determined. Food intake in the first period will fall (or at least not rise) as the price of food in the second period rises. Finally, we return to the implications of this discussion for the statement in equation 5.6 of chapter five. There, the effective price of food int the second period equals p_F under regime 1, and it equals the higher value q_F under regime 0. Under the additional conditions, we expect that food intake in the first period will be lower for infrequent shoppers than for frequent shoppers, or equal under the two regimes.

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