



United States
Department
of Agriculture

Contractor
and Cooperator
Report No. 46

July 2008



Electronic Report from the Economic Research Service

www.ers.usda.gov

Longer Run Earnings and Food Stamp Participation

By Sam Elkin and Lesley Turner, The Lewin Group

ERS project representative: Constance Newman,
cnewman@ers.usda.gov, 202-694-5598

Abstract

This study looks at the relationship between food stamp participation and historical earnings over periods of 10-15 years. Earlier research found that households eligible for the Food Stamp Program that had short-term income declines were less likely to participate than those that had sustained low incomes. This analysis expands on that research by using a data set that matched historical Social Security earnings records to the 1996 Survey of Income and Program Participation, allowing examination of the relationship between participation and earnings over a longer timeframe than available previously. The results show some evidence that historical annual earnings as far back as 5 years earlier are negatively and significantly associated with households' decisions to participate in the Food Stamp Program; that future earnings, which may proxy for earnings expectations, are also negatively and significantly associated with participation; and that monthly income volatility plays an important role. However, because of weaknesses in the specification of the regression models, findings in this paper are suggestive rather than precise descriptions of the relationship between longer run income and participation.



Food Assistance
& Nutrition
Research Program

This study was conducted by The Lewin Group under a research agreement with the Economic Research Service. The views expressed are those of the authors and not necessarily those of ERS or USDA.

Table of Contents

I. INTRODUCTION	1
II. BACKGROUND.....	3
A. TRENDS IN PARTICIPATION RATES	3
B. POTENTIAL REASONS FOR LACK OF PARTICIPATION	5
C. FEDERAL POLICIES AFFECTING PARTICIPATION.....	7
D. SHORT-TERM EARNINGS DECLINES, INCOME VOLATILITY, AND PARTICIPATION	8
III. DATA AND METHODOLOGY	11
A. DATA SOURCES	11
B. CONSTRUCTING THE ANALYSIS DATA SET	12
1. <i>Defining Food Stamp Units</i>	12
2. <i>Focusing on Working-Age Food Stamp Units</i>	12
3. <i>Attributing Annual Earnings to Food Stamp Units</i>	13
C. SAMPLES AND OUTCOME MEASURES.....	14
D. TYPES OF ANALYSIS CONDUCTED	16
IV. DESCRIPTIVE RESULTS.....	17
A. PARTICIPATION RATES	17
B. DESCRIPTIVE STATISTICS	18
1. <i>Demographic Characteristics of Participant and Non-Participant Food Stamp Units</i>	18
2. <i>Earning Characteristics of Participant and Non-Participant Food Stamp Units</i>	20
3. <i>Eligibility and Benefits of Participant and Non-Participant Food Stamp Units</i>	22
4. <i>Characteristics of SIPP Households in which Food Stamp Units are Contained</i>	23
5. <i>Characteristics of Participant and Non-Participant Food Stamp Units by Earnings Quartile</i>	24
C. EARNINGS OVER TIME	25
V. REGRESSION RESULTS	29
A. REGRESSION FRAMEWORK	29
B. METHODOLOGICAL ISSUES	32
C. REGRESSION RESULTS: ELIGIBILITY IN A SPECIFIC MONTH	33
D. ELIGIBILITY IN ANY MONTH OF THE YEAR	36
E. INTENSITY OF PARTICIPATION	39
VI. CONCLUSIONS AND FUTURE RESEARCH.....	42
REFERENCES	44
APPENDIX A: ADDITIONAL TABLES AND CHARTS.....	1
APPENDIX B: DESCRIPTION OF THE MID-SIPP	1
A. MID-SIPP SIMULATION APPROACH.....	1
1. <i>Step 1: Classify Persons into Food Stamp Units and Reweight</i>	5
2. <i>Step 2: Determine Each FSU's Eligibility and Potential Benefits for Every Month</i>	7
3. <i>Step 3: Correct Eligibility and Reported Participation Spells for the Seam Problem</i>	9
APPENDIX C: A COMPARISON OF EARNINGS DATA IN THE SURVEY OF INCOME AND PROGRAM PARTICIPATION WITH SOCIAL SECURITY EARNINGS RECORDS.....	1
A. INTRODUCTION.....	1
B. PREVIOUS FINDINGS ON ACCURACY OF SURVEY DATA ON EARNINGS	3
1. <i>Aggregate Comparisons to Benchmark</i>	3
2. <i>Individual-Level Comparisons to Administrative Data</i>	4
C. DATA	6
D. ANALYSIS OF RECIPIENCY MATCH	8

E.	COMPARISON TO PAST PAPERS.....	13
F.	ANALYSIS OF DIFFERENCES IN EARNINGS MEASURES	15
G.	CONCLUSION	18
REFERENCES CITED IN APPENDIX C.....		20

I. INTRODUCTION

The Food Stamp Program is one of the government's key tools for supporting the well-being of low-income households and helping them to maintain a sufficient level of nutrition. However, benefits are not collected by many of the individuals and families to whom they are available. According to estimates published by the U.S. Department of Agriculture (USDA), the average monthly individual "food stamp participation rate," or the share of eligible individuals who received food stamps was 65 percent in federal fiscal year (FY) 2005. The household participation rate, or share of eligible households receiving benefits, was 59 percent. (Wolkwitz, 2007). In other words, these estimates suggest that more than 40 percent of households eligible for food stamps did not receive them. The participation rate has changed over time, but a substantial portion of eligible households have consistently not accessed their benefits.

With considerable numbers of eligible households – who are low-income and could presumably benefit from receiving food stamps – not receiving them, there have been many studies within the policy research field that attempt to understand who does and does not participate, and what drives this decision. Several of these studies have found that households with short-term declines in income are less likely than those with sustained low income to participate in the program. For instance, Farrell et al. (2003) used data from the 1996 panel of the Survey of Income and Program Participation (SIPP) and found that average earnings of eligible households not participating had decreased sharply in the four months prior to the month in which they were eligible, and grew substantially faster after the month of eligibility than did the average income of participating households. Moreover, the study found evidence that past and future income over a longer time period are also significantly related to the likelihood that a food stamp eligible household participates in the program. There are several reasons this may be the case: for example, a household with higher past income may expect its income to rebound in the future and may decide to 'weather the storm' instead of applying for food stamps, or may expect to only be eligible for low benefits in the future, reducing the payoff it can expect by going through the application process. In addition, a household experiencing a drop in income may need to learn about program rules and the system for applying for the first time.

From their analysis, Farrell et al. (2003) concluded that "the predictive power of past or future income deteriorates as one moves away in either direction from the current period" but that there was still a "negative, large and statistically significant" relationship as much as two-and-a-half years earlier between earnings and participation. They speculated that "earnings in the more distant past (three or more years earlier) might have substantial predictive power" and suggested as a direction for future research investigating the relationship of longer-term historical earnings data and food stamp participation.

The analysis in this paper attempts to contribute to the research on food stamp participation by looking at the effects of longer term earnings on participation. The authors of this paper were granted clearance to work with a restricted-access data set that matched historical earnings records from Social Security earnings between 1951 and 2000 to the 1996 SIPP. This allows us to examine the relationship between food stamp participation and earnings over a much larger timeframe than has been available in previous studies and to test the hypothesis suggested by

Farrell et al. (2003) that longer-term historical earnings may have a significant effect on participation.

We do not replicate the participation model used in Farrell et al. (2003), and instead rely on the determination of eligibility and benefit receipt in the SIPP calculated as part of The SPHERE Institute's MID-SIPP model (MaCurdy and Marrufo, 2006), which corrects for seam bias in the SIPP. Our analysis focuses on the significance that current and long run earnings, as measured in the Social Security earnings records, play in the decision to participate in food stamps while controlling for demographic and family characteristics measured in the SIPP. We also include short-term income volatility in our model, which prior research demonstrated as impacting participation. Unfortunately, our access to the matched Social Security-SIPP data expired while we were conducting analysis and therefore we did not have an opportunity to correct weaknesses in our regression models. (These weaknesses are indicated in the body of the report.) As a result, findings in this paper are suggestive and indicate areas for useful future research, rather than precise descriptions of the relationship between long-run income and participation. Nonetheless, we find some evidence that historical annual earnings as far back as five years earlier are negatively and significantly associated with households' decisions to participate in food stamps; that future earnings, which may proxy for earnings expectations, are also negatively and significantly associated with participation when other characteristics of the food stamp unit are controlled for; and, in all cases, that monthly income volatility plays an important role as well.

In the next section, we review in further depth the research literature on food stamp participation and the policy context in which to understand participation rates. In the third section, we describe our data sources and methodology. Sections IV and V present findings from descriptive analysis and regressions. The final section concludes. The appendices contain tables with more detailed results, additional explanation of the MID-SIPP model, and an analysis of comparisons between earnings data in the SIPP and SER data sets.

II. BACKGROUND

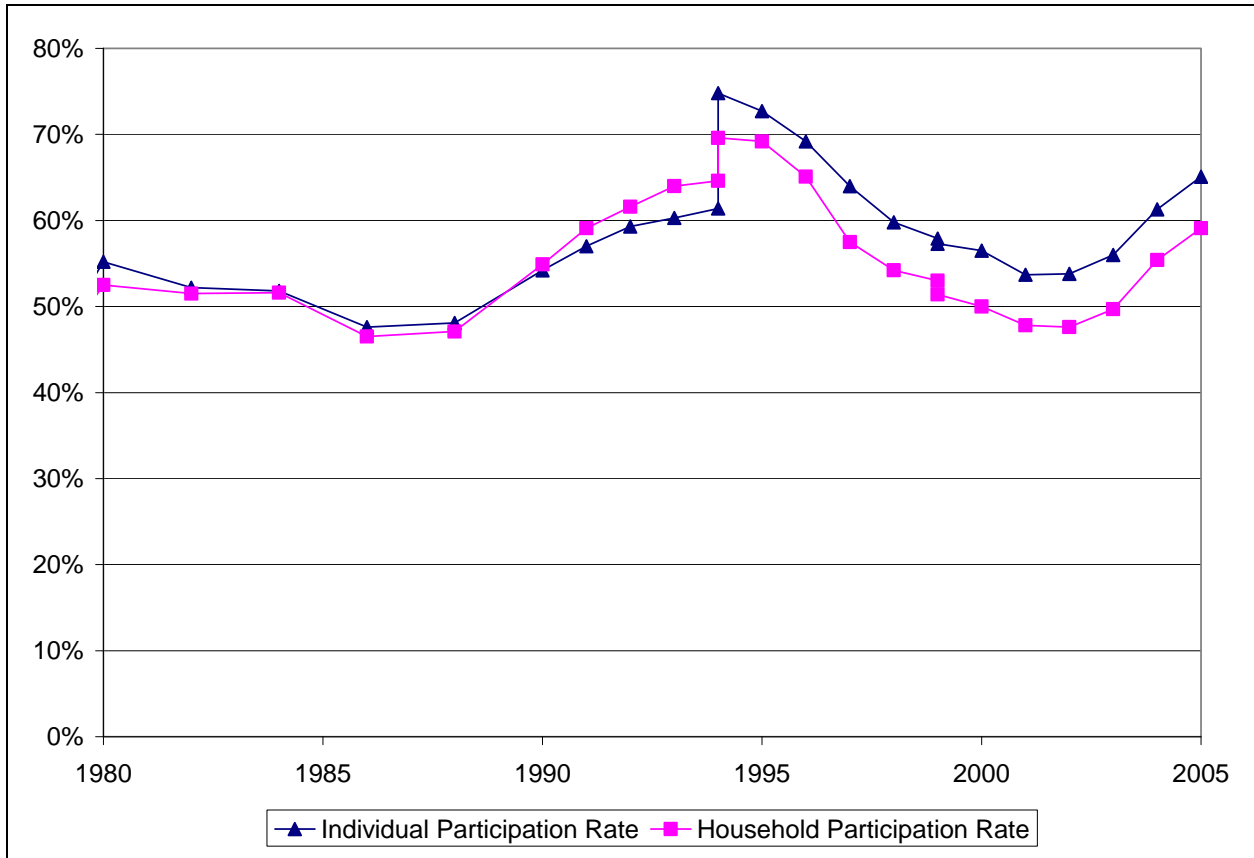
A. Trends in Participation Rates

In federal fiscal year (FY) 2006, 26.7 million individuals lived in households receiving food stamp benefits. In a given month, participating households received an average of \$214 in benefits.¹ However, a substantial portion of individuals and families eligible for food stamps do not receive the benefits for which they are eligible. According to one set of estimates, calculated by Mathematica Policy Research and published by USDA, the individual “food stamp participation rate,” or the share of individuals eligible for food stamps who received them was only 65 percent in the average month of FY 2005. The household participation rate, or share of eligible households receiving benefits, was 59 percent in the same year. In other words, these estimates suggest that more than 40 percent of households eligible for food stamps did not receive them. (Wolkwitz, 2007).

According to the USDA figures, the participation rate has changed over time, with participation increasing in 2005. However, a portion of eligible households have consistently not accessed their benefits. *Exhibit II.1* shows USDA-reported participation rates over a 26-year period. While this chart must be interpreted with a degree of care because various occurred changes in the methodology for measuring the participation rate over the years, it demonstrates that the rate increased in the early 1990s, and fell over the mid- to late-1990s, and that in more recent years, participation has been increasing again. In all years, though, the data suggest that about one third to one half of eligible households have not participated in the program.

¹ USDA Food and Nutrition Service monthly Food Stamp Program data posted online at <http://www.fns.usda.gov/pd/34fsmmonthly.htm> (accessed April 29, 2008.)

Exhibit II.1: Food Stamp Participation Rates, 1980 – 2004

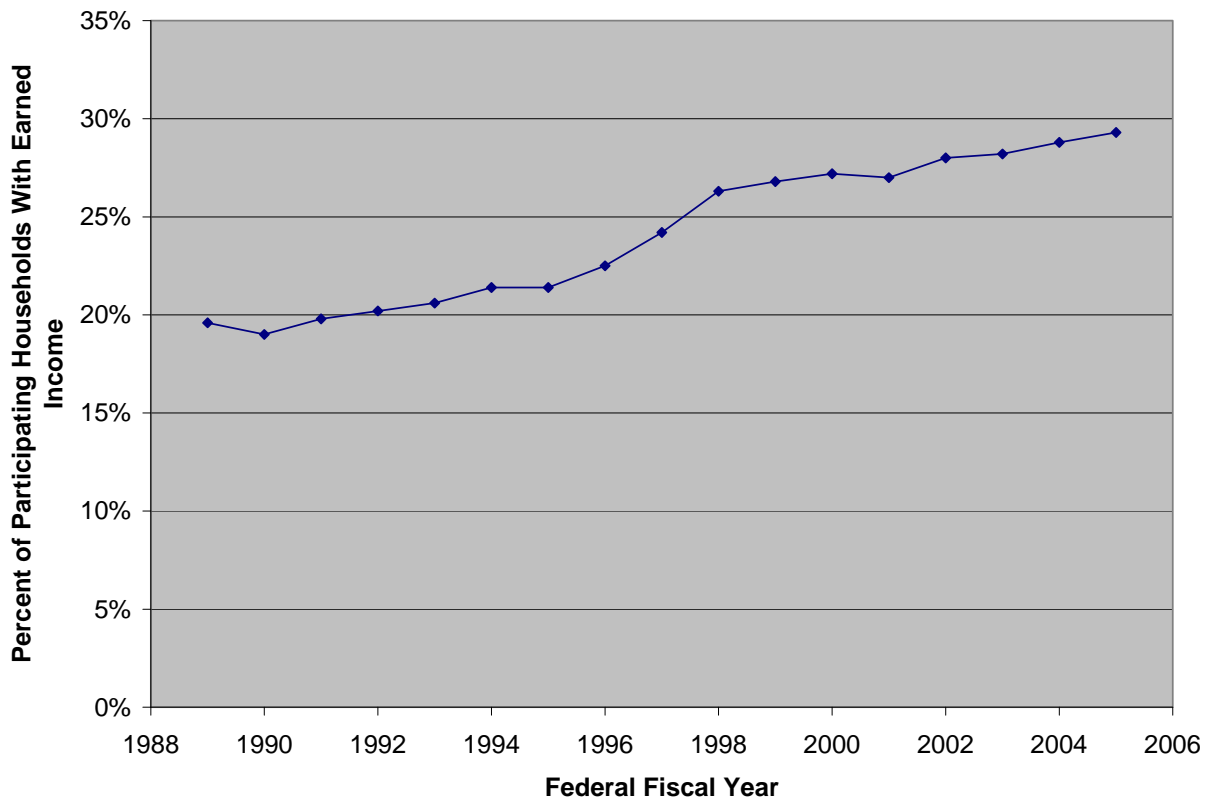


Source: Wolkwitz, 2007, based on Food Stamp Program Operations data, Food Stamp Program Quality Control data, and CPS data. Discontinuities in the two series at 1994 and 1999 reflect changes in methodology. For these years, participation rates calculated according to both the older and the newer methodologies are shown. Rates calculated according to the different methodologies are not strictly comparable.

Wolkwitz (2007) identifies different household participation rates among various types of households. Households with children participate at higher rates, as do households receiving Temporary Assistance for Needy Families (TANF) or Supplemental Security Income (SSI), while households with elderly members participate at lower rates. Households with lower income participate at higher rates, while only about 20 percent of households with income above the poverty line participate.² Households with earnings participate at lower rates as well - the household participation rate for households with earnings in FY 2005 was 51 percent. The proportion of food stamp participants with earnings has increased over time, particularly starting in 1996. (See *Exhibit II.2*.)

² Households eligible for food stamps may have monthly incomes up to 130 percent of the poverty line, as subject to other eligibility requirements. Some households eligible under categorical eligibility rules may have higher income.

Exhibit II.2: Percent of Participating Food Stamp Households with Earnings



Source: Barrett, 2006, based on Food Stamp Program Quality Control data.

B. Potential Reasons for Lack of Participation

There are many reasons that households may not claim food stamps when they are eligible. Bartlett et al. (2004), in a report on findings from the Food Stamp Program Access Study funded by USDA, identifies several impediments to participation at various stages of the food stamp application process. Eligible households may not know they are eligible and individuals may choose to not apply due to personal reasons (like a desire for personal independence, a perception of stigma, or a desire for privacy), costs related to applying, or “office policies” (defined to include prior bad experience with the program and confusion about how to apply, among other things). Eligible households fail to complete the recertification process for similar reasons. This section discusses some findings from previous research that gives evidence of factors that may be important to consider in understanding the participation rate.

Lack of awareness. A number of studies find evidence that a large share, and perhaps the majority, of non-participating eligibles are not aware they are eligible. In a survey by Ponza et al (1999), 72 percent of non-participants considered likely to be eligible reported that they were not aware that they were eligible for the program. McConnell and Ponza (1999) cite other surveys including the PSID and the SSI/Elderly Cashout Demonstration study and report that “between one-third and one-half of non-participants say they think they are ineligible.” The Food Stamp

Program Access Study (Bartlett et al., 2004) similarly found that only 43 percent of potentially eligible non-participants believed they might be eligible. A small number – four percent – were not aware of the program’s existence.

Personal reasons and stigma. Bartlett et al. (2004) report that 97 percent of eligible but non-participating survey respondents who said they would not apply for food stamps if they knew were eligible cited personal reasons, the most common being the desire for personal independence. Nearly half of these individuals cited a reason the authors categorized as stigma of participation. Ponza et al (1999) report that only about a quarter of the 28 percent of non-participating households aware of their eligibility for the program responded that stigma or related reasons were the main reason for their non-participation. The same survey asked questions aimed at identifying perceptions of stigma, and 44 percent of non-participants answered “yes” to at least one of these questions (as compared to 38 percent of participants). GAO (2004) notes that stigma could be heightened for working families due to the need of the program to occasionally verify wages and employment with employers.

Costs of participation and administrative burden. The time and effort spent initially applying for food stamps and later recertifying include the time spent learning about the program, filling out forms, gathering documentation to demonstrate eligibility, traveling to the food stamp office, and the loss of privacy in divulging personal information. All of these obligations impose burdens on food stamp eligible households. These households may judge that the benefits they will receive are not worth taking on these burdens. Zedlewski and Brauner (1999, as cited in Dion and Pavetti, 2000), using the National Survey of America’s Families, find that ten percent of former welfare families and 17 percent of non-welfare families reported leaving the Food Stamp Program due to administrative problems or hassles. For working families, the time costs of application and recertification may be higher than those for non-working families given inflexible work schedules. McKernan and Ratcliffe (2003) find that households where adults work traditional hours are less likely to participate in the Food Stamp Program than households where adults work nontraditional hours. Bartlett et al. (2004) identify a number of ways in which local office policies can affect accessibility to benefits or the burden of applying, including (among others) hours of operation, available transportation, bilingual caseworkers, child friendliness of the offices, the overall pleasantness of the office, and local office discretion over how certification requirements are implemented.

Failure to complete recertification. In recent years, several studies have found that the length of the recertification period – which differs across states, ranging from a few months to over a year – has a notable impact on participation. Kornfeld (2002) and Kabbani and Wilde (2003) find that frequent recertification is associated with lower caseloads. Other papers have demonstrated that frequent recertifications hasten exits; for example, Ribar and Edelhoich (2006) find that families in South Carolina have a higher probability of leaving food stamps in a recertification month than in other months. The Food Stamp Program Access Study (Bartlett, 2004) estimates that more than half of households who were in their recertification month in June 2000 and left the Food Stamp Program may still have been eligible (though the study notes that this estimate is based on limited data and “should be viewed with caution”). Most states now have a six-month reporting or recertification schedule as allowed by the 2002 Farm Bill.

Measurement issues: In addition, mismeasurement in administrative and survey data may affect participation rate estimates. Models of food stamp participation using data from surveys such as the Survey of Income and Program Participation (SIPP) or Current Population Survey (CPS) may be affected by misreporting of earnings and other income. Underreporting of income in surveys that are used to calculate participation rates could lead to an overestimate of the number of households eligible for benefits and an underestimate of the true participation rate, as some of these households are not, in fact, eligible. An analysis by the authors of this paper comparing earnings data in the 1996 panel of the SIPP with earnings data in Social Security administrative data found substantial number of cases where earnings in the SIPP were underreported relative to the administrative data; however, there were also cases where the SIPP showed higher earnings than the administrative data and we did not directly measure the net impact on the food stamp eligibility determination. This analysis is included as *Appendix C*. Imputation of income or assets where such information is missing may also affect the accuracy of estimated eligibility.

Participation may also be misreported. Bollinger and David (2001, as cited in Farrell et al., 2003) compared administrative data in three states to responses in the 1984 SIPP and found that 13.8 percent more households participated than reported that they participated. Based on this, as well as higher participation rates found in USDA-reported figures, Farrell et al (2003) estimate that their determination of participation rates based on SIPP data may underestimate participation rates by 10 to 20 percent. Models such as the MID-SIPP and that used by Mathematica Policy Research in measuring the participation rate incorporate data from the Food Stamp Quality Control database to correct for underreporting of participation in survey data.

C. Federal Policies Affecting Participation

Several legislative changes over the past decade may have affected food stamp participation rates. The 1996 welfare reform legislation, the Personal Responsibility and Work Opportunity Reconciliation Act, made most legal immigrants ineligible for food stamps and placed a three-month limit on food stamp benefit receipt for non-working, able-bodied adults between the ages 18 and 49 not living in a household with a dependent child. The Agricultural Research, Extension, and Education Act of 1998 and the 2002 Farm Security and Rural Investment Act restored eligibility to certain groups of legal immigrants, including children and those who had been in the country at least five years. Federal legislation in 2001 allowed a more generous shelter deduction and vehicle allowance. The 2002 farm bill also gave options to states for program simplification. According to Greenstein (2007), the majority of states subsequently opted to simplify program participation by taking such steps as moving to longer (six-month) reporting periods with simpler reporting requirements and coordinating income and resource definitions with TANF and Medicaid. Additionally, 20 states provide transitional food stamps to families who leave TANF without requiring reapplication.

Food stamp caseloads declined steeply during the second half of the 1990s. Thirty-seven percent fewer people received food stamps in the average month of 2000 than in 1994. ³ *Exhibit II.1* shows that this was also a period of declining participation rates. Researchers have examined

³ USDA Food and Nutrition Service Food Stamp Program data posted online at <http://www.fns.usda.gov/pd/fssummar.htm> (accessed April 23, 2008.)

the extent to which the decline in participation rates reflected welfare reform versus changes in the economy or other factors. According to a review of literature by McKernan and Ratcliffe (2003), studies have found that between five and 24 percent of the caseload decline from 1994 to 1998 was due to welfare reform, and 19 to 45 percent was due to the strong economy in the late 1990s.

Welfare reform, and the coincident decline in the TANF caseload, potentially impacted the food stamp participation rate in various ways. For families participating in TANF, the additional administrative burden of applying for food stamps is relatively low (particularly given categorical eligibility rules) and the decline in the TANF caseloads suggests that many people face a higher burden of applying for food stamps after leaving or if they do not apply for welfare. Additionally, many families began to work as a result of the new TANF work requirements, and employed families tend to also have lower food stamp participation rates. Changing perceptions of welfare may have increased the stigma many potential applicants associate with food stamps, and misconceptions about how food stamp rules have changed may lead eligible households not to apply.

Studies have found evidence that those leaving the welfare rolls are less likely to participate in the Food Stamp Program. For example, in seven out of eight studies reviewed by Acs and Loprest (2001), fewer than half of welfare leavers received food stamps in the quarter after they left TANF. Rosenbaum (2006) cites USDA studies that show part of the decline in the participation rate was due to difficulties the program experienced in adapting to changes in the welfare system following welfare reform. To address the issue of low food stamp participation among welfare leavers, the 2002 Farm Bill established a state option for transitional food stamps, which allowed current benefit amounts to be locked in place for families leaving welfare for six months following exit.

The food stamp participation rate increased between 2002 and 2004. The 2004 increase likely reflects state reforms allowed under the 2002 Farm Bill (Greenstein, 2007), while increases in earlier years may reflect families adapting to the post-welfare reform system (Rosenbaum, 2006) or the economic downturn in the early 2000s.

D. Short-Term Earnings Declines, Income Volatility, and Participation

A number of studies consider the role that income volatility plays in program-eligible households' decisions to participate in public programs. Income volatility refers to fluctuations in a household's income over a given time period. There is evidence that income volatility has increased over recent decades (see, for example, Dynan et al., 2007) making this consideration particularly salient.⁴ Income volatility could affect the participation decision in several ways. For example, in programs where participants must report income changes, higher income volatility will mean a higher reporting burden. As mentioned earlier, recent literature has focused on the effects of recertification periods and other administrative requirements. Farrell et al. (2003) focus on a different effect of income volatility: households seeing a sudden decline in

⁴ The literature is not unanimous that income volatility is increasing; for example, an analysis by the Congressional Budget Office (2007) found little change in the variability of individual earnings over the past 20 years. Dynan et al. (2007) provide a review of the literature on the topic and a comparison of their own findings with those of the Congressional Budget Office.

income may expect it to be temporary and may expect higher income (and therefore an end to their eligibility for food stamps) within a short period of time.

In general, the expected relationship between income volatility and participation in the Food Stamp Program is that higher volatility will be associated with lower participation rates. In other words, given two households with the same average income over a particular time period, a household with stable, moderately low income is more likely to participate than a household with the same average income but with short periods of extremely low income balanced with short periods of higher income. Farrell et al (2003) derive this thesis from the permanent income hypothesis (Friedman, 1957). The strong version of that hypothesis states that expected long-term income, rather than current income, determines an individual's or household's consumption at a given time. Households smooth consumption over time, and do not reduce consumption due to a downturn in income or increase consumption due to an increase in income unless it is expected to be more than a transitory change. A weaker version of the hypothesis simply acknowledges that expected future income and past income are important determinants of current consumption. Applied to the question of how income affects participation in the Food Stamp Program, the hypothesis is that someone who expects an increase in income will be less willing to bear the time and effort costs of applying for benefits or of recertification.

Limitations on the permanent income hypothesis for low-income households are well known. Food stamp eligibility rules contain asset limits, and so an eligible household will have few, if any assets. For such households, smoothing consumption over time would require borrowing against expected future income, and low-income households may face "liquidity constraints" preventing them from doing so. Nonetheless, there are several reasons why expected future income might affect Food Stamp Program participation. First, a household expecting higher income in the future may decide to temporarily batten down. An increase in income will reduce the amount of benefits the household can receive in the future or make the household ineligible, lowering the benefits of applying for food stamps in the current time period. A household experiencing a sudden drop in income may need to learn about program rules and the system for applying for the first time. Further, the reporting burdens may be higher for a household with fluctuating income. (During the period of analysis of this study, 1997 and 1998, changes in monthly income of more than \$25 had to be reported to the program, though state rules have changed since the 2002 Farm Bill.)

In addition, despite the limited assets of eligible households, they may nonetheless be able to smooth consumption over time without accessing food stamps. These households may have accumulated assets not reported to the program, they may be able to tap into home equity, or they may have access to resources that do not factor into the asset test such as ability to borrow from or rely on friends or family outside the food stamp household or other rainy day strategies.

Farrell et al.'s findings supported the weak version of the permanent income hypothesis, at least with regards to near-term income. They found that "before the months leading up to the reference month, mean income of non-participating, food-stamp eligible households fell by much more than mean income of participant households; similarly, their mean income grew much more rapidly after the reference month ... This is consistent with the premise that

expectations of higher future income explain why some non-participant households do not participate.” The remainder of this paper explores whether earnings over a longer-term period than that analyzed by Farrell et al. also bear a significant relationship to participation.

III. DATA AND METHODOLOGY

A. Data Sources

The descriptive and statistical analyses in this report are derived from a restricted access data set consisting of the 1996 SIPP matched to the Social Security Administration's Summary Earnings Records (SER). The SIPP is a multi-panel, longitudinal survey of households and is commonly used in analyses of food stamp participation (e.g., McKernan and Ratcliffe, 2003). The 1996 panel includes data covering income and program participation over a four-year period, which limits the timeframe over which analysis can be conducted. However, the matched data set contains historical earnings data from the SER matched to SIPP individuals, making possible analyses of the association between data contained in the SIPP panel and earnings over a longer historical period.

The 1996 SIPP followed a sample of approximately 37,000 households over a period of four years. Households were grouped into four "rotation groups" that were approximately equal in size and were interviewed every four months on a staggered schedule (i.e., the first rotation group was interviewed in one month, the second rotation group was interviewed in the next, etc.). One group was interviewed in each of the 48 months the panel covers. At each interview, SIPP household members were asked retrospectively about their income and program participation for the preceding four months. Thus information on the income and program participation for respondents is available for the entire 48 month period.⁵ The first interviews were conducted between April and July of 1996 and the final interviews were conducted in December 1999 through March 2000. The SIPP contains detailed household and individual-level information on demographic characteristics, assets, income, and program participation.

The SER is a restricted-use data set maintained by the Social Security Administration that contains information on individuals' annual earnings and quarters of employment. The SER includes only "covered earnings" - that is, earnings to which the Social Security payroll tax applied - reported through payroll tax records, up to the taxable maximum, for the years between 1951 and 2000.⁶ Earnings of individuals working in uncovered sectors, including some state and local government workers, some long-term federal government workers, domestic workers who were not paid substantial amounts by any particular household, and some agricultural workers, do not show up in the SER. Matched individuals with no earnings recorded in the SER for a year - including children who were too young to have earnings over the period covered by the SIPP panel - were ascribed a value of zero earnings. Even individuals with no earnings in any year were included in the matched data set and have SER earnings records of zero in all years.

The data set used in this analysis matched the earnings records in the SER to SIPP data for individuals in SIPP households for whom a valid social security number (SSN) was reported to the SIPP. If a SIPP respondent did not provide a social security number (SSN) or provided an

⁵ The SIPP Users' Guide contains detailed information on the design, sampling methodology, and structure of the SIPP. Available at: <http://www.sipp.census.gov/sipp/usrguide/sipp2001.pdf>

⁶Maximum taxable earnings for Social Security taxes were \$62,700 in 1996 and rose to \$76,200 by 2000. See the Social Security Administration's website for a historical listing of maximum taxable earnings (<http://www.ssa.gov/planners/maxtax.htm>, accessed July 5, 2007).

incorrect SSN, he or she was not matched to the SER.⁷ Additionally, the version of the SER data set available to Lewin researchers only included SER earnings records for SIPP respondents participating in the first SIPP interview. Thus, individuals who joined SIPP households following the first interview were not matched to the SER.

B. Constructing the Analysis Data set

Preparing the SIPP-SER data set for this analysis consisted of assigning SIPP individuals to “food stamp units” (FSU), which serve as the unit of analysis, and then attributing annual earnings to the FSU from the SER. This process was complicated by several factors, including monthly changes in household composition in the SIPP and incomplete matching between the SIPP and SER. Because of our study’s focus on earnings, we limited the analysis data set to units with at least one working-age member.

1. Defining Food Stamp Units

Food stamp eligibility and benefit determination is based on the FSU, which includes members of a household who purchase and prepare food together. The FSU can be different from both the household and the family as food expenses may not be shared among all members of a household or family, and individuals from separate families may prepare food together within a household. For ease of discussion, however, we will often use the terms “household” and “FSU” interchangeably.

We grouped individuals in the SIPP into FSUs based on the MID-SIPP model, developed by The SPHERE Institute. The model was designed to simulate the effects of changes in food stamp policies using SIPP data. In defining FSUs and estimating food stamp eligibility, participation, and benefit amounts, it corrects for “seam bias” in the SIPP (i.e., the tendency for respondents to underreport changes in characteristics during the four months asked about in a single interview, and over-report changes between the periods asked about in consecutive interviews). The MID-SIPP model is described at more length in *Appendix B*; for a full description, see MaCurdy and Marrufo (2006). This paper uses the MID-SIPP’s assignment of individuals in the SIPP into FSUs, monthly eligibility determinations, and estimated benefit levels. FSU participation in the Food Stamp Program is determined using reported receipt of food stamps by SIPP individuals, but adjusted by the MID-SIPP model to account for seam bias. In some cases, this results in a FSU receiving benefits in a non-eligible month. However, for the analyses that follow, a FSU is only considered to be a FSU participant if it is eligible and receiving benefits in a given month.⁸

2. Focusing on Working-Age Food Stamp Units

As this report focuses on the relationship between earnings and participation, we focus our analysis on FSUs that contain at least one working-aged member. FSUs without a working-age member are therefore excluded from the analysis data set. We define working aged individuals to be those who are between 18 and 65 years of age.

⁷ During the match, SSA validated social security numbers using the Enumeration Verification System.

⁸ The eligibility and benefit data provided to Lewin by The SPHERE Institute do not incorporate the MID-SIPP’s calibration to the Food Stamp Quality Control Data.

3. *Attributing Annual Earnings to Food Stamp Units*

SIPP sample members may move into and out of households and create new FSUs from month to month due to divorces, marriages, children leaving for or returning from college, etc.⁹ However, since the SER contains annual rather than monthly earnings data, it is necessary to ascribe individuals to a particular FSU for the year in order to attribute their annual earnings to one. We do so based on their FSU membership in June of the calendar year. For example, if an individual is residing in FSU A in January through June and moves to FSU B in July, his or her annual earnings will be attributed to FSU A.¹⁰ We treat each year as a separate observation, and individuals not part of any FSU in June are excluded from our analysis set for that year.

Because of various complications in working with a data set that combines the monthly SIPP data and the annual SER data, it is necessary to restrict the analysis data set in several additional ways:

- We only include FSUs that have at least one working aged member who was present in the SIPP for all months during the calendar year. There are several reasons why an individual may be present in the SIPP for some months of a year but not others. Most notably, the SIPP (like other longitudinal surveys) suffers from attrition and members of the sample who participate in one interview may not participate in interviews in later months. Of all SIPP individuals in the 1996 panel, 39 percent were lacking at least one month of data in 1997, and for 1998, this figure is 42 percent. Since we cannot break down the SER's annual earnings data by month, to increase the comparability of the two data sources, we only use cases where the SIPP-reported earnings used in the determination of the FSU's eligibility is available for all 12 months in the calendar year. Those who attrite may be lower income (Weinberg, 2003), and may be more likely to fail to report participation (Bollinger and David, 2001, as cited in Farrell et al., 2003), which may affect descriptive statistics from our sample. However, it is not clear how attriters differ, if at all, from other households with regard to the relationship between earnings and participation.
- We restrict our analysis to FSUs present in 1997 and 1998. Due to the staggered structure of SIPP interviews across the four rotation groups, 12 months of data for the years 1996 and 1999 are not available for many SIPP individuals.¹¹ We exclude these years from our analysis.
- Finally, we exclude a number of FSUs because of incomplete matching between the SIPP and the SER. In particular, we drop from our analysis FSUs without any working aged members successfully matched to the SER. For these FSUs, it would be impossible to

⁹ Once an individual has joined a SIPP household, he or she will be included in subsequent surveys, regardless of whether he or she remains in the original household.

¹⁰ June was used because it is in the middle of the year and therefore more likely than months closer to the beginning or end of the year to represent the household composition present in the most months of the year.

¹¹ This is because the half of all households that were first interviewed in June or July of 1996 were only asked about the preceding four months (February through May or March through June 1996). Similarly, the quarter of all households last interviewed in December of 1999 were only asked about the preceding four months (August through November 1999).

track earnings over time. In 1997 and 1998, 6 percent of working-aged adults in a FSU were not matched to the SER.¹² As discussed above, these may have been individuals that did not provide a SSN, individuals who provided an invalid SSN, or individuals not present at the first SIPP interview.

Our final analysis data set consists of 33,499 FSU-year observations.¹³

C. Samples and Outcome Measures

This study investigates the reasons why FSUs identified as eligible for food stamps decide to participate in the Food Stamp Program or not, and in particular, whether current, past, and future earnings have a significant association with participation. Therefore, the analysis focuses on FSUs eligible for food stamps. Determining the sample of eligible FSUs within our analysis data set is complicated by the fact that eligibility for the Food Stamp Program is calculated on a monthly basis, but our analysis focuses on the annual earnings contained in the SER. We perform analysis on two different samples selected to represent food stamp eligibility in a year, based on two different definitions:

- (1) FSUs eligible in a specific month of the year
- (2) FSUs eligible in at least one month of the year

The first sample, consisting of FSUs eligible for the Food Stamp Program in one specific month in the year, is based off a more strict definition of eligibility. The second sample, by definition, contains all FSUs belonging to the first sample, as well as FSUs eligible in other months.

It should be noted that the specific month chosen for the first definition of eligibility in our descriptive analysis differs from the month chosen for our regression analysis. For the descriptive analysis, we use June as the specific month to define eligibility (the same month we used to assign individuals to FSUs for the year). For the regression analysis examining the relationship between income and participation, we use December as the specific month to define eligibility.¹⁴

¹² Of individuals present in the SIPP for all of 1997, irrespective of age, 12,060 did not match to the SER; this figure is 12,957 for 1998.

¹³ Given the nature of the dataset, it would have been preferable to correct standard errors for FSUs present as observations in both 1997 and 1998 to allow for within-FSU dependence over time. However, the dataset did not identify repeated observations of FSUs (identifiers of FSUs were not consistent from year to year). While it would have been possible to identify repeated observations through different means, it was infeasible in the period of time in which we had access to the matched dataset. As a result, measurements of standard errors may be somewhat too small, although as there are at most two observations of each FSU (small relative to the total number of FSUs) this effect is likely to be small.

¹⁴ December was initially chosen for the regression analysis due to considerations regarding an alternate model we ultimately did not use. Once the decision was made to discard that model, it would admittedly have been preferable to rerun the analysis using June, to be consistent with the descriptive analysis. However, time constraints on our access to the restricted SIPP-SER dataset prevented us from doing so at that point.

The measures of participation we use correspond to the definitions of eligibility defining each sample. Where the sample is defined by eligibility in a specific month, we examine whether the FSU participates in that month. Where the sample is defined by eligibility in any month during the year, we examine whether the FSU participates in any month of the year. We also use a third measure of participation when the sample is defined by eligibility in any month of the year: whether the FSU participates in none, some, or all of the months in which it is eligible during the calendar year. We refer to this as the “intensity” of participation.

Together, the different definitions of eligibility and participation characterize three models used in this study. These are summarized in *Exhibit III.1*.

Exhibit III.1: Measures of Eligibility and Participation

<i>Model</i>	<i>Eligibility Definition (sample)</i>	<i>Participation Definition (outcome)</i>
1.	The FSU is eligible for food stamps in a specific month <i>Sample sizes: 5,316 (June) or 4,444(December)</i>	The FSU is participating in the Food Stamp Program in that specific month (June or December)
2.	The FSU is eligible for food stamps in at least one month in the calendar year <i>Sample size: 7,598</i>	The FSU is participating in the Food Stamp Program in at least one month that it is also eligible during the calendar year
3.	Same as Model 2	The FSU is participating for every month it is eligible for the Food Stamp Program –or– the FSU is participating for some of the months it is eligible for the program –or– the FSU is participating for none of the months it is eligible for the program

The two samples can be expected to have somewhat different characteristics. In particular, FSUs eligible for longer periods of time would be expected to make up a higher percentage of the sample defined by eligibility in a single month.¹⁵ Similarly, FSUs meeting the corresponding participation definition may be expected to have longer spells of participation in the Food Stamp Program than those meeting the second criteria. Our assumptions about how this will affect responsiveness to changes earnings are somewhat ambiguous. On the one hand, those with longer eligibility spells may face lower impediments to participation from factors such as newly learning about the program and how to apply for food stamps, and therefore, may be more likely to enter the Food Stamp Program when faced with a sudden loss of earnings. On the other hand, it may be that a change in earnings within a long eligibility spell would be less likely to lead a FSU that had already made the decision to participate to stop participating or one that had decided not to participate to begin participating.

¹⁵ This is a commonly recognized feature of spell analysis. Of the food stamp eligibility spells captured in sample Model 2, the longer ones are more likely than the shorter ones to be ongoing in the specific month used to define eligibility in Model 1.

D. Types of Analysis Conducted

This paper presents the results of both descriptive and regression analysis of the samples. After presenting eligibility and participation characteristics of the two samples, we discuss descriptive statistics comparing demographic, economic, and other characteristics of FSUs that participate with those that do not. We also examine households by their quartile of current earnings (i.e., in the year they are determined to be eligible), likewise comparing participants and non-participants within each quartile. This allows us to see whether differences between households that use food stamps and those that do not vary according to earnings levels. We then examine the earnings of FSUs meeting our two eligibility criteria, comparing total earnings measured in the SER among all FSU members up to 15 years prior to when a FSU meets the eligibility criteria and up to two years in the future.

We use regression analysis to examine the extent to which past, current, and future earnings are related to participation decisions. While descriptive statistics allow us to observe how the earnings of participants and non-participants differ, other characteristics associated with participation or nonparticipation may explain some, or all, of any relationship between earnings and participation decisions we observe. Using regression analysis, we are able to control for differences in observable characteristics, using the broad range of characteristics measured by the SIPP as well as the historical earnings and employment information provided by the SER, to see if the association between earnings over time and participation in the Food Stamp Program remains significant. We examine three outcomes using regression analysis as described in *Exhibit III.1* – whether a FSU participates in the program in a particular month (December), whether a FSU participates during any month in the year, and whether the FSU participates for all, some, or none of the months it is eligible for benefits.

It must be noted that our analysis contains a potential source of bias in that, as discussed in the previous section, 6 percent of working-aged adults in the FSUs do not have corresponding records in the SER. This could bias our results in two ways – by excluding entire FSUs that have no working-aged members matching to the SER and by reducing the earnings we observe for FSUs that have at least one working-aged member matching to the SER but other members that do not match. Data analysis we performed on the entire SIPP sample show some differences between working-age individuals not matched to the SER and those that are matched – e.g., those that are not matched are a little younger on average (38 years old, compared with 40), more likely to be Hispanic (17 percent versus 9 percent), and have somewhat lower average earned and unearned income – but differences with regards to food stamp participation are not large. Of those not matched to the SER, 23 percent are eligible for food stamps, compared to 19 percent of those matched; and among those eligible 33 percent of the non-matched individuals received food stamps compared to 37 percent of the matched individuals.

IV. DESCRIPTIVE RESULTS

A. Participation Rates

As shown in *Exhibit IV.1*, of the FSUs in the sample defined based on eligibility for food stamps in any month of the year, approximately 37 percent participated in the Food Stamp Program at some point during that year. Similarly, in the sample defined based on eligibility for the program in a specific month (June), 36 were participating in that month.¹⁶ There were higher participation rates in 1997 than in 1998 (in the sample defined by eligibility in any month of the year, 39 percent of eligible FSUs participated in 1997, compared to 35 percent in 1998), but these differences are not large.

USDA-reported food stamp participation rates (Wolkwitz, 2007) in 1997 and 1998 indicate that 57.5 and 54.2 percent of eligible households participated in the Food Stamp Program, respectively. Our model finds lower rates of participation. A primary reason for this difference is that the eligibility and benefit data provided from the MID-SIPP do not incorporate the MID-SIPP's calibration to the Food Stamp Program Quality Control (FSP-QC) data set. In contrast, both the USDA-reported figures and figures in other reports based on the full MID-SIPP model are calibrated to that data set. Background data provided by The SPHERE Institute show that the number of food stamp participants in the MID-SIPP model before calibration represents approximately 78 percent of the number of participants found using the FSP-QC data. The fact that fewer food stamp participants are captured in the SIPP accounts for about half of the difference between the rates we find and those found using the FSP-QC data.

Another factor contributing to our rates being lower than USDA's is that eligibility determination based on the SIPP may lead to lower participation rates than eligibility determination based on the CPS. The methodological appendix of Wolkwitz (2007) shows that in 1997 and 1998, individual participation rates calculated from the SIPP were lower than the CPS-based individual participation rates. Other potential sources of differences include the different models used to determine eligibility and the particular sample used by this study (FSUs with working-age adults that matched to the SER).¹⁷

¹⁶ Given that the sample eligible specifically in June contains proportionally more FSUs eligible for longer periods than the other sample (who are generally more disadvantaged than shorter-term eligibles), we might expect it to have a higher participation rate. It is unclear why we did not find more of a difference in the participation rates of the samples. One contributing factor is that the definition of participation for this sample will exclude FSUs who receive food stamps in months other than June, while the other sample will capture FSUs that participate in some months but not others. However, it is unlikely that this is the sole explanation.

¹⁷ Although it would not be an additional source of differences between the USDA estimate and our own, it is worth noting that survey measurement error may also affect our estimated participation rates. Comparing earnings data in the 1996 panel of the SIPP with the SER, we found that of the 17.5 percent of working-aged individuals in the SIPP who reported no earnings in a year, about a fifth (3.3 percentage points) had positive annual earnings in the matched administrative data, averaging about \$5,600. Further, for individuals with positive but relatively modest earnings in the SIPP (less than \$20,000) and earnings shown in the administrative data, the administrative data showed earnings that were 10 percent or more higher than was reported on the SIPP in at least one-third of cases. If the administrative data are

As *Exhibit IV.1* shows, participation rates are not constant across quartiles of current earnings. Participation among households in the first quartile of earnings is 12 percentage points higher than that of all households.¹⁸ In fact, only in the fourth quartile of earnings is participation substantially lower than for the entire sample. FSUs in the first quartile had zero earnings, those in the second earned \$2,474 on average, those in the third earned \$10,528, and FSUs in the fourth quartile earned, on average, \$22,670. (See *Appendix Exhibit A.1*)

Exhibit IV.1: Food Stamp Participation Rates

	Total Eligible FSUs	Participants	Participation Rate
Any eligibility in specific month (June)	5,316	1,939	36%
Any eligibility in June 1997	2,484	1,113	39%
Any eligibility in June 1998	2,468	826	34%
Any eligibility in year	7,598	2,783	37%
Any eligibility in 1997	4,068	1,567	39%
Any eligibility in 1998	3,530	1,216	35%
First quartile of annual earnings	2,351	1,156	49%
Second quartile	1,424	664	47%
Third quartile	1,874	681	36%
Fourth quartile	1,949	282	14%
Eligible for 12 months	2,487	1,519	61%

Note: Data are weighted.

B. Descriptive Statistics

4. Demographic Characteristics of Participant and Non-Participant Food Stamp Units

We next examine FSU characteristics, comparing participant households with non-participant households. We present statistics from the sample of FSUs that were eligible for the Food Stamp Program in at least one month during the year; as discussed above, this sample has more short-term eligibles than the sample eligible specifically in June. To ascribe individual-level characteristics such as race or education level to the household, we identify a “head” of each FSU, which we define as the oldest working aged FSU member that matched to the SER, and treat that individual as a representative of the FSU. We also use the “head” concept in our analysis of FSU composition.

Exhibit IV.2 provides an overview of the composition of participating FSUs, compared to those that do not participate. Participating FSUs are more likely to be female-headed and have

more reliable than the SIPP, such underreporting on the SIPP would inflate the estimate of eligible households. On the other hand, there were also cases where the SIPP showed higher income than the administrative data; we did not directly measure the net impact on the food stamp eligibility determination. See *Appendix C* for more discussion of earnings comparisons between the SIPP and SER.¹⁸ The first quartile contains families with zero earnings only. As over 25 percent of the sample of eligible FSUs had zero current earnings, the first quartile is larger, and the second quartile is smaller, than the third and fourth quartiles.

children present. Of FSUs that had children, participating FSUs are also more likely to have younger children.

Exhibit IV.2: Composition of FSUs Eligible for Food Stamp Benefits in at Least One Month during the Year

	Non-Participants	Participants	Total Eligible
Female headed	53.2%	71.3%	59.5%
Number of FSU members	2.2	2.8	2.4
Any children present	41.9%	65.7%	50.2%
<i>Of those FSUs with children present:</i>			
Youngest child is between 0 and 3 years old	13.2%	24.0%	17.0%
Youngest child is between 4 and 10 years old	31.7%	52.8%	39.1%
Youngest child is eleven or more years old	55.1%	23.2%	43.9%
Any elderly present	2.2%	*	*
<i>Number of observations</i>	4,815	2,783	7,598

Notes: Data are weighted. Asterisks indicate results suppressed due to sample size considerations. Results are suppressed when there are less than 75 observations in a cell. In addition, if a result is suppressed in the “non-participants” or “participants” column, the result is also suppressed in the “total eligible” column.

Additionally, participating FSUs are more likely to be headed by individuals who are non-white (38 versus 24 percent) and who have not received a high school diploma or GED (42 versus 28 percent). These individuals are also less likely to have a college or advanced degree (3 versus 15 percent). However, these individuals were similar in age to the heads of non-participating households.

**Exhibit IV.3: Characteristics of FSU Heads,
FSUs Eligible for Food Stamp Benefits in at Least One Month during the Year**

	Non-Participants	Participants	All Eligible FSUs
Age of head of household (average)	41	40	40
<i>Race</i>			
White	76.0%	62.3%	71.2%
Black	19.8%	32.9%	24.4%
Native American	2.2%	*	*
Asian/Pacific Islander	2.0%	*	*
Hispanic origin	13.3%	15.5%	14.1%
<i>Education Level</i>			
Less than high school diploma or GED	28.1%	41.6%	32.8%
High school diploma or GED	34.6%	34.0%	34.4%
Some college, no degree	22.6%	18.4%	21.4%
College/graduate/professional degree	14.7%	3.2%	11.7%
<i>Number of observations</i>	4,815	2,783	7,598

Notes: Data are weighted. Asterisks indicate results suppressed due to sample size considerations. Results are suppressed when there are less than 75 observations in a cell. In addition, if a result is suppressed in the “non-participants” or “participants” column, the result is also suppressed in the “total eligible” column.

5. *Earning Characteristics of Participant and Non-Participant Food Stamp Units*

Overall, FSUs that participate in the Food Stamp Program in at least one month during the year are more disadvantaged than eligible non-participants (*Exhibit IV.4*). Summing earnings reported in the SER across all FSU members (that have a record in the SER), there are large differences in earnings between participants and non-participants, both in the current year and over time. Since our sample groups together FSU observations from 1997 and 1998, we denote earnings over time in relation to the observation year; thus, earnings in the year of observation are displayed as $t = 0$, which represents annual earnings in 1997 or in 1998 depending on when we observe the FSU. Likewise, earnings at $t - 1$ represent either annual earnings in 1996 or 1997, depending on which year the observation is drawn from, and so on. Historical averages of earnings do not include the current year, so, for example, the 2-year average shown in the table is the average of earnings in $t - 1$ and $t - 2$.

Our measure of historical earnings for a FSU is the sum of the historical earnings of its current members. Although it is certainly plausible that the composition of FSUs has changed over time and that some of its current members had not lived together in years in the past, it is the current members' past earnings that are relevant to the factors hypothesized to affect participation – e.g., expectations of future earnings of the FSU and resources not factored into food stamp eligibility.

As shown in the exhibit, on average, participating households earned \$7,545 less than households that did not participate. This difference in average earnings does not simply appear in the current year, but is fairly consistently present when we examine historical earnings.

Exhibit IV.4: FSU Earnings According to SER Records, FSUs Eligible for Food Stamp Benefits in at Least One Month during the Year

	Non-Participants	Participants	Difference	All Eligible FSUs
Current year earnings				
Earnings t = 0	\$12,891	\$5,346	\$7,545	\$10,248
Historical earnings				
Earnings t - 1	\$12,226	\$4,660	\$7,566	\$9,576
Earnings 2 year average	\$11,990	\$4,592	\$7,397	\$9,398
Earnings 5 year average	\$11,281	\$4,735	\$6,546	\$8,988
Earnings 10 year average	\$10,859	\$4,841	\$6,017	\$8,751
Future earnings				
Earnings t + 1	\$14,191	\$6,881	\$7,310	\$11,630
Earnings 2 year average	\$14,693	\$7,440	\$7,252	\$12,152
Quarters with earnings				
t = 0	2.6%	1.7%	0.8%	2.3%
2 year total	5.0%	3.0%	2.0%	4.3%
5 year total	12.1%	7.5%	4.6%	10.5%
10 year total	23.1%	15.2%	8.0%	20.3%
Lifetime total	60.6%	42.1%	18.5%	54.1%
Lifetime years with earnings	18.2%	14.1%	4.1%	16.7%
<i>Number of observations</i>	4,815	2,783	--	7,598

Notes: Data are weighted. Dollar amounts presented in 1996 dollars, adjusted for inflation using the CPI-W.

Background calculations, which we do not present here, show that in the more restrictive sample of households eligible for benefits specifically in June (rather than any month in the year), the trends are quite similar. Earnings for both participants and non-participants are lower in this sample, which is consistent with our assumption that this sample contains a higher proportion of households eligible for food stamps for longer time periods and who therefore are likely to be more disadvantaged. However, the percentage difference in earnings between participants and non-participants in this sample is remarkably similar to the percentage difference in the sample based on eligibility in any month of the year. For example, *Exhibit IV.4* shows that current year earnings of participants in the sample based on eligibility in any month in the current year is 59 percent lower than earnings of non-participants. Our background calculations find that in the sample based on eligibility in June, participants earned \$3,596, or 58 percent less than the \$8,525 earned by non-participating FSUs.

Self-reported earnings in the SIPP (not shown in a table) have a similar pattern to the earnings reported in the SER. For the sample of FSUs eligible for benefits in at least one month, annual SIPP earnings differ by approximately \$7,000 between participants and non-participants (\$12,477 versus \$5,416, respectively). Taking into consideration not just earnings but total income from all sources measured in the SIPP, the difference between participating and non-participating FSUs shrinks to \$5,233 (\$15,190 versus \$10,184, respectively), mainly due to the large amount of transfer income participating households receive from programs like TANF

(\$2,756). Analyses of the sample of FSUs eligible in June yield similar findings, although earnings were again lower across participants and non-participants.

Consistent with these differences in earnings, eligible FSUs that receive food stamps have members that worked fewer quarters in the current year, previous year, and past 2, 5, and 10 years than eligible FSUs that did not receive benefits.¹⁹ It is important to note that the SER only contains information on covered sectors of employment; thus, a household may have a small number of quarters of employment because there were no members with earnings for the majority of the year or because household members worked and received earnings in uncovered sectors.

The heads of FSUs that participated in the Food Stamp Program were similar in age to non-participants but these individuals worked fewer years (14.1 versus 18.2) and quarters (42.1 versus 60.6 total) than did non-participants.²⁰ This may indicate that households that choose to receive food stamps in the current year experienced more variation in their earnings over time, though we did not investigate the extent to which years or quarters with earnings occurred in spells.

6. Eligibility and Benefits of Participant and Non-Participant Food Stamp Units

As shown in *Exhibit IV.5*, households that received food stamps were on average eligible for almost 10 months out of the year, while eligible non-participants were only eligible for benefits for a little over half the year. FSUs participating in the program were also eligible for larger benefits than households that were eligible but did not participate.

**Exhibit IV.5: Food Stamp Eligibility and Participation,
FSUs Eligible for Food Stamp Benefits in at Least One Month during the Year**

	Non-Participants	Participants	All Eligible FSUs
Months of eligibility for Food Stamp Program	6.2	9.8	7.5
Average months of participation in Food Stamp Program	0	8.7	3.1
Average benefit amount for which FSU is eligible (only in eligible months; as measured in MID-SIPP model)	\$126	\$165	\$140
<i>Number of observations</i>	4,815	2,783	7,598

Notes: Data are weighted. Dollar amounts presented in 1996 dollars, adjusted for inflation using the CPI-W.

¹⁹ If non-participating FSUs were headed by older members (with more prime-aged working years) or contained more adult members (who could have contributed quarters of work to the FSU) than participating FSUs, it would be a potential explanation for the differences found between the two groups. However, as shown in *Exhibits IV.2* and *IV.3*, neither the age of the FSU head nor the number of adult members differ substantially according to participation status.

²⁰ The SER only contains records of earnings and quarters covered for the years between 1951 and 2000. To the extent that FSUs contain individuals aged 65 or older that had earnings prior to 1951, we will underestimate the total years of earnings for all FSU members.

7. Characteristics of SIPP Households in which Food Stamp Units are Contained

Next, we examine the characteristics of the SIPP households that include eligible FSUs. A SIPP household may contain multiple FSUs and eligibility for each is determined independently. Still, additional resources may exist within the household that are available, to some degree, to members of an eligible FSU. In fact, 15 percent of non-participating FSUs belonged to a SIPP household that received food stamp income within the year. This suggests a household's total resources, including food stamps received by another FSU within the household, may provide one explanation for why a FSU eligible for the program chooses not to participate.

When we compare the SIPP-measured income received by the households that participants and non-participants belonged to, the differences are striking. The households that included non-participating FSUs reported annual income 59 percent higher than households containing participating FSUs, and were more likely to receive earnings. Additionally, non-participating FSUs were more likely to belong to a "non-family" household (i.e., a household consisting entirely of unrelated individuals; approximately one third of non-participating FSUs versus approximately one quarter of participants). Non-participating FSUs were also more likely to belong to a married family household (37 versus 25 percent) while a larger portion of participating FSUs belonged to a single-female headed household (48 versus 24 percent).

**Exhibit IV.6: Household Type and Income by Source According to SIPP Records,
FSUs Eligible for Food Stamp Benefits in at Least One Month during the Year**

	Non- Participants	Participants	Difference	All Eligible FSUs
<i>Income</i>				
Total household income	\$23,695	\$14,922	\$8,773	\$20,622
Percent households with earnings	84.1%	65.7%	--	77.6%
Household earnings for receivers	\$22,589	\$13,149	\$9,440	\$19,791
Percent households with food stamp income	6.2%	99.9%	--	39.0%
Household food stamp income for receivers	\$1,256	\$1,684	-\$428	\$1,640
Percent households with TANF income	4.2%	41.6%	--	17.3%
Household TANF income for receivers	\$2,332	\$2,968	-\$636	\$2,867
Percent households with SSI income	14.9%	32.5%	--	21.1%
Household SSI income for receivers	\$4,559	\$4,389	\$170	\$4,467
<i>Type of Household</i>				
Married family	37.3%	24.6%	--	32.9%
Non-married family				
Male household head	*	*	--	*
Female household head	23.6%	48.4%	--	32.3%
Non-family				
Male household head	18.1%	9.6%	--	15.1%
Female household head	14.6%	12.9%	--	14.0%
Group quarters	*	*	--	*
<i>Number of observations</i>	4,815	2,783		7,598

Notes: Data are weighted. Asterisks indicate results suppressed due to sample size considerations. Results are suppressed when there are less than 75 observations in a cell. In addition, if a result is suppressed in the "non-participants" or "participants" column, the result is also suppressed in the "total eligible" column. Share of food stamp participants receiving benefits is slightly below 100% because household food stamp income measured in the SIPP is not adjusted for seam bias in the same way as participation data from the MID-SIPP model. Dollar amounts presented in 1996 dollars, adjusted for inflation using the CPI-W.

8. Characteristics of Participant and Non-Participant Food Stamp Units by Earnings Quartile

Finally, we divide the sample of FSUs eligible for benefits at any month in the year by quartile of earnings in that year.²¹ As shown earlier in *Exhibit IV.1*, participation rates differ substantially across quartiles, with about half of eligible FSUs in the first quartile (who had no earnings in the current year) participating compared to only one out of seven in the fourth quartile. This is consistent with other studies (such as Wolkwitz, 2007) that show households with earnings participating at lower rates than households without earnings. It probably largely reflects a combination of the higher level of need among households with lower earnings and the higher level of benefits for which these FSUs are eligible.

²¹ Because approximately 30 percent of all eligible FSUs had zero earnings reported in the SER, each quartile does not contain exactly 25 percent of the sample. In particular, Q1 contains 31 percent of FSUs and Q2 contains 19 percent. Q3 and Q4 both contain approximately 25 percent of FSUs each.

Appendix Exhibit A.1 presents FSU characteristics by quartile. Participants and non-participants in the same quartile are relatively similar for some characteristics, such as age and education level. Nonetheless, there are consistent (if sometimes modest) differences in characteristics between participants and non-participants across quartiles. For example, in all quartiles, participants are somewhat more likely to be non-white, and to have a head of household with less than a high school diploma. A higher proportion of participant FSUs in each quartile also have a head of household who is female, although in the top quartile the proportion is very similar between participant and non-participant FSUs.

When we examine average earnings over a 10 year period, a more substantial difference between participants and non-participants emerges. In each quartile, 10-year historical earnings are between 27 and 40 percent lower for participants than non-participants

In contrast, differences in total current year income as measured in the SIPP are much smaller between participants and non-participants; this is primarily due to higher transfer income (including food stamp benefits) received by participants. Notably, in the bottom quartile, where FSUs had zero earnings reported in the SER in the year of observation, the SIPP shows non-participants as having received close to \$3,000 in earnings in the current year. Additionally, the households these FSUs belonged to had additional resources (\$16,480 in income in the current year for participants; \$11,172 in income for non-participants). This suggests, non-participants may have received earnings in uncovered employment or lived in households where resources were shared informally. See *Appendix C* for further discussion of differences in earnings data in the SIPP and the SER.

C. Earnings over time

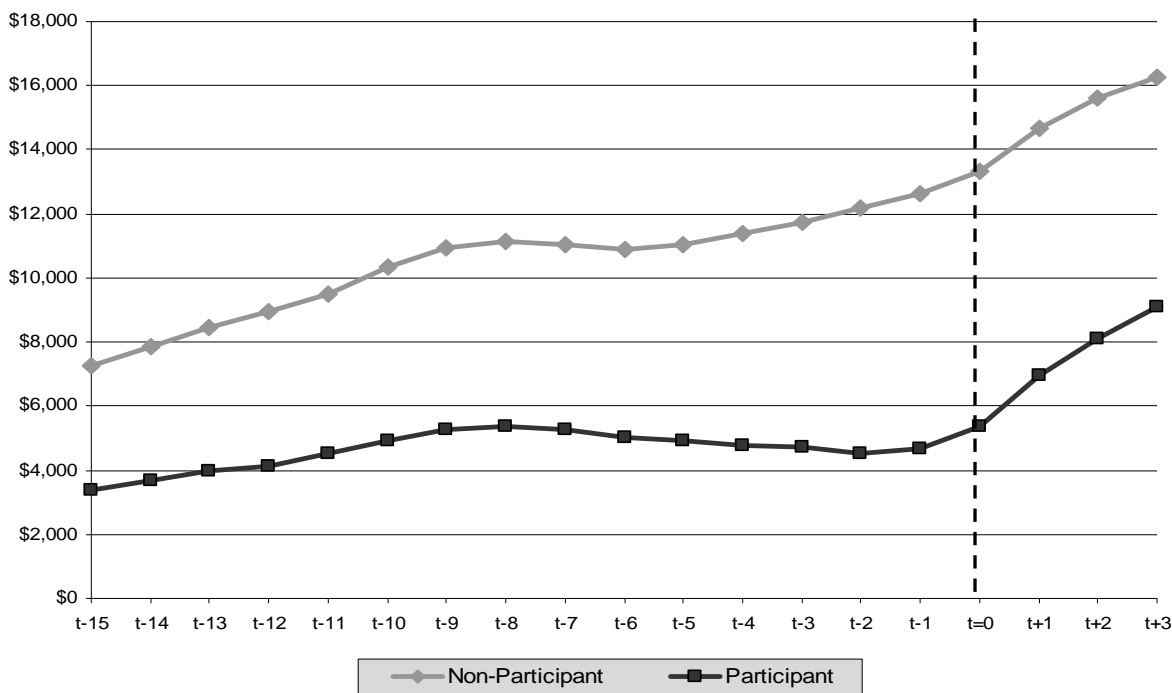
Farrell et al. (2003) examined monthly earnings for participants and non-participants and found that the earnings of households not receiving food stamps had a V-shaped pattern – i.e., a sharp drop in average earnings in the four months leading up to the month in which they were eligible, followed by rapid growth in average earnings after the month of eligibility. Those that did participate in the Food Stamp Program had consistently low earnings. In this section we look at the earnings patterns of participants and non-participants over time using our model and the annual earnings data from the SER. Like Farrell et al. (2003) we find consistently lower earnings among participants than non-participants, but we do not find the same V-shaped pattern.

Exhibit IV.7 depicts annual earnings over time for FSUs eligible for benefits, using the sample based on eligibility in any month in the year, and combining FSUs observed in 1997 and 1998.²² All amounts are adjusted for inflation and presented as 1996 dollars. In the year of eligibility ($t = 0$, representing either 1997 or 1998) the difference in earnings between households receiving food stamps and those that did not was \$7,545, a sizeable difference, considering that average earnings for all eligible FSUs in the year of eligibility was \$10,248. Differences in average earnings between participants and non-participants persist and are substantial over the

²² We also examine the two years separately, and, as shown in *Appendix Exhibit A.2*, trends over time for both years are very similar.

previous 15 years, showing that current participation rates bear a relationship with earnings from more than a decade earlier.²³

Exhibit IV.7: Annual Earnings by Participation Status, FSUs Eligible in at Least One Month during the Year



Notes: Data are weighted. t = 0 indicates 1997 or 1998. All amounts presented in constant 1996 dollars, adjusted for inflation using the CPI-W.

For both participants and non-participants, trends in earnings are substantially affected by economic trends and/or life-cycle factors, but there are some notable differences between the groups. Approximately seven years prior to the year of eligibility, the earnings of participating households begin to decrease, in comparison to earnings in the prior year (t - 8), and continue declining for most of the subsequent years before the year of eligibility. Conversely, non-participants experience a growth in earnings over this period. In particular, over this time period, non-participants saw their earnings increase by 21 percent, from \$11,047 to \$13,323. Participants experienced an 11 percent decline in earnings between t - 7 and t - 1, followed by an increase to \$5,377 in the year of eligibility, which is 2 percent larger than earnings in t - 7.

However, these differences in growth rates turn out to largely reflect the fact that participants have lower earnings to begin with. *Appendix Exhibits A.3 through A.6* show historical earnings by earning quartile in t = 0. When the food stamp units are grouped based on earnings in this manner, it turns out that growth rates in earnings in the seven years leading up to food stamp eligibility are similar or higher among participants than non-participants. This is shown in

²³ Some of the growth in both series may be due to aging of members of the two groups over time; in particular, some individuals within the FSUs in the two groups may not have been old enough have earnings in the earlier years in the period covered.

Exhibit IV.8. That exhibit also compares growth ending the year before eligibility to separate out the impact of short-term decreases in earnings that led to temporary eligibility in $t = 0$; in the top quartile, earnings growth is higher for non-participants, but only by a small amount.

Exhibit IV.8: Earnings Trends over Time, FSUs Eligible for Food Stamp Benefits in at Least One Month during the Year, By Quartile

	Non-participants	Participants	Total eligible
Changes from $t - 7$ to $t = 0$			
Lowest Quartile			
Earnings $t - 7$	\$4,768	\$3,067	\$3,924
Earnings $t = 0$	\$0	\$0	\$0
Percent change	-100%	-100%	-100%
Second Quartile			
Earnings $t - 7$	\$6,681	\$3,977	\$5,422
Earnings $t = 0$	\$2,558	\$2,439	\$2,503
Percent change	-62%	-39%	-54%
Third Quartile			
Earnings $t - 7$	\$8,566	\$6,354	\$7,740
Earnings $t = 0$	\$10,351	\$9,541	\$10,049
Percent change	21%	50%	30%
Highest Quartile			
Earnings $t - 7$	\$18,327	\$13,614	\$17,652
Earnings $t = 0$	\$27,921	\$22,290	\$27,115
Percent change	52%	64%	54%
Changes from $t - 7$ to $t = -1$			
Lowest Quartile			
Earnings $t - 7$	\$4,768	\$3,067	\$3,924
Earnings $t = -1$	\$793	\$472	\$633
Percent change	-83%	-85%	-84%
Second Quartile			
Earnings $t - 7$	\$6,681	\$3,977	\$5,422
Earnings $t = -1$	\$4,570	\$2,985	\$3,832
Percent change	-32%	-25%	-29%
Third Quartile			
Earnings $t - 7$	\$8,566	\$6,354	\$7,740
Earnings $t = -1$	\$10,177	\$7,484	\$9,170
Percent change	19%	18%	18%
Highest Quartile			
Earnings $t - 7$	\$18,327	\$13,614	\$17,652
Earnings $t = -1$	\$24,856	\$17,790	\$23,844
Percent change	36%	31%	35%

Notes: Data are weighted. We examine future earnings at $t + 2$, rather than $t + 3$; because this is the last year we observe earnings for all sample members.

The differences in the overall growth rates between participants and non-participants occur because they are distributed differently among the quartiles. Underlying data (not shown in the table) indicate that 42 percent of participants fall into the lowest quartile, compared to only 25 percent of non-participants; conversely, ten percent of participants fall into the highest quartile, compared to 35 percent of non-participants.

Differences in future earnings between participating FSUs and those not receiving benefits are large, although for both groups, earnings increase after the year of eligibility. This may be a result of the United States' economic expansion during the late 1990s, as $t + 1$ through $t + 3$ represent either 1998 through 2000 or 1999 through 2001.

To check whether the overall trends reflect our sample selection, we also look at earnings over time for the sample based on FSU eligibility in a single month. We still observe a sizeable difference in earnings in the current and past years, although earnings for both groups are lower in all years. (These figures are not presented in a table.) This is not surprising; FSUs eligible in a given month can be expected to, on average, have consistently lower earnings in the current year as the sample excludes households included in the other sample who had only temporary dips in earnings in any other month.

Notably, we did not find the V-shaped pattern found by Farrell et al. (2003).²⁴ There are several potential reasons why this is the case. Most notably, our annual earnings measure smooths over much of the variation contained in the monthly earnings data. However, analysis of background data provided by the authors of Farrell et al. (2003) suggests that this does not fully explain the differences between their results and ours; taking annual averages of their monthly data does not completely eliminate the dip in earnings of non-participants in the year of eligibility. Other possible factors include that unlike Farrell et al., our eligibility model (from the MID-SIPP) smooths over changes in eligibility and participation due to seam bias; and that Farrell et al. measure earnings as a percent of the poverty line, essentially measuring earnings relative to household size in a way our model does not.

Despite not finding the V-shape, it is worth noting that within similar earnings groups, participants saw higher earning growth (or lower earning declines) in recent years than non-participants, a finding that is consistent with the predictions of the permanent income hypothesis. The difference in growth rates reflects the fact that among food stamp units with similar earnings in $t = 0$, non-participants had higher earnings in the past. Such households may expect higher earnings in the future and therefore be less likely to take on the costs of participating in the Food Stamp Program. The regression analysis discussed below takes a more sophisticated approach to controlling for differences in earnings levels, and controls for other characteristics of food stamp units as well.

²⁴ We did find a V-shaped pattern in the lowest and second-lowest quartiles (*Appendix Charts A2 and A3*), where average earnings of non-participants declined more sharply in $t = 0$ than average earnings of participants, and earnings for both participants and non-participants rebounded in $t = 1$. In the lowest quartile, this is almost definitional, as the lowest quartile was defined by the set of FSUs with zero earnings in $t = 0$. (More than one quarter of FSUs – 31 percent – had zero earnings in $t = 0$.)

V. REGRESSION RESULTS

When we compared the earnings histories of working-age participants and non-participants in the previous section, we found that participants have lower earnings in the current and past years. These households are more likely to have children, are headed by individuals with lower levels of education, and are more likely to be female headed. We found that in years leading up to being eligible for Food Stamps, participants on average had stable or decreasing earnings, while non-participants experienced an increase in earnings, but that this trend did not hold for all subgroups.

With regression analysis, we are interested in disentangling the association between FSU characteristics, current earnings, and long-run earnings. We test the hypothesis that higher long-term earnings may lead some households not to participate in the Food Stamp Program despite a short-term downturn that makes them eligible for at least one month in the year we calculate eligibility. This could be because their past earnings or other factors related to past earnings lead them to expect higher earnings in the future. Additionally, these households may have been better able to accumulate assets that are unreported or do not factor into the food stamp eligibility determination. Previous research has shown that month-to-month fluctuations in income play a large role in the decision to participate (Farrell et al., 2003). We investigate the additional question of whether longer term earnings and earnings patterns also help to explain the decision to participate. We find some evidence that past earning levels are related to a household's decision to participate even after taking into account current earnings and earnings volatility, measured by the length of eligibility for the program.

A. Regression Framework

We employ three regression models to examine the decision to participate in the Food Stamps Program as was summarized in *Exhibit III.1*. To recapitulate:

Model (1) examines the probability that a FSU participates in a specific month, conditional on eligibility in the month. In this model, we use December as the specific month for defining eligibility and participation.²⁵ There are 4,444 FSUs that were eligible for benefits in December. This model offers a standardized method of determining eligibility and participation as we know that all FSUs faced the same decision of whether to participate in this particular month. Two consequences of using December as the reference month are worth noting. First, since the participation decision in question is at the end of the year, current year earnings and other independent variables related to the current year (such as months of earnings) can properly be interpreted as primarily occurring prior to the time the participation decision was made. Second, as discussed in the methodology section of this paper, FSUs eligible for longer periods are a higher proportion of this sample than a sample based on eligibility in any month of the year, as FSUs with short eligibility spells are less likely to be represented in the eligible population in a given month.

²⁵ December was chosen as the month for defining eligibility and participation for the regressions in an early stage of the analysis. Due to our access to the matched SIPP-SER data set expiring, we did not have an opportunity to redo the regression analysis using June as the reference month, which would have been consistent with our descriptive analysis.

Model (2) examines the probability that a FSU participates in any month in the year, conditional on any eligibility in the year. In this model we use a broader definition of eligibility and participation and examine the probability of any participation in the calendar year, conditional on any eligibility in the year. While our data contain individuals who receive food stamps in months where they are not eligible, for this model we only consider a FSU to be participating in a month if it is also eligible in the month. There are 7,598 FSUs that were eligible for benefits at least one month in the calendar year.

Model (3) examines the intensity of participation. Our third model examines the probability that a FSU receives food stamps in all months in which it is eligible (full participation); or in only some of the months in which it is eligible (partial participation); or in no months in which it is eligible (no participation), conditional on any eligibility in the year. This model uses a categorical dependent variable to determine the association between FSU characteristics and earnings and the decision to fully or partially participate, relative to no participation.

We use probit models in (1) and (2), reporting the marginal effects evaluated at the mean value of the independent variables. For binary variables, such as an indicator for having a female FSU head, the coefficient reported represents the change in probability of participation based on a discrete change from 0 (not having a female head) to 1 (having a female head) in the independent variable. The coefficient for continuous variables represents the percentage point change in the probability of participation associated with a one-unit change in the independent variable, at its mean. In all cases, we take the natural log (ln) of earnings and average earnings. As a result, our findings estimate the percentage point change in the probability of participation based on a one percent change in earnings.

Model (3) uses a multinomial probit model (with no participation as the excluded category), also reporting marginal effects. All regressions are weighted using weights developed as part of the MID-SIPP model to properly reflect that model's assignment of individuals to FSUs, and robust standard errors are reported.

Independent Variables

The SIPP and SER data sets allow us to include a rich set of independent variables in the regressions. We include measures of earnings, as reported in the SER, over different time periods to see whether past earnings play a role in households' expectations of future income and in the decision to participate. We include earnings in the year of observation ($t = 0$, which will represent either 1997 or 1998), average earnings in the two prior years ($t - 1$ to $t - 2$), three to five years before the observation year ($t - 3$ to $t - 5$) and six to ten years before the observation year ($t - 6$ to $t - 10$).²⁶ We also include future earnings in some models ($t + 1$ to $t + 2$) as a proxy of expectations of future earnings levels.

²⁶ Averages over discrete periods were taken to limit the number of (presumably closely related) earnings variables among the set of independent variables. As our intention is to test the hypothesis suggested in Farrell et al. (2003) that earning more than two years in the past may help explain participation, we look separately at historical earnings within the two most recent years and historical earnings from more than two years earlier. Earnings six to ten years in the past are included to distinguish between moderate-term and long-term historical earnings.

Using the MID-SIPP's calculations, we include indicators for the length of eligibility the FSU experienced in the year of eligibility: whether the household was eligible for benefits one to four months, five to eight months, or nine to 11 months, relative to being eligible for the entire year. While earnings and eligibility are highly correlated, the measure of current earnings we include is annual, so adding information on eligibility allows us to examine variability in eligibility (and by proxy variability in a household's earnings), holding the level of the current year's annual earnings constant. For example, this could help to compare two hypothetical households with \$18,000 of earnings in the current year, where one received \$1,500 per month for 12 months and the other received \$9,000 per month for two months and \$0 for the remaining months. While both households have the same current income, their monthly income and eligibility for the food stamps differs greatly, and including indicators for the length of eligibility allows the regression specification to capture these differences. In addition, we include a variable for months of earnings in the year, which also provides information on earnings variability.

We also take into consideration the average benefit amount that the household could have received in months of eligibility, since households are likely to weigh the costs associated with participating against potential benefits. Although benefits are highly correlated with earnings and with household composition and should be a part of the regression model, the data we are using only include annual earnings (from the SER) and household composition in a particular month (which in our model is June). Since both of these factors may change through the year, the average benefit amount a FSU is eligible for will capture additional information that may be related to the decision to participate. In addition, including them allows the model to distinguish between the effects of earnings and household composition on participation that operate through changes in the average benefit level over the year, and effects of earnings and household composition on participation that operate independently of the benefit level.

In some models, we include an indicator for whether the household was observed in 1998, to see whether general macroeconomic conditions were related to participation. We also include demographic characteristics of the FSU head, including race, gender, age and age-squared (which is a proxy for experience and allows the regression model to reflect a non-linear relationship that reflects the fact that past a certain point, increases in age have diminishing returns), level of education, and years of earnings (since 1951). All of these variables were calculated using data from the SIPP except for years of earnings, which we generate using the SER.

We use a number of indicators relating to FSU composition to see whether the presence of elderly or child members is related to participation. We include indicators for the number of children present and the age of the youngest child. All household composition variables are based on FSU membership in June. Finally, we include an indicator for whether the FSU belonged to a household which received TANF benefits during the year. Model (1) and (2) also include the number of months that the FSU received earnings during the year, calculated using SIPP data.

The key relationship we are studying is whether past, current, and future earnings are related to participation decisions, under the hypothesis that past or future earnings may be related either to their expectations for future earnings or to the availability of resources not factored into food stamp eligibility determination, which in turn influence a household's decision of whether to

participate in the Food Stamp Program given a downturn in earnings. It should be noted, however, that as is generally the case with regression analysis, a finding of a relationship between two variables – in this case past or future income and food stamp participation – may have alternate explanations. For example, if particular earnings patterns are somehow correlated with characteristics associated with perceiving stigma in food stamp participation (in ways not controlled for using the variables included in our regression models), a relationship may be found that has nothing to do with expected future earnings or resource availability.

B. Methodological Issues

The results presented below must be viewed in light of a number of caveats. Due to the large portion of households with zero earnings, our specification of earnings variables in the regressions limits the interpretation of coefficient estimates. Additionally, while we do include age and age-squared in our models that include our full set of covariates, we do not take into account the fact that some FSUs may be headed by individuals too young to have received earnings in the $t - 10$ or later years. These problems, which we were not able to correct while we still had access to the data, are discussed below.

Earnings Variables. We use the natural log of earnings to determine the percentage point change in probability of food stamp participation associated with a percentage change in earnings, since a dollar amount change in earnings may have different effects depending on the level of total earnings. For instance, a \$1,000 increase in earnings for a household earning \$10,000 would likely be welcomed, but would probably have less of an impact than the same increase for a household earning \$2,000. In all cases when a FSU received zero earnings, the natural log of earnings was set to zero. In the year of eligibility, approximately 30 percent of food stamp eligible households received zero earnings.

In a preferable specification, we would disentangle the effects on participation of marginal changes in positive earnings from the effects of changing employment status (i.e., going from no earnings to some earnings, or vice versa). To do so, we would replace the natural log of earnings included in our models with two terms: 1) an indicator for whether a FSU had any earnings, and 2) the interaction term of this indicator and the natural log of earnings. The specification would state:

$$P(\text{participation}) = \hat{a}_0 + \hat{a}_1 E_1 * E_2 + \hat{a}_2 (1 - E_2)$$

Where E_1 represents the natural log of earnings and E_2 is an indicator that takes the value of 1 if a FSU had positive earnings and 0 if it did not. With this model, \hat{a}_1 would capture the impact of a marginal increase in earnings on participation among those FSUs with earnings, and \hat{a}_2 would measure the relationship between working at all and participating in the Food Stamp Program. As they do not have the interaction term to disentangle these two effects, our models should not be interpreted as a precise measurement of the marginal effect of earnings on participation, and

we suggest viewing our findings instead merely as an indication of the likely significance of past earnings only.²⁷

Age of FSU Members. As discussed above, although we control for the age of a FSU's oldest working-aged member, taking into account potential experience (age-squared), we do not include any controls to take into account whether the FSU contained members old enough to have received earnings over the time horizons we examine. One solution to this problem would be to include age splines in our regressions, which control for this.

C. Regression Results: Eligibility in a Specific Month

Exhibit V.1 shows the results of the regressions using Model (1). For our sample of households eligible for benefits in December, we first examine the bivariate relationship between current earnings and participation (Column 1). We find the expected negative and significant relationship. Adding past and future earnings, (Column 2), we see that some of this relationship is captured by earnings in other years, as the coefficient for current earnings decreases when we include earnings received in the past and future. Current earnings remain significantly associated with the decision to participate. Additionally, average earnings between one and two years in the past and earnings between three and five years in the past are significantly related to the decision to participate. These findings suggest that for two FSUs with the same earnings in the current year, households who had lower earnings in past years (at least, going back five years) are more likely to receive food stamp benefits when eligible. Future earnings are included, under the hypothesis that actual future earnings will proxy for households' expectations of their future earnings, and future earnings are indeed significantly associated with participation, though in the opposite direction as anticipated; the positive coefficient suggests households with higher expected earnings are more likely to participate. This is an interesting finding; however, it may simply indicate that households that receive higher earnings in the future have certain attributes which also make them more likely to participate. Indeed, this hypothesis is supported by the results in Column 3.

²⁷ Another methodological issue with regards to earnings relates to potential mismeasurement of earnings in both the SIPP and the SER. Disagreement between the SER and SIPP with regards to earnings is discussed in *Appendix C*. Such disagreement could affect regression results in two ways. First, as the sample of those eligible for food stamps is determined based on SIPP data, individuals with earnings shown in the SER may be included in the sample if they do not have earnings (or have low earnings) shown in the SIPP. To the extent that there are FSUs with relatively high SER earnings included in the sample, who do not participate in the Food Stamp Program because they are not in actuality eligible, it may bias our regression findings with regards to the relationship between current, past, or future earnings and participation towards the negative. *Appendix C* shows that about 3 percent of working-age individuals with no earnings shown in the SIPP have earnings in the SER, but that on average these earnings are low, so this bias will probably be limited. Second, if FSUs with high earnings in the SIPP are excluded from the sample but actually have lower earnings (as reflected in the SER), there would only be a bias if this group differs non-randomly from low-earning FSUs who do not overreport on the SIPP. Findings in *Appendix C* are suggestive that this impact is likely to be small as well, as we find that individuals with zero earnings in the SER but positive earnings on the SIPP do not differ noticeably in demographic or income characteristics from the SIPP population as a whole.

Column 3 includes our full set of control variables. The length of time a FSU was eligible for the Food Stamp Program is significantly related to participation. When we include indicators for the period of time a FSU was eligible, the negative coefficients on these variables and declining magnitude as eligibility length increases suggest that among households with the same average income and earnings in the current year, those who were eligible for a larger portion of the year – and thus had more consistently low income – were more likely to receive benefits than those that experienced both high income and income low enough to qualify them for food stamps in December. Specifically, shorter periods of eligibility are related to a lower probability of participation. This is consistent with the findings of Farrell et al. (2003), who showed that non-participants experienced a higher variability in monthly income, characterized by a dip during the month of eligibility, than non-participants, who, on average, had consistently low income.

Race and gender are significantly associated with participation – households with non-white heads are also more likely to participate, all else equal, as are female headed FSUs and FSUs headed by older working-age adults, although the magnitudes of these effects are small. Households headed by individuals with lower education levels are more likely to participate, although FSUs headed by adults without a high school diploma are less likely to receive benefits in this month than households headed by adults with a high school diploma. As the composition of a FSU determines, to a large degree, benefit levels, it is not surprising that when we include information on the number and age of children and presence of elderly members (results not shown), benefit levels are no longer related to participation. As we would expect, families that live in households receiving cash assistance (TANF) are significantly more likely to receive food stamps. This may be somewhat of a mechanical effect, as families who apply for welfare are often applying for food stamps at the same time. Finally, the number of months that a household received any earnings,²⁸ regardless of the level, is also significantly and negatively related to participation. In this model, in fact, the number of months of earnings in the year is one of the largest predictors of participation in December. Here, we know that 11 out of the 12 months preceded the month for which we measure participation.

When these control variables are added, significance among the earnings variables changes. The significant relationship between current earnings and participation remains. However, the relationship between earnings in the recent past ($t - 1$ to $t - 2$) and participation is no longer significant. The relationship between participation and past earnings in years $t - 3$ through $t - 5$ remains significant at a 95% confidence level. Future earnings are again negative and significantly associated with receipt of food stamps, supporting our hypothesis that difference in characteristics were influencing the positive association in Column (2), since once we include measures of household characteristics, the sign once again is in the expected direction.

As discussed before, we expect that selecting on eligibility in a particular month will result in a group of households to be more disadvantaged, on average, than the group selected on eligibility for food stamps in any month in a year. We find that for these households, current income and changes in current income, as well as expectations for income in the near future are more important factors in the decision to participate than low earnings levels in the past.

²⁸ This is the only case where we develop a measure of earnings using the SIPP rather than the SER. This is because the SER only contains information on annual earnings and the number of quarters in a year in covered employment. Thus, it misses a good deal of information on monthly variation in earnings.

Although it is difficult to determine which of these factors has the strongest association with participation, these findings are consistent with those of Farrell et al. (2003).

Exhibit V.1: Regression Results, Dependent Variable Food Stamp Receipt in December, Conditional on Eligibility in December

	(1)	(2)	(3)
<i>Earnings</i>			
Earnings t = 0	-0.022 (0.002)**	-0.015 (0.003)**	-0.010 (0.004)**
Av. Earnings t - 1 to t - 2		-0.012 (0.004)**	-0.004 (0.004)
Av. Earnings t - 3 to t - 5		-0.012 (0.003)**	-0.007 (0.003)*
Av. Earnings t - 6 to t - 10		0.003 (0.003)	0.006 (0.003)
Av. Earnings t + 1 to t + 2		0.009 (0.003)**	-0.012 (0.003)**
<i>Months of Eligibility in Year</i>			
1 to 4 months			-0.288 (0.019)**
5 to 8 months			-0.197 (0.019)**
9 to 11 months			-0.101 (0.021)**
Year = 1998			-0.017 (0.016)
Average FS Amt in Year			-0.022 (0.016)
<i>FSU head demographics</i>			
Race = nonwhite			0.039 (0.019)*
Hispanic			-0.045 (0.023)
Sex = Female			0.089 (0.019)**
Age			0.029 (0.005)**
Age squared			-0.000 ^d (0.000)**
Less than HS degree			0.104 (0.036)**
HS degree/GED			0.135 (0.036)**
Some college, no degree			0.110 (0.040)**
Years of earnings			-0.001 (0.001)

Exhibit V.1 (Cont'd)

	(1)	(2)	(3)
<i>FSU composition</i>			
Number of adults			0.073 (0.019)**
1 or 2 children			0.090 (0.031)**
3 or 4 children			0.205 (0.044)**
5 or more children			0.183 (0.075)*
Any elderly members			-0.078 (0.052)
Youngest child <1			0.074 (0.073)
Youngest child 1 to 3			0.071 (0.039)
Youngest child 4 to 6			0.067 (0.037)
Youngest child 7 to 10			-0.006 (0.036)
Any HH AFDC/TANF receipt			0.355 (0.023)**
Average months earnings in year			-0.522 (0.259)*
Observations	4444	4444	4444

Notes: Data are weighted. Robust standard errors in parentheses. Marginal effects at mean of independent variable reported. * significant at 5%; ** significant at 1%; ^a less than 0.0005 in absolute value

D. Eligibility in Any Month of the Year

We next examine the probability of participation in the Food Stamp Program at any point in a year, conditioning on any food stamp eligibility in the year (*Exhibit V.2*). Again, we find a significant and negative relationship between current income and participation. Including additional information in Column (2), we find results similar to Model (1), including a significant and negative association between earnings in the recent past (averaged over one to two years in the past) and participation as well as between earnings three to five years in the past and participation. As in Model (1), future earnings and participation show a positive relationship, which, when controls are added, reverses signs.

However, adding our full set of control variables, as shown in Column 3, yields somewhat different results from Model (1). Belonging to the 1998 cohort of FSUs (rather than the 1997 cohort) is significantly and negatively related to participation. (In Model (1) it had also been negatively related to participation, but the coefficient was smaller and not significant.) This may reflect the generally favorable macroeconomic conditions in the United States during the latter half of the 1990s that helped reduce poverty rates and unemployment among low-income groups, and also may reflect changing perspectives on program participation following welfare

reform in the mid-1990s. The different findings of significance in the two models may be related to the fact that the second model contains proportionally fewer long-term eligibles than the first sample and therefore potentially includes more households who may be expected to have benefited from the income and job growth that occurred during that period.

The length of eligibility for food stamps in the year and many demographic characteristics, including the race, sex, age, and education of the FSU head remain significantly associated with participation. However, unlike in Model (1), the age of the youngest child in the FSU is significantly and positively associated with participation, indicating that, holding all else constant, families with younger children are more likely to participate.

Also dissimilar to Model (1), in our second model, only earnings between one and two years prior to $t = 0$ and future earnings are remain significantly related to participation. This may be due to the fact that the Model (2) sample includes a larger portion of short-term eligible households than the first sample, and that for households that have only recently become eligible for food stamps, earnings in the recent past are more important than current earnings in the decision to participate.

Exhibit V.2: Regression Results, Dependent Variable Any Food Stamp Participation in Year, Conditional on Eligibility in at Least One Month during the Year

	(1)	(2)	(3)
<i>Earnings</i>			
Earnings $t = 0$	-0.024 (0.001)**	-0.009 (0.003)**	0.001 (0.003)
Av. Earnings $t - 1$ to $t - 2$		-0.016 (0.003)**	-0.010 (0.003)**
Av. Earnings $t - 3$ to $t - 5$		-0.011 (0.003)**	-0.003 (0.003)
Av. Earnings $t - 6$ to $t - 10$		-0.002 (0.002)	0.001 (0.003)
Av. Earnings $t + 1$ to $t + 2$		0.006 (0.003)*	-0.013 (0.003)**
<i>Months of Eligibility in Year</i>			
1 to 4 months			-0.354 (0.016)**
5 to 8 months			-0.215 (0.015)**
9 to 11 months			-0.087 (0.018)**
Year = 1998			-0.029 (0.013)*
Average FS Amt in Year			-0.002 (0.008)

Exhibit V.2 (cont'd)

	(1)	(2)	(3)
<i>FSU head demographics</i>			
Race = nonwhite			0.059 (0.016)**
Hispanic			-0.044 (0.018)*
Sex = Female			0.086 (0.014)**
Age			0.027 (0.004)**
Age squared			-0.000 ^a (0.000)**
Less than HS degree			0.119 (0.026)**
HS degree/GED			0.110 (0.025)**
Some college, no degree			0.105 (0.027)**
Years of earnings			0.001 (0.001)
<i>FSU composition</i>			
Number of adults			0.073 (0.013)**
1 or 2 children			0.092 (0.023)**
3 or 4 children			0.216 (0.033)**
5 or more children			0.172 (0.060)**
Any elderly members			-0.059 (0.046)
Youngest child <1			0.184 (0.054)**
Youngest child 1 to 3			0.122 (0.030)**
Youngest child 4 to 6			0.099 (0.029)**
Youngest child 7 to 10			0.025 (0.028)
Any HH AFDC/TANF receipt			0.482 (0.018)**
Average months earnings in year			-0.257 (0.185)
Observations	7598	7598	7598

Notes: Data are weighted. Robust standard errors in parentheses. Marginal effects at mean of independent variable reported. * significant at 5%; ** significant at 1%; ^a less than 0.0005 in absolute value

E. Intensity of Participation

Finally, we examine whether certain factors may be related to a household's decision to participate in the Food Stamp Program immediately or wait a certain number of months before participating, rather than not participating at all. *Exhibit V.3* displays results from the multinomial analysis of participation, examining the probability of partial participation, relative to no participation and the probability of full participation, relative to no participation. We define partial participation as participation in the program for between 1 and 99 percent of eligible months and full participation as participation for 100 percent of eligible months. This allows us to examine how earnings and other characteristics are related to the intensity of benefit use among eligible households. Thus, a household eligible for four months that participates all four months would be considered to have the same intensity of participation as a household eligible for 12 months that participates all 12 months.

As *Exhibit V.3* displays, the association between earnings, FSU head and household characteristics, and food stamp participation differ remarkably between FSUs receiving benefits for a portion of eligible months and those receiving benefits during their full period of eligibility. While earnings in the recent past (between $t - 1$ to $t - 2$) are significantly and negatively related to full participation, these factors are not related to partial participation. Current and future earnings, length of eligibility, ethnicity, education, the age of the youngest child, and receipt of welfare are significantly related to partial participation. Our coefficient estimates for current earnings are positive, which may indicate unobservable characteristics, such as motivation or resourcefulness, that are associated both with the ability to navigate the food stamp application process and with higher earnings. The results for full participation mirror those found in *Exhibit V.2*, although in many cases, the magnitude of the effects are somewhat smaller. The lack of significant coefficient estimates for past earnings for those with partial participation may suggest that the findings in *Exhibits V.1 and V.2* are largely driven by those who participate for the full period of eligibility.

Exhibit V.3: Multinomial Regression Results, Probability of Partial or Full Participation, Relative to No Participation, Conditional on Eligibility in at Least One Month during the Year

	(1)		(2)		(3)	
	Partial	Full	Partial	Full	Partial	Full
<i>Earnings</i>						
Earnings t = 0	-0.003 (0.009)**	-0.021 (0.001)**	0.000 (0.002)	-0.009 (0.002)**	0.005 (0.002)*	-0.004 (0.002)
Av. Earnings t - 1 to t - 2			-0.002 (0.002)	-0.014 (0.002)**	0.000 (0.002)	-0.010 (0.002)**
Av. Earnings t - 3 to t - 5			-0.001 (0.002)	-0.010 (0.002)**	0.001 (0.002)	-0.004 (0.002)
Av. Earnings t - 6 to t - 10			-0.003 (0.001)	-0.000 (0.002)	0.001 (0.002)	0.001 (0.002)
Av. Earnings t + 1 to t + 2			-0.000 (0.002)	0.006 (0.002)**	-0.006 (0.002)**	-0.007 (0.002)**
<i>Months of Eligibility in Year</i>						
1 to 4 months					-0.188 (0.010)**	-0.156 (0.014)**
5 to 8 months					-0.076 (0.009)**	-0.134 (0.012)**
9 to 11 months					-0.006 (0.011)	-0.084 (0.013)**
Year = 1998					-0.014 (0.008)	-0.013 (0.010)
Average FS Amt in Year					0.009 (0.005)	-0.012 (0.006)
<i>FSU head demographics</i>						
Race = nonwhite					0.012 (0.010)	0.047 (0.013)**
Hispanic					-0.026 (0.010)*	-0.016 (0.015)
Sex = Female					0.017 (0.009)	0.068 (0.011)**
Age					0.004 (0.003)	0.024 (0.003)**
Age squared					-0.000 (0.000)	-0.000 ^a (0.000)**
Less than HS degree					0.042 (0.017)*	0.078 (0.022)**
HS degree/GED					0.020 (0.016)	0.092 (0.022)**
Some college, no degree					0.032 (0.018)	0.076 (0.024)**
Years of earnings					0.001 (0.001)	0.000 (0.001)

Exhibit V.3 (cont'd)

	(1)		(2)		(3)	
	Partial	Full	Partial	Full	Partial	Full
<i>FSU composition</i>						
Number of adults					0.010 (0.009)	0.060 (0.011)**
1 or 2 children					0.024 (0.015)	0.068 (0.019)**
3 or 4 children					0.036 (0.022)	0.185 (0.032)**
5 or more children					-0.016 (0.030)	0.196 (0.058)**
Any elderly members					-0.023 (0.026)	-0.039 (0.035)
Youngest child <1					0.065 (0.036)	0.120 (0.051)*
Youngest child 1 to 3					0.046 (0.020)*	0.075 (0.026)**
Youngest child 4 to 6					0.024 (0.018)	0.076 (0.025)**
Youngest child 7 to 10					0.016 (0.018)	0.009 (0.022)
Any HH AFDC/TANF receipt					0.120 (0.015)**	0.362 (0.019)**

Notes: Data are weighted. Robust standard errors in parentheses. Marginal effects at mean of independent variable reported. * significant at 5%; ** significant at 1%; ^a less than 0.0005 in absolute value

VI. CONCLUSIONS AND FUTURE RESEARCH

The analysis in this paper investigated the hypothesis that earnings in periods other than the current month may bear on a food stamp-eligible household's decision as to whether to receive benefits. Building off Farrell et al (2003), we have discussed this relationship within the theoretical framework of a weak version of the permanent income hypothesis that suggests that households facing temporary declines in income may be less likely to participate because of expectations of higher income, reliance on resources not factoring into food stamp eligibility, or potentially higher costs of participation for households with fluctuating incomes. Farrell et al (2003) found evidence that monthly income volatility helps explain why some eligible households do not claim benefits; households with only short-term downturns in income are less likely to receive benefits than others with consistently low income. Results from our regression models are consistent with this finding and show that FSUs that are eligible for food stamps in only part of the year, rather than all 12 months, are less likely to participate in the program.

Our analysis goes beyond this to look at historical earnings from as much as ten years before the year in which the food stamp unit is determined to be eligible, as well as future earnings over the following two years. Indeed, we find evidence of a relationship between past earnings and the participation decision. First, as *Exhibit IV.7* showed, among food stamp units eligible in a given year, those who participate in the program that year consistently had lower income on average than those who do not participate for at least 15 years earlier. Second, our regression models provide some evidence that even controlling for current earnings, lower earnings as far back as five years are associated with a higher likelihood that an eligible food stamp unit receives food stamps; in some of the models (including one with the full set of independent variables included) higher average earnings between three and five years before the year of eligibility is significantly associated with lower participation. To put it another way, for two eligible households with the same current earnings, the household with lower income as much as five years earlier is more likely to receive benefits. To different extents in our different models, this holds when controlling for consistency of eligibility over the months of the current year and for demographic factors. Further, we find that higher earnings two years into the future, which may proxy for expected earnings, are also significantly associated with lower participation in models with the full set of independent variables.

However, because of weaknesses in the specification of our regression models, it remains unclear how important prior and expected income are as determinants. Among these weaknesses, which have been indicated throughout the report, our specification did not disentangle the effects on participation of marginal changes in positive earnings from the effects of having some versus no earnings (particularly important given that approximately 30 percent of food stamp eligible households in our dataset had zero earnings in the year of eligibility), and did not take into account whether the FSU contained members old enough to have received earnings over the time horizons we examine. Consequently, findings in this paper should be considered suggestive rather than precise descriptions of the relationship between long-run income and participation.

While our suggestive findings are consistent with our hypothesis that higher past incomes may lead a household to be less likely to participate because of expectations of future income, other

resources available or high costs of participation, we reiterate that other hypotheses could also explain these findings, including that past earnings are correlated with characteristics not controlled for in our model, or not otherwise observable, such as stronger perceptions of stigma.

Future research, using differently specified models, could perhaps better determine the magnitude of the association between past earnings and participation. In particular, future research could correct the specification errors that we were not able to correct during the period during which we had access to the matched SIPP-SER data set. In addition, analysis of data covering different periods than what we analyzed could determine whether similar relationships exist under different policy and economic conditions. In particular, following the 2002 Farm Bill, most states have simplified the systems for applying for food stamps and for reporting information related to continuing eligibility used in the food stamp application and reporting process, and many have adopted transitional food stamp programs for families leaving welfare. Increases in the participation rate in recent years (particularly 2004) suggest that these efforts have had some success in increasing the number of eligible low-income households who receive benefits. If so, it is likely that these steps have also reduced the relationship between income volatility and food stamp participation, and may have also changed the relationship between past earnings and current participation. As later SIPP panels have been matched to earnings data, it would be possible to conduct similar analysis to ours in a more recent period.

REFERENCES

Acs, Gregory and P. Loprest (2001). *Final Synthesis Report of Findings from ASPE's "Leavers" Grants*. Report to the U.S. Department of Health and Human Services. Washington, DC: The Urban Institute.

Barrett, Allison (2006). *Characteristics of Food Stamp Households: Fiscal Year 2005*. Prepared for the U.S. Department of Agriculture. Washington, DC: Mathematica Policy Research, Inc.

Bartlett, Susan, N. Burstein, and W. Hamilton (2004). *Food Stamp Program Access Study: Final Report*. Report to the U.S. Department of Agriculture. Lexington, MA: Abt Associates.

Bollinger, Christopher R and M. H. David (2001). "Estimation with Response Error and Nonresponse: Food-Stamp Participation in the SIPP" *Journal of Business and Economic Statistics* 2001 19 (2)129-41. As cited in Farrell et al, (2003).

Farrell, Mary, M. Fishman, M. Langley, and D. Stapleton (2003). *The Relationship of Earnings and Income to Food Stamp Participation: A Longitudinal Analysis*. Report to the U.S. Department of Agriculture. Falls Church, VA: The Lewin Group.

Friedman, Milton (1957). *A Theory of the Consumption Function*. Princeton, NJ: Princeton University Press.

Greenstein, Robert (2007). Testimony Before the Committee on Agriculture, Nutrition, and Forestry, January 31, 2007. Washington, DC: Center on Budget and Policy Priorities.

Kabbani, Nader S. and P. Wilde (2003). "Short Recertification Periods in the U.S. Food Stamp Program," *Journal of Human Resources* 38(S) 1112-1138.

Kornfeld, Robert (2002). *Explaining Recent Trends in Food Stamp Program Caseloads: Final Report*. Report to the U.S. Department of Agriculture. Cambridge, MA: Abt Associates.

MaCurdy, Thomas and G. Marrufo (2006). *The MID-SIPP Model: A Simulation Approach for Projecting Impacts of Changes in the Food Stamp Program*. Report to the U.S. Department of Agriculture. Burlingame, CA: SPHERE Institute.

McConnell, Sheena and M. Ponza (1999). *The Reaching the Working Poor and Poor Elderly Study: What We Learned and Recommendations for Future Research*. Report to the U.S. Department of Agriculture. Washington, DC: Mathematica Policy Research, Inc.

McKernan, Signe-Mary and C. Ratcliffe (2003). *Employment Factors Influencing Food Stamp Program Participation*. Report to the U.S. Department of Agriculture. Washington, DC: The Urban Institute.

Newman, Constance (2006). *The Income Volatility See-Saw: Implications for School Lunch*. Economic Research Report Number 23. Washington, DC: U.S. Department of Agriculture.

Ponza, Michael, J. Ohls, L. Moreno, A. Zambrowski, and R. Cohen. *Customer Service in the Food Stamp Program: Final Report*. Report to the U.S. Department of Agriculture. Washington, DC: Mathematica Policy Research, Inc.

U.S. General Accounting Office (2004). *Food Stamp Program: Steps Have Been Taken to Increase Participation of Working Families, but Better Tracking of Efforts Is Needed*. GAO-04-346. Washington, DC: U.S. General Accounting Office.

Ribar, David C. and M. Edelhoach (2006). *South Carolina Food Stamp and Well-Being Study: Transitions in Food Stamp and TANF Participation and Employment Among Families With Children*. Report to the U.S. Department of Agriculture. Washington, DC: George Washington University and Columbia, SC: South Carolina Department of Social Services.

Rosenbaum, Dorothy (2006). *The Food Stamp Program is Growing to Meet Need*. Washington, DC: Center on Budget and Policy Priorities.

Weinberg, Daniel H. (2003). "Using the Survey of Income and Program Participation for Policy Analysis," Bureau of the Census, SIPP Working Paper #240.

Wolkwitz, Kari (2007). *Trends in Food Stamp Program Participation Rates: 1999-2005*. Report to the U.S. Department of Agriculture. Washington, DC: Mathematica Policy Research, Inc.

Zedlewski, Sheila R. and S. Brauner (1999). *Are the Steep Declines in Food Stamp Participation Linked to Falling Welfare Caseloads?* Washington, DC: The Urban Institute. Cited in Dion, M. Robin and L. Pavetti (2000). *Access to and Participation in Medicaid and the Food Stamp Program: A Review of the Recent Literature*. Prepared for the U.S. Department of Health and Human Services. Washington, DC: Mathematica Policy Research Inc.

APPENDIX A: ADDITIONAL TABLES AND CHARTS

Exhibit A.1: FSU Characteristics by Quartile of Earnings, FSUs Eligible in at Least One Month during the Year

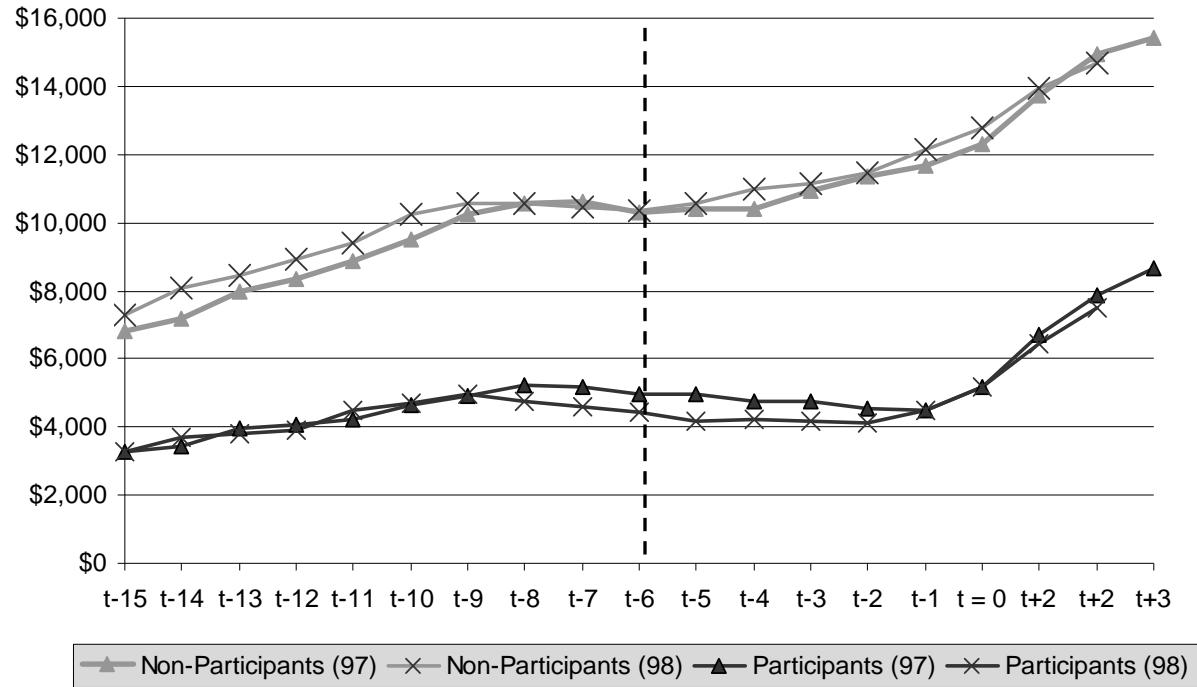
	<u>Q1</u>			<u>Q2</u>			<u>Q3</u>			<u>Q4</u>		
	<u>Non-Participants</u>	<u>Participants</u>	<u>Total</u>	<u>Non-Participants</u>	<u>Participants</u>	<u>Total</u>	<u>Non-Participants</u>	<u>Participants</u>	<u>Total</u>	<u>Non-Participants</u>	<u>Participants</u>	<u>Total</u>
<i>FSU Head Characteristics</i>												
Female	55.0%	70.0%	62.5%	57.2%	81.5%	68.5%	60.5%	72.8%	65.1%	44.2%	45.7%	44.4%
Age	49.3	45.3	47.3	37.6	36.3	37.0	37.2	35.3	36.5	38.3	36.0	38.0
Race												
White	77.0%	62.0%	69.5%	70.3%	58.7%	64.9%	76.4%	62.7%	71.3%	77.2%	66.4%	75.7%
Black	19.1%	34.2%	26.6%	23.9%	36.4%	29.7%	19.6%	31.0%	23.8%	19.2%	*	20.2%
Native American	*	*	*	*	*	*	*	*	*	*	*	*
Asian/Pacific Islander	*	*	*	*	*	*	*	*	*	*	*	*
Hispanic Origin	12.7%	17.0%	14.9%	11.0%	12.8%	11.8%	14.2%	14.7%	14.4%	14.1%	*	14.7%
Education Level												
Less than high school diploma or GED	46.3%	50.8%	48.5%	27.0%	39.5%	32.8%	23.6%	31.8%	26.6%	18.2%	33.4%	20.3%
High school diploma or GED	24.6%	29.2%	26.9%	36.3%	36.0%	36.4%	39.0%	37.3%	38.4%	37.4%	39.1%	37.7%
Some college, no degree	17.4%	15.3%	16.4%	24.0%	17.8%	21.1%	24.1%	23.1%	23.8%	25.1%	*	24.4%
College/graduate/professional degree	11.8%	*	8.2%	12.7%	*	9.7%	13.3%	*	11.2%	19.3%	*	17.6%
<i>FSU Earnings</i>												
Current year earnings												
Earnings t = 0	\$0	\$0	\$0	\$2,604	\$2,474	\$2,543	\$10,528	\$9,705	\$10,220	\$28,460	\$22,670	\$27,631
Historical earnings												
Earnings t - 1	\$793	\$472	\$633	\$4,570	\$2,985	\$3,832	\$10,177	\$7,484	\$9,170	\$24,856	\$17,790	\$23,844
Earnings 2 year average	\$1,249	\$727	\$990	\$4,964	\$3,086	\$4,089	\$9,904	\$7,097	\$8,855	\$23,986	\$16,786	\$22,956
Earnings 5 year average	\$2,579	\$1,592	\$2,089	\$5,721	\$3,634	\$4,749	\$9,120	\$6,682	\$8,209	\$21,372	\$15,020	\$20,463
Earnings 10 year average	\$3,999	\$2,408	\$3,209	\$6,181	\$3,831	\$5,087	\$8,639	\$6,296	\$7,763	\$19,332	\$13,604	\$18,512
Future earnings												
Earnings t + 1	\$948	\$690	\$820	\$5,195	\$5,066	\$5,135	\$11,789	\$11,292	\$11,603	\$28,927	\$24,768	\$28,332
Earnings 2 year average	\$1,416	\$1,067	\$1,243	\$5,930	\$5,919	\$5,925	\$12,395	\$11,851	\$12,191	\$29,217	\$25,417	\$28,673

	<u>Q1</u>			<u>Q2</u>			<u>Q3</u>			<u>Q4</u>		
	<u>Non-Participants</u>	<u>Participants</u>	<u>Total</u>	<u>Non-Participants</u>	<u>Participants</u>	<u>Total</u>	<u>Non-Participants</u>	<u>Participants</u>	<u>Total</u>	<u>Non-Participants</u>	<u>Participants</u>	<u>Total</u>
<i>Work History</i>												
Working quarters covered t = 0	0.0	0.0	0.0	2.4	2.0	2.2	3.7	3.4	3.6	3.6	3.8	3.6
Total working quarters covered	46.5	33.8	40.2	51.1	38.8	43.4	61.3	49.7	57.0	72.6	60.8	70.9
Years of earnings	15.5	12.2	13.9	16.8	13.8	15.4	18.0	15.4	17.0	20.3	17.5	19.9
<i>Food Stamp Eligibility and Participation</i>												
Months of eligibility	9.4	11.3	10.3	8.6	10.8	9.6	6.0	9.0	7.1	4.0	7.0	4.4
Average months of benefits	0.0	10.1	5.0	0.0	9.3	4.3	0.0	7.9	2.9	0.0	6.7	1.0
Percent of eligible months	0.0%	86.0%	42.7%	0.0%	78.8%	36.7%	0.0%	67.0%	25.0%	0.0%	56.7%	8.1%
Average monthly benefit (in eligible months)	\$93	\$128	\$110	\$120	\$197	\$156	\$117	\$182	\$141	\$158	\$193	\$163
<i>FSU Income Reported in the SIPP</i>												
FSU Income Reported in the SIPP	\$2,903	\$622	\$1,771	\$5,649	\$3,587	\$4,689	\$12,312	\$10,087	\$11,481	\$23,945	\$18,483	\$23,163
Total Income	\$8,680	\$7,163	\$7,927	\$8,693	\$8,359	\$8,537	\$13,872	\$13,066	\$13,571	\$25,088	\$20,625	\$24,449
Earnings	\$2,903	\$622	\$1,771	\$5,649	\$3,587	\$4,689	\$12,312	\$10,087	\$11,481	\$23,945	\$18,483	\$23,163
Transfer Income	\$1,444	\$3,873	\$2,649	\$647	\$2,877	\$1,686	\$226	\$1,372	\$654	\$167	\$1,227	\$319
Property Income	\$87	\$23	\$55	\$39	\$24	\$32	\$53	\$13	\$38	\$66	\$33	\$61
<i>Household Income Reported in the SIPP</i>												
Household Income Reported in the SIPP	\$16,480	\$11,172	\$13,845	\$20,432	\$14,510	\$17,674	\$22,565	\$17,220	\$20,567	\$29,374	\$22,554	\$28,398
Percent households with earnings	43.6%	24.0%	33.9%	84.8%	85.6%	85.2%	99.1%	96.6%	98.1%	99.0%	98.8%	99.0%
Household earnings for receivers	\$17,823	\$11,761	\$15,689	\$17,934	\$9,131	\$13,815	\$19,814	\$13,855	\$17,623	\$27,771	\$20,149	\$26,682
Percent households with food stamp income	8.5%	100.0%	53.9%	8.4%	100.0%	51.0%	4.3%	99.6%	39.9%	*	100.0%	16.1%
Household food stamp income for receivers	\$1,261	\$1,543	\$1,521	\$1,582	\$2,036	\$1,996	\$1,394	\$1,722	\$1,701	\$1,309	\$1,355	\$1,350
Percent households with TANF income	5.1%	38.3%	21.6%	6.3%	53.7%	28.4%	3.1%	36.1%	15.4%	*	30.8%	6.7%
TANF income for receivers	\$2,695	\$3,504	\$3,408	\$2,303	\$3,044	\$2,956	\$2,876	\$2,171	\$2,259	\$1,852	\$2,661	\$2,382
Percent households with SSI income	33.6%	53.9%	43.7%	17.0%	28.3%	22.2%	7.5%	11.2%	8.8%	4.8%	*	5.1%
Household SSI income for receivers	\$5,122	\$4,237	\$4,580	\$4,280	\$5,282	\$4,874	\$3,414	\$3,959	\$3,671	\$4,293	\$4,898	\$4,413

	<u>Q1</u>			<u>Q2</u>			<u>Q3</u>			<u>Q4</u>		
	<u>Non-Participants</u>	<u>Participants</u>	<u>Total</u>	<u>Non-Participants</u>	<u>Participants</u>	<u>Total</u>	<u>Non-Participants</u>	<u>Participants</u>	<u>Total</u>	<u>Non-Participants</u>	<u>Participants</u>	<u>Total</u>
<i>Type of Household</i>												
Married Family	28.6%	15.5%	22.1%	21.3%	17.9%	19.7%	26.7%	31.8%	28.6%	57.1%	62.9%	58.0%
Non-married family												
Male household head	*	*	*	*	*	*	*	*	*	*	*	*
Female household head	19.5%	38.5%	28.9%	27.6%	60.0%	42.7%	30.1%	55.6%	39.7%	17.6%	28.8%	19.2%
Non-family												
Male household head	24.8%	16.7%	20.8%	25.4%	*	19.4%	20.0%	*	14.0%	11.5%	*	10.2%
Female household head	21.8%	24.8%	23.3%	19.5%	*	14.6%	17.9%	*	12.9%	7.5%	*	6.6%
Group quarters	*	*	*	*	*	*	*	*	*	*	*	*
<i>Number of observations</i>	1,195	1,156	2,351	760	664	1,424	1,193	681	1,874	1,667	282	1,949

Notes: Data are weighted. Asterisks indicate results suppressed due to sample size considerations. Results are suppressed when there are less than 75 observations in a cell. In addition, if a result is suppressed in the “non-participants” or “participants” column, the result is also suppressed in the “total” column for the appropriate quartile.

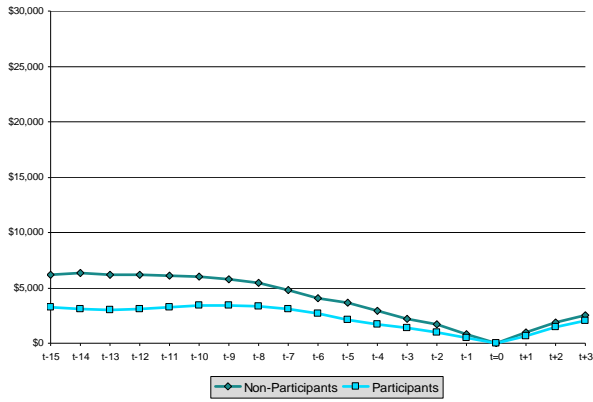
**Exhibit A.2: Annual Income by Participation Status and Year,
FSUs Eligible in at Least One Month during the Year**



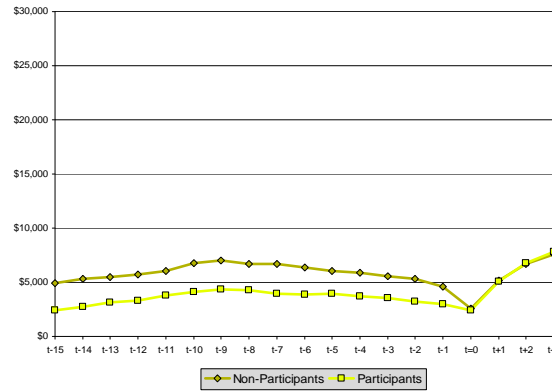
Notes: Data are weighted. t = 0 indicates 1997 or 1998. All amounts presented in constant 1996 dollars, adjusted for inflation using the CPI-W.

Exhibits A3 through A6: Annual Income by Earnings Quartile in t = 0, FSUs Eligible in at Least One Month during the Year

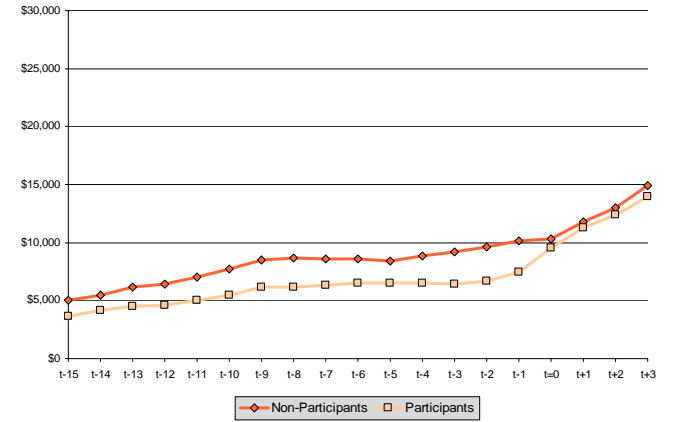
A.3: Lowest Quartile



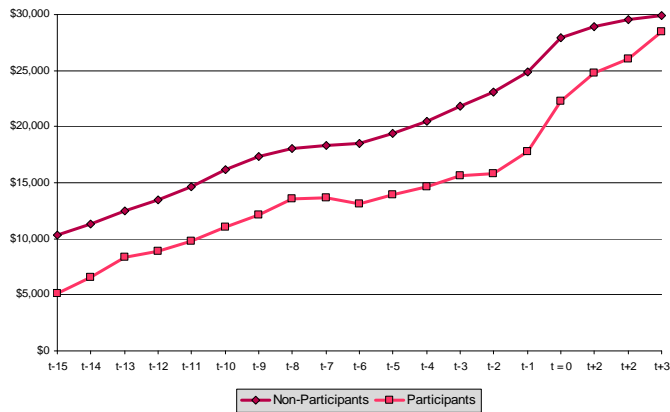
A.4: Second Quartile



A.5: Third Quartile



A.6: Highest Quartile



Notes: Data are weighted. t = 0 indicates 1997 or 1998. All amounts presented in constant 1996 dollars, adjusted for inflation using the CPI-W.

APPENDIX B: DESCRIPTION OF THE MID-SIPP

This appendix reprints sections of MaCurdy, Thomas and G. Marrufo, *Food Assistance for the Working Poor: Simulating the Impact of the Nutrition Tax Credit on the Food Stamp Program* relevant to the analysis in this paper. In particular it reprints the sections describing the construction of Food Stamp Units within the SIPP; determination of eligibility, potential benefits, and participation spells; and correction for the seam bias. MaCurdy and Marrufo go on to describe the calibration of the MID-SIPP to the Food Stamp Program Quality Control data set; however, that section is not reprinted here as the MID-SIPP data used in this analysis came from an earlier version of the model where participation spells were determined separately from calibration, and the data used in this report did not incorporate this calibration.

A. MID-SIPP Simulation Approach

Our simulation approach involves seven steps, described in this section. As a model for simulating the effects of Food Stamps, the central element of our approach is to construct a representative sample of “food stamp units” (FSUs) drawn from SIPP and to use the information available for each FSU to emulate its FSP eligibility and participation over designated time horizons. We infer eligibility assuming particular assignment rules governing FSU formations, eligibility rules, benefit levels and FSP reporting requirements.

After allocating all individuals in SIPP into FSUs – essentially structuring the SIPP sample into a sample of FSUs – we create monthly data for each FSU describing its economic and demographic circumstances. For a given policy regime, we calculate FSP eligibility for each FSU for each month.

A policy regime is a set of eligibility and benefit rules that determine:

- Which individuals are eligible for FSP, including work and immigration status
- Benefit/eligibility determination criteria including:
 - Gross and net income cutoffs
 - Treatment of income by source
 - Deductions and exclusions
 - Asset limitations
 - Treatment of housing and utility costs
- Reporting plans
 - Retrospective or prospective budgeting
 - Budget period
 - Reporting period (monthly, quarterly, semi-annual)
 - Reporting type (fixed interval or change)
 - Recertification period

If eligible, we use these monthly data to calculate benefits for which the FSU is eligible. The assignment algorithms for eligibility maintain the critical assumption that FSUs do not change their behavior – altering their earnings or family structure – in response to changes in FSP reporting regimes. A model of FSP participation then determines whether an FSU takes up food stamp benefits. If it does, we track monthly changes in circumstances relevant for continued eligibility.

In doing so, our analysis creates a longitudinal data set depicting the FSP eligibility and participation experiences for individual FSUs. These data can be used to project outcomes in four domains:

- 1) Eligibility for program benefits,
- 2) Duration of eligibility and ineligibility,
- 3) Collection of food stamp benefits, and
- 4) Administrative activity as measured by number of mandated reports.

These outcomes produce a rich description of FSUs' experiences under each policy regimes. Comparison across regimes using our MID-SIPP model allows policymakers to weigh the differences in costs associated with different policy regimes.

Exhibit B.1 provides an overview of how these simulation tasks are accomplished in the seven steps. The remainder of the chapter describes each of these seven steps.

Exhibit B.1a: Steps in the Simulation Approach Part I

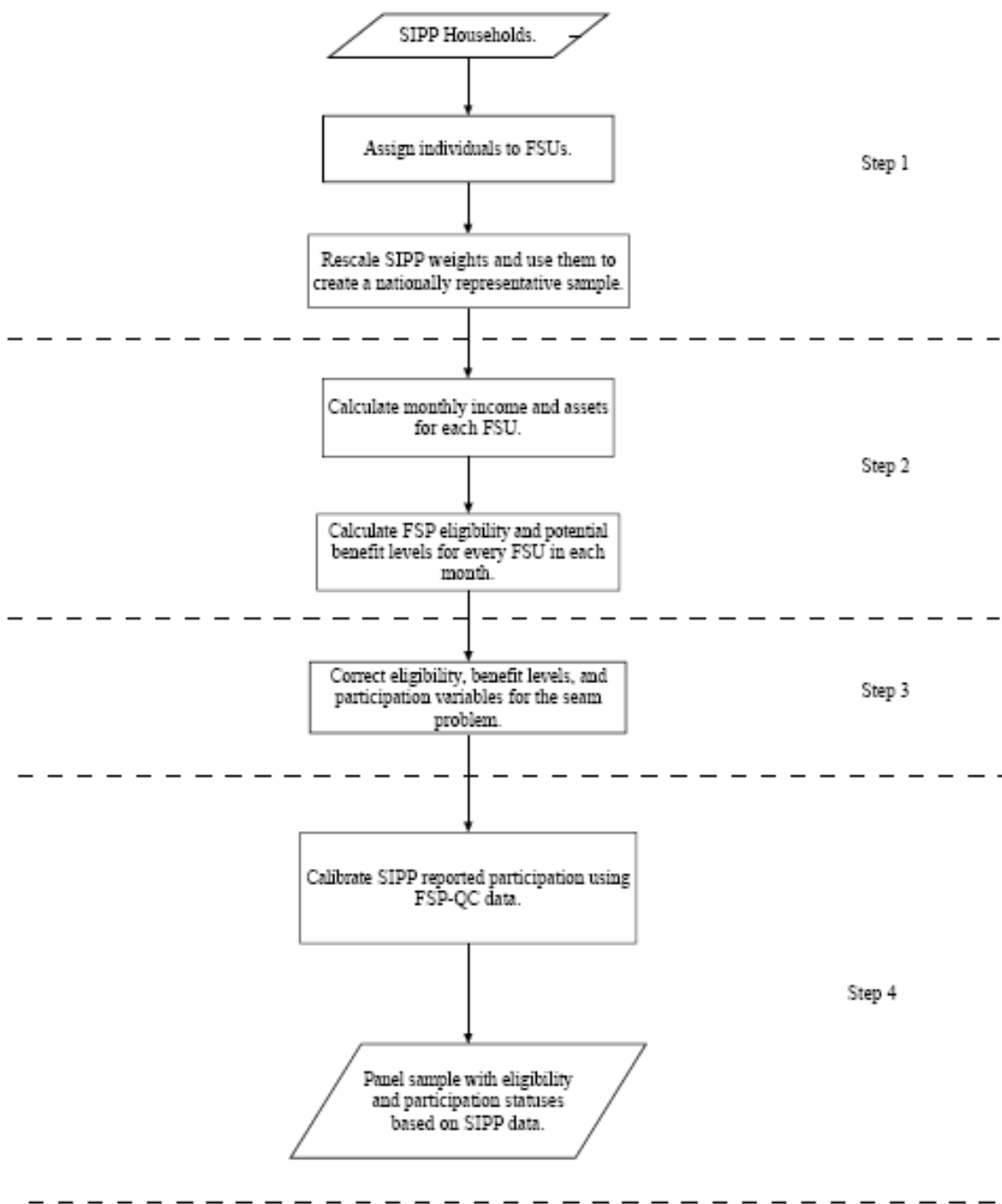
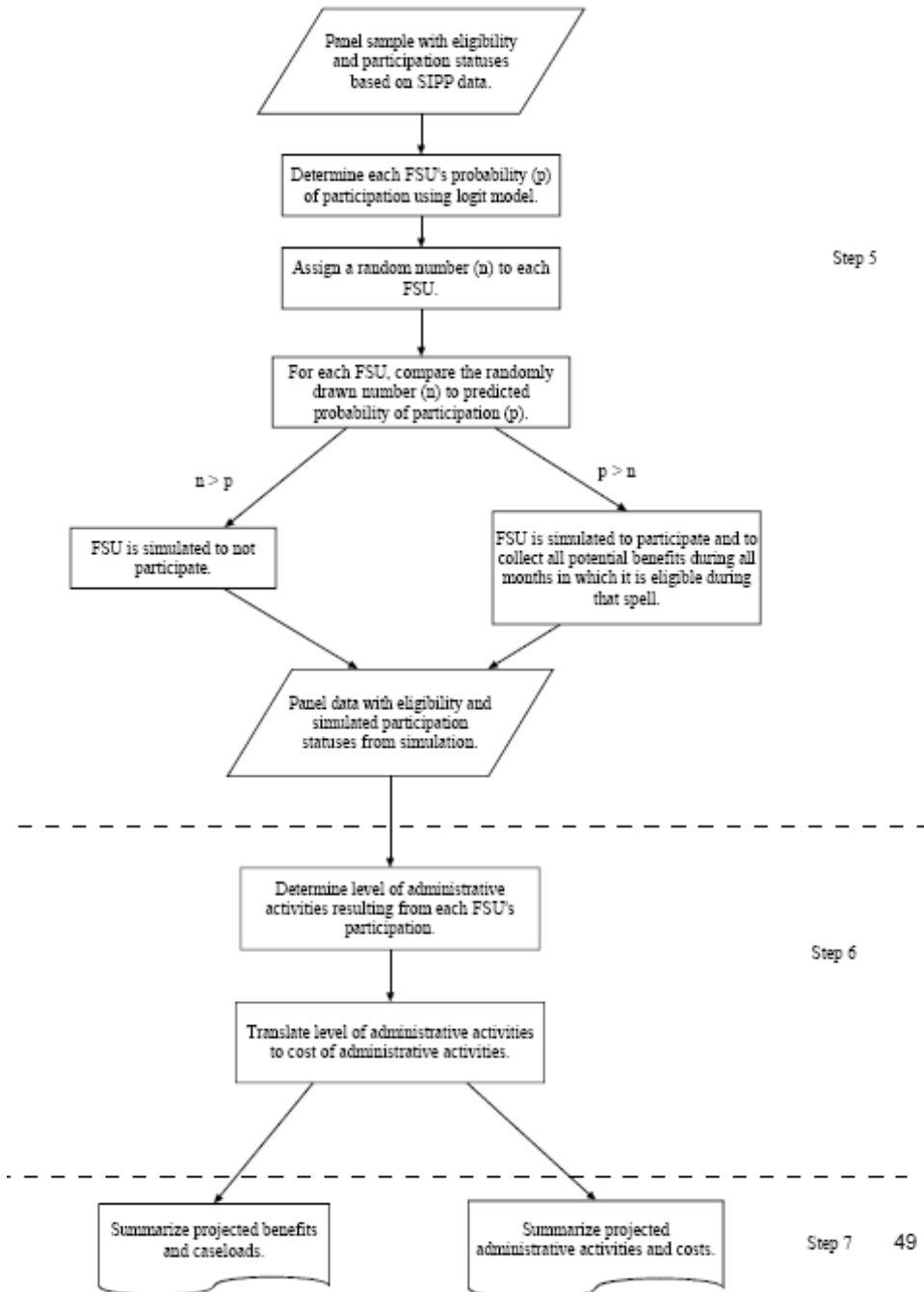


Exhibit B.1b: Steps in the Simulation Approach Part II



1. *Step 1: Classify Persons into Food Stamp Units and Reweight*

The first step of our simulation is to convert the SIPP into observations based on FSUs, assigning all people in the SIPP to an FSU. We assign individuals to an FSU consistent with the way the Food Stamp program would consider the household or family if they applied for Food Stamps. Thus, an FSU is a group of people, not necessarily related, who purchase and prepare meals together. In most cases, an FSU includes all members of a household, but sometimes households composed of unrelated individuals or multiple families can split into more than one FSU when food expenses are not shared by all members.

Because the SIPP does not provide detailed information on how household members divide their food expenditures and activities, we make these assignments by applying the rules stipulated by the Code of Federal Regulations, 7 U.S.C 2012 3(I). In particular, we adopt the following assignment rules:

- (a) A single family household forms one FSU;
- (b) Unrelated subfamilies are assigned to different FSUs, except in the following cases:
 - Unmarried couples, and
 - Foster children younger than 19 years and their guardians;
- (c) Related subfamilies are assigned to different FSUs, with the following exceptions:
 - Parents and their children under age 22, and
 - Guardians and children under age 18;
- (d) Elderly and disabled persons are allowed to file separately when total income of the remaining household members is less than 165% of poverty;
- (e) Post-secondary students working less than 20 hours per week are separated to form their own FSU.¹

Given these allocation rules, MID-SIPP's default approach is to divide households into the maximum number of FSUs allowable by the FSP regulations. Of course, there are undoubtedly instances when more than one related family live in the same residence, buy meals together, and should be combined in one FSU. Hence, an alternative approach would be to aggregate all families living in the same household into a single FSU rather than separate FSUs as done in our base analysis. The simulation framework is flexible and could readily incorporate alternative FSU assignments. Our tests indicate that aggregating all families living in the same household into one FSU decreases the number of FSUs by nearly 8%. All findings presented here use the default FSU allocation described above.

Because we follow FSUs over multiple months, the structure of an FSU can change over time. In the current simulation model, we treat any change in an FSU's composition that potentially alters its eligibility as the formation of new FSUs—or "split-offs"—each one with a different identity from the original unit. For example, if a husband leaves a husband-wife-child FSU, then two new FSUs are formed: an FSU composed of a mother and child and another composed of a male adult. Consequently, an individual can belong to more than one FSU over the course of the year.

¹ According to FSP rules, income from post-secondary students working less than 20 hours a week is not counted in FSU income and is excluded when calculating FSP benefits.

For all FSUs appearing in our sample in any month covered by the sample period, we generate statistics on eligibility and benefits for subpopulations of FSUs distinguished by their characteristics, such as working-poor FSUs (those primarily supported by low-wage earnings) and female-headed FSUs with children. When examining these numbers, bear in mind that the length of time for which an FSU collects or remains eligible for Food Stamps does not necessarily reflect the length of time for which individuals within that FSU collect benefits or remain eligible.² The focus on FSUs, rather than individuals, and the particular strategy for assigning FSUs, are adopted as our base case. However, the MID-SIPP simulation framework can readily calculate statistics for individuals rather than for FSUs. As noted above, it can also accommodate a variety of other approaches for defining and tracking divided FSUs.

The empirical analysis for the baseline MID-SIPP relies on SIPP data from the 1997 federal fiscal year, incorporating complete histories for all available FSUs during this sample period. We exclude an FSU when (i) it is missing crucial data within the sample period – e.g., data exists for April and June but not for May; (ii) none of its members are in SIPP in the first month of the sample period, and (iii) the FSU leaves the SIPP through attrition (as opposed to splitting) before the end of the sample period. Thus, our simulations keep FSUs that stay in SIPP throughout the sample period or that are generated from a splitting FSU whose members remain in SIPP throughout the period.

The latter two exclusion rules preserve the SIPP’s longitudinal sample design and avoid the need to make sophisticated adjustments to SIPP weights to account for sample attrition.³ To account for the exclusion of units with missing crucial data (our first exclusion rule), we adjust the monthly household SIPP weights. We construct a common monthly adjustment factor equal to the number of FSUs in the SIPP observed in a particular month divided by the number of FSUs in our sample observed in the same month. We then apply this adjustment to all units in our simulation sample. This calculation essentially assumes that the crucial data are missing at random. This minor adjustment does not affect the composition of households in the sample. As shown in Table 2.1, the distribution of households in different categories in our sample using re-scaled weights approximates the raw SIPP distributions.

Even after controlling for attrition and missing data, we still need to ensure that the SIPP data yields a “representative” population of FSUs for projecting annual statistics. Given a revolving population of FSUs over time, including FSU split-offs that by definition are observed for only part of the sample period, there are many options for defining a representative population. For

² For example, assume the original FSU was eligible for FSP from January to March and that the new mother-child FSU remains eligible after the husband leaves in March until the end of the year. In this case, both mother and child would have a 12 month long eligibility spell. Instead, we assume these individuals constitute two different FSUs with durations of 3 and 9 months respectively. However, in both cases we calculate correctly each individual’s number of months on FSP within a year.

³ The original design of the SIPP called for an initial selection of a nationally representative sample of households, with all adults in those households being interviewed once every 4 months over a 32-month period. For subsequent waves, the SIPP includes in its sample all other adults living with original sample members. By including all FSUs ever formed by members who remain in the SIPP throughout the period, we are also including in our sample all original sample members and adults living with them through the period.

the analysis presented here, our simulations include the population of all individuals observed in September 1997 and all FSUs formed by these individuals during the fiscal year. In this way, including split-offs in our population permits computation of annual figures that account for families who were eligible for short intervals during the period of analysis. In the analyses below, we use weights for the latest month an FSU is seen in our sample period to create a sample of FSUs that would be nationally representative for the end of the period if no FSU split-offs had been created within the sample period.

2. *Step 2: Determine Each FSU's Eligibility and Potential Benefits for Every Month*

At the completion of Step 1, we have a sample of FSUs developed from the SIPP data. For each FSU specified in Step 1, the next step is to impute this FSU's program eligibility and the level of benefits it is eligible for on a monthly basis. As the second step in our framework, the eligibility and potential benefit imputation applies the set of Food Stamp rules defined under the policy regime to be simulated. Given a specification for FSUs and rules prescribed for an FSP policy regime, we impute each FSU's program eligibility and level of benefits from FSU level data on gross and net income, FSU size and composition, financial assets minus deductions, vehicle assets minus deductions, and categorical eligibility status.

SIPP supplies on a monthly basis much of the information needed to conduct monthly gross and net income tests and the resource test, as well as tests related to the demographic structure of the FSU (such as citizenship). We are also able to assign disability status on a monthly basis to apply the appropriate FSP rules for FSUs that contain disabled persons. We classified individuals as disabled if they received non-earned income due to disability, including non-elderly individuals receiving Supplemental Security Income (SSI).

Unfortunately, data on an FSU's assets and some deductible expenses are available only once a year in special topical modules (in Waves 3, 6, 9 and 12).⁴ We adopt the following rules to assign assets and expenses to the other months in the panel:

- (a) Monthly averages reported in Wave 3 are assigned to all months comprising Waves 1, 2, 3, and 4;
- (b) Monthly averages reported in Wave 6 are assigned to all months included in Waves 5, 6, and 7;
- (c) Monthly averages reported in Wave 9 are assigned to all months making up Waves 8, 9, and 10; and
- (d) Monthly averages reported in Wave 12 are assigned to all months included in Waves 11 and 12.

Income tests require information on both FSU-level gross income and admissible deductions. We calculate gross income by summing all sources of earnings and income for all adult members included in the unit. For earned income, we include all wages and salaries of employees, as well as any

⁴ The sample in the model data set excludes households with incomplete asset information in the corresponding topical module. We excluded these households from the model data set during the year there was not topical module information available, but retained them in the remaining years. For example, a household missing asset information in only 1996 is not included in our sample for 1996, but it is included in our samples for 1997 through 1999.

net income from self-employment. For unearned income, we account for all types of financial and property income, social security, foster child payments, and all transfers from means-tested programs except Food Stamps. Similarly, we make the appropriate deductions to calculate net income, following the rules of the policy regime. To anchor our results in known FSP information, we start from existing policy, so to calculate net income, we deduct the following:

- A state-based standard deduction of \$134,
- 20% of the FSU's earned income (the "earned income deduction"),
- Dependent care expenses up to a \$175 maximum per dependent and up to \$200 per children younger than two,
- Legally mandated child support payments,
- Medical expenses in excess of \$35 if there is an elderly or disabled person in the FSU, and
- An excess shelter deduction. For the excess shelter deduction, we subtract the monthly rent and utility expenses above 50% of the FSU's net income after applying all remaining deductions. Following the rules, we limit the excess shelter deduction to a maximum of \$250 if there are no elderly or disabled members in the FSU.

For an FSU passing the income and demographic-structure tests in a month, we assess whether the asset tests exclude it from benefits. In calculating assets, we aggregate amounts in checking accounts, savings accounts, stocks, bonds, and mutual funds for all members of the FSU, as well as savings in IRA and Keogh Accounts after deducting withdrawal penalties. Again, our example case uses existing rules, so we apply the follow tests: Eligible households with an elderly member (60 or older) cannot have counted liquid assets above \$3,000, whereas eligible households without an elderly member are restricted to counted liquid assets of no more than \$2,000.⁵ Counted liquid assets include cash, checking and savings accounts, savings certificates, stocks and bonds, IRAs and Keogh plans (less early withdrawal penalties), and nonrecurring lump-sum payments like insurance settlements. In addition, the equity value of property not producing income consistent with its value (such as recreational property) is included in this measure. We accounted for vehicles by applying the following three rules: 1) for the first vehicle, or any vehicle used to commute to work, any market value above \$4,650 was counted; 2) for other vehicles, the higher of either any fair market value above \$4,650 or any equity was counted; and 3) for vehicles used to produce income or to transport disabled persons, all value was excluded from the resource test according to regulation 273.8, Section (e)(3)(I). A similar set of calculations is done for each alternative policy regime. At this stage in the simulation, our benefit calculations assume that any eligible FSU applies and collects full potential benefits in that month. This is treated as a reference or baseline calculation, since not all eligible FSUs will in fact take-up benefits. At any take-up less than 100%, this reference case will by definition be an over-estimate of the benefits actually collected. (In Step 5, we address benefit take-up rates to simulate participation among those eligible.)

Reporting rules are handled as follows: When an FSU first becomes eligible or becomes eligible after a period of non-certification, we treat the first month of eligibility as the certification time and assign to the FSU the level of benefits calculated at the time of certification and certify it for the assumed reporting period. At the end of this certification period, we assume that FSUs remaining

⁵ In the case of units containing only persons on SSI, TANF, or General Assistance (GA), asset eligibility is automatic.

eligible reapply for the benefits and receive payments consistent with conditions at the time of recertification. If a reporting regime requires households to report changes, then we presume that FSUs perfectly abide by the prescribed rules and caseworkers immediately adjust eligibility and benefits accordingly. If an FSU becomes ineligible in a month, then we treat it as reapplying at its first opportunity if and when eligibility reoccurs.

These steps create a simulated panel of FSUs observed on a monthly basis, with eligibility status and benefit levels directly computed from the information contained in SIPP. The next step is to adjust this panel of data to account for SIPP reporting inaccuracies that cause distortions in the data.

3. *Step 3: Correct Eligibility and Reported Participation Spells for the Seam Problem*

The SIPP interviews households three times each year. At each interview, the respondent is asked about family members' circumstances during the previous four months. In a recall survey such as this, individuals are more likely to report that changes in circumstances occurred at the beginning of the first month or at the end of the last month of an interview period. Thus, the survey structure induces a disproportionate number of changes in income, asset levels, and program participation reported to occur at the 'seam' between two interview periods, yielding artificial breaks in the profiles of variables used to impute FSP eligibility and benefits, and also of the participation variable. Known as the seam problem, this factor potentially contaminates analyses of dynamic behavior estimated with data from longitudinal surveys. Thus we first adjust the eligibility, benefit level and participation variables for the seam problem.

To better understand the seam problem and our approach to address it, consider an eight month time line:

Month	1	2	3	4	5	6	7	8
Interview				I				I
Eligibility: Reported	E	E	E	E	NE	NE	NE	NE
Actual	E	E	E	E	E	NE	NE	NE

Suppose a SIPP family is interviewed (I) in months 4 and 8. In each month, a family is in one of two states: eligible for FSP (E) or not eligible (NE). A seam problem arises if the family in period 8 reports a change in circumstances as though it occurred in month 4, when in fact it occurred sometime after month 4 but before month 8. For the example above, we know from the interview that the family was in state E in month 4 and in state NE in month 8. Because of the seam problem, the family may report termination in month 4, even though the duration of the family's eligibility spell may have extended beyond month 4 (through month 5 in the above example). The seam problem can affect reported participation itself as well as reports on income and other information used to determine eligibility. In our simulation analysis, the seam problem is particularly an issue for the estimation of duration distributions for eligibility, denoted $f(\bullet)$. If the family's spell started in month 1 and the family misreports the spell ending in month 4, then the estimated value of $f(4)$ is too high, because we have counted the family as $f(4)$ instead of $f(5)$.

The MID-SIPP compensates for the distortions induced by the seams in SIPP.⁶ In essence, the analysis adjusts for this estimation error by specifying a “smooth” functional form for $f(\bullet)$ that redistributes part of the occurrence of events in period 4 to periods 5, 6, and 7 in a way consistent with patterns in the data. In particular, we use a logit function to fit the probability that a spell that lasted $t-1$ months would end in the following month, allowing for a rich set of demographic covariates and a flexible function that captures duration dependence. This conditional probability is called the hazard rate at t . Using this logit specification, we constructed the likelihood function for all observed spells, distinguishing completed spells, censored spells and spells ending on a seam month. To account for potential misreporting of termination at the seam month, the likelihood of a spell that ended in a seam at $t-1$, is specified as the conditional probability that it will end at t , or at $t+1$ or at $t+2$, which is simply the sum of the hazard rates at t , $t+1$ and $t+2$.⁷ The estimated hazard rates resulting from this method do not have the spikes at seam months (4, 8 or 12) followed by unusually low values in the subsequent months (5, 9 or 13) seen in the empirical hazard rates.

At the end of Step 3, we have a seam-corrected panel data set of SIPP FSUs observed on a monthly basis, with monthly estimations of eligibility and potential benefits. Because we want to make projections about the Food Stamp Program at the national level, before this data set is ready for analysis, we must derive weights so that our projections are nationally representative and match administrative totals.

⁶ Appendix A demonstrates the relevance of the seam problem in SIPP and describes our approach to compensate for the distorting influence of artificial patterns induced by seams.

⁷ See Appendix A for a detailed description of the estimation methods used to correct the seam problem.

APPENDIX C: A COMPARISON OF EARNINGS DATA IN THE SURVEY OF INCOME AND PROGRAM PARTICIPATION WITH SOCIAL SECURITY EARNINGS RECORDS

A. Introduction

The Census Bureau's Survey of Income and Program Participation (SIPP), which was designed "to provide accurate and comprehensive information about the income and program participation of individuals and households in the United States,"¹ has been one of the primary sources of data on the economic situations of low-income individuals and families. Among the strengths of the SIPP for use in social research are its longitudinal structure, which allows researchers to analyze data on individuals over time, and the detailed data it collects on program benefits. As a result, it is a valuable tool for researching participation in low-income programs.

Given its broad use in these areas, knowing the level of accuracy of earnings data in the SIPP is of substantial interest to policy researchers and other social scientists. Inaccurately measured earnings can lead to distorted conclusions about program participation. For example, the main body of this paper uses the SIPP to investigate why a substantial share of individuals who are eligible for food stamps do not participate in the programs. If survey data fails to capture earnings by some individuals, research based on those data could be confounded by the fact that those individuals may appear from the survey data to be eligible for food stamps when in fact their income is high enough to make them ineligible.

This appendix investigates the accuracy of earnings data from the 1996 panel of the SIPP. The analysis is based on a data set in which SIPP data are matched to Social Security administrative earnings records. This matching of data provides the opportunity to compare earnings amounts reported by SIPP respondents to earnings amounts in the Social Security earnings records. Such a comparison can provide information on the extent of nonsampling error, and in particular measurement error, in the SIPP's earnings data.

There are several well-acknowledged sources of potential nonsampling error in survey data on earnings.² Nonresponse – either failure of part of the sample to participate in the survey as a whole, or nonresponse to particular questions – can lead to biases in statistics generated with the survey data if the nonresponsive portion of the sample is not randomly determined. In longitudinal surveys like the SIPP, attrition is a particular problem, where members of the sample who participate in one wave of the survey do not participate in later waves. According to Weinberg (2003), attrition from the 1996 panel exceeded 25 percent by the end of the panel's second year, and sample loss reached as high as 35.5 percent in the last wave of the panel (Bureau of the Census, 2001). The Census Bureau performed various adjustments to the SIPP data to account for nonresponse in the 1996 SIPP, including weighting adjustments when entire households do not respond to the survey and imputations of data when one person in a household does not respond. (Bureau of the Census, 2001).

¹ Bureau of the Census (2001).

² For a general overview of sources of survey measurement error, see Bound, Brown, and Mathiowetz (2000). For a general overview of issues with the SIPP, see Weinberg (2003).

Survey respondents may also misremember amounts they have earned in past months, particularly if they do not refer to records to confirm their memory or if they work in jobs in which earnings vary from month to month. Given its four-month wave structure, the SIPP suffers from “seam bias” in which reported earnings change more in consecutive months between waves (the “seam”) than within waves because respondents tend to report similar earnings for all four months they are asked about in each questionnaire, causing an artificial concentration of changes at each new interview.

Respondents may misunderstand the questions; for example - some responders may report after-tax earnings even though the SIPP requests information on gross income - or may not have sufficient knowledge to accurately answer the question if, for example, one member of the household reports his or her own employment and earnings as well of the employment and earnings of all other household members. In addition, respondents may deliberately misreport under certain circumstances, such as if they have “off-the-books” earnings that they do not want to report to the interviewer.

In addition, the SIPP’s design may lead to some inaccuracies. The SIPP only collects information about two jobs in each wave, plus additional earnings from “moonlighting” and earnings from self-employment. While some attempt is made to record total earned income from additional jobs this variable is likely to involve more measurement error as it represents a total of possibly several jobs over a four-month period.

The basic method of this analysis will be to compare individual-level earnings records from the 1996 SIPP with the earnings records for the same individuals in the Social Security data. Administrative data are often considered more accurate than survey data, and the usual assumption made in these types of studies is that the administrative data provide an accurate external measure of earnings. Discrepancies are consequently attributed to error in the survey data. However, the Social Security earnings records are also subject to certain sources of error and limitations, particularly when being treated as a representation of all earnings among the general population instead of being used within their intended programmatic purposes. Social Security data will not contain data on any earnings not reported to SSA, such as “off-the-books” earnings or some earnings not covered by the Social Security system. While some respondents may be reluctant to report off-the-books earnings in their responses to the SIPP, the survey is likely to capture more such earnings than the administrative data, and in these cases the survey data will be more accurate. In addition, the administrative data set to which we had access, Summary Earnings Record, does not contain “uncovered” earnings to which the Social Security payroll tax does not apply, such as earnings above the taxable maximum (around \$70,000 during the years covered by the 1996 SIPP panel) or earnings from certain types of jobs. (Other sets of Social Security administrative data contain uncovered earnings.) Interpreting differences between earnings as represented in the two data sources should take into account error in both data types.

Following a distinction established by Pedace and Bates (2000), the analysis has two separate stages. The first stage looks at agreement and disagreement between the two data sources in their identification of who has any earnings (regardless of the amount) and who has no earnings. The second stage looks just at those individuals that both data sources identify as

having earnings, and looks at discrepancies in the amounts of earnings shown in the two data sets.

After this introduction, the next section provides a brief discussion of past literature on the accuracy of survey data on earnings. The third section discusses the data used in the analysis. The fourth and fifth sections present the results of the analysis. The final section concludes.

B. Previous Findings on Accuracy of Survey Data on Earnings

This discussion highlights some of the key studies that have looked at the accuracy of annual earnings data in national surveys. Several very helpful reviews of literature on the accuracy of survey data exist. Among these are Bound, Brown, and Mathiowetz (2000) and Moore, Stinson, and Welniak (1997) and Hotz and Scholz (2002); we rely heavily on these three papers.³

Studies of the accuracy of income and earnings data take two main forms: “benchmark” comparisons of aggregate statistics derived from the survey to some other aggregate measure, and comparisons of individual-level responses to independent individual-level data such as administrative records.

1. Aggregate Comparisons to Benchmark

Two relatively recent studies compare aggregate earnings data derived from the SIPP and the Census’s Current Population Survey (CPS) to each other and to independent benchmarks derived from the Bureau of Economic Analysis’s National Income and Product Accounts (NIPA), the database used to create GDP and other national income statistics. Both studies find that the SIPP tends to miss earnings data, while the CPS is closer to the benchmark.

Coder and Scoon-Rogers (1996) find that aggregate wage and salary income in the CPS March supplement is closer to the benchmark derived from the NIPAs than aggregate wage and salary income from the SIPP. Wages and salaries in the 1990 panel of the SIPP equal 92 percent of the benchmark, while wages and salaries measured in the 1990 CPS equal 97 percent of the benchmark. On the other hand, The SIPP is closer to the benchmark on many other measures of income, including self-employment income, where the SIPP data in 1990 equals 78 percent of the benchmark as compared to 66 percent in the CPS.⁴

Roemer (2000) takes a similar approach using more recent data to show comparisons for years from 1990 to 1996. Roemer finds the SIPP’s measurement of wages and salaries in 1996 to equal 91 percent of the NIPA benchmark and its measurement of self-employment earnings to equal 69 percent of the benchmark; taken together, SIPP-measured earnings are 88 percent of the benchmark. In comparison, March CPS measurements in 1996 as a percentage of the benchmark

³ Table 1 of Bound, Brown, and Mathiowetz (2000) summarizes findings from 18 studies assessing error in survey measurements of earnings. The paper can currently be found at <http://www.psc.isr.umich.edu/pubs/pdf/rr00-450.pdf> (accessed February 7, 2007).

⁴ In discussing these results which show survey-based aggregates below the NIPA benchmark, Moore, Stinson, and Welniak (1997) “urge caution” in concluding that survey respondents underestimate their income. They note that there are several other potential sources of differences, such as time frame or definitions used.

are 102 percent for wages and salaries, 53 percent for self-employment earnings, and 96 percent for earnings taken together. SIPP wages and salaries remain consistently around 90 percent to 91 percent of the NIPA benchmark, which Roemer describes as “perhaps disappointing” because of attempts to improve collection of wage data in the 1996 panel. The SIPP in general shows lower aggregate income and a higher number of people receiving that income than the CPS, and based on distributional estimates, Roemer hypothesizes that the higher burden of responding to the SIPP leads to fewer higher-wage earners participating in the survey.

2. Individual-Level Comparisons to Administrative Data

Validation studies comparing survey data on earnings to administrative data typically use IRS, Social Security, or employer records as the administrative data sources. As mentioned earlier, the typical assumption in such studies is that the administrative data are accurate and therefore differences between the survey data and the administrative data are interpreted as survey error. Some exceptions exist. Many of these studies find survey data to overstate earnings at lower earnings levels, and to understate earnings at higher levels.

A validation study of the Panel Study of Income Dynamics (PSID) looked at a sample of employees at a single manufacturing firm and compared their responses to a PSID-like interview to data from the employers’ records. The study found very small differences in mean earnings – for example, Duncan and Hill (1985) report that mean earnings for 1981 and 1982 from the interviews were underreported by less than one percent for annual earnings and by about four percent for hourly earnings. Average absolute differences were substantially bigger (seven to nine percent for annual earnings; 14 to 16 percent for hourly earnings), suggesting little bias in responses but more substantial random error. A follow up study (Rodgers, Brown, and Duncan (1993)) also found little bias, though higher random error.⁵

Coder (1992) compared earnings of married couple SIPP respondents to IRS records. The comparison was limited to those couples who could be matched to the tax returns, and excluded couples with zero earnings in both data sources. Little difference was found (a simple correlation of 0.83), but Moore, Stinson, and Welniak characterize the sample as “very restricted”.⁶ Hendrick, King, and Bienias (1997) make a similar comparison among a data set matching the 1990 SIPP panel to IRS data as part of an analysis of nonresponse bias in the SIPP, using a different sample (matched cases with non-zero earnings in both SIPP and IRS). They find that SIPP-measured earnings are lower than earnings measured with the IRS returns, and that there is “SIPP overestimation at the low earnings level and/or SIPP underestimation at the high earnings level”.

Roemer (2000), discussed above for its comparisons with NIPA-based benchmarks, also looked at matched CPS-IRS data. With this comparison, Roemer concludes that both underreporting and overreporting of earnings occur in the CPS relative to IRS data, with net underreporting only occurring at the top end of the income spectrum. Roemer did not analyze a similar match between the SIPP and the IRS data.

⁵ Findings summarized in Bound, Brown, and Mathiowetz (2000) and Moore, Stinson, and Welniak (1997).

⁶ Findings summarized in Bound, Brown, and Mathiowetz (2000) and Moore, Stinson, and Welniak (1997).

Looking at a data set matching the CPS to Social Security earnings for 1977 and 1978, Bound and Krueger (1991) find high correlations between the two measurements of earnings, and little bias in the errors, despite a high variance in differences in the earnings measures. For men, errors are larger at the lower end of the earnings spectrum (as measured in the Social Security data), which a later analysis by Bollinger (1998) finds to be due to a small group of low earners either overreporting their earnings in the CPS or for whom earnings are not captured in the Social Security data set.⁷

Abowd and Stinson (2003) diverge from the typical operational assumption that administrative data are fully accurate and question the extent to which differences between SIPP-measured annual earnings and Social Security earnings data (as contained in the Detailed Earnings Records file, or DER) are due to errors in the survey versus errors in the administrative data. They look at matches in earnings from particular jobs, as opposed to matches between persons.⁸ They find that a somewhat higher proportion of variance in earnings in the DER is attributable to error than in the SIPP.⁹

In our analysis we have chosen to follow closely a paper by Pedace and Bates (2000). Pedace and Bates worked with a data set matching the 1992 SIPP panel to Social Security administrative data on earnings from the Summary Earnings Record (SER). They distinguish between accuracy in reciprocity – i.e., accurate reporting in the survey data whether individuals have received any earnings or not – and accuracy in reporting earning amounts, and point out that studies like Roemer (2000) and Coder (2002) find underreporting of amounts, but little understatement of reciprocity. In their own data analysis, they find a high level of agreement between the SIPP and the SER in whether individuals receive earnings (90 percent of matched cases either have positive earnings in both data sets or have zero earnings in both data sets) but a substantial amount of differences in amounts. Cases in which there are positive earnings in the SIPP and zero earnings in the SER are about twice as common as cases where there are zero earnings in the SIPP and positive earnings in the SER, which the authors see as evidence of a “systematic failure to capture earnings on the SER.” They find substantial misreporting of amounts; where both data sets have positive earnings, the SIPP values are on average \$459 lower than the SER values. At the lower end of the earnings spectrum (as measured by the SER), the SIPP showed higher earnings than the SER, but at higher earnings level (\$20,000 and above) – and in total overall – the SER showed higher earnings. Econometric models show that a number of demographic factors and types of occupations affect the accuracy of reporting (or at least the match between SIPP-reported data and the SER.)

⁷ Findings of both papers summarized in Bound, Brown, and Mathiowetz (2000) and Moore, Stinson, and Welniak (1997).

⁸ The DER contains all wages and other compensation reported on the IRS’s W-2 form. Therefore, unlike the SER, it contains earnings reported to the IRS regardless of whether the earnings are covered by the Social Security system. The DER also contains earnings separated out by different jobs, while the SER only contains total annual earnings from all jobs for each individual. Abowd and Stinson’s methodology takes advantage of the job-by-job earnings records.

⁹ Abowd and Stinson construct a model that differentiates between “shared effects” in the two earnings measures, which they treat as noise in true earnings, and “separate effects” from one data source or the other which they treat as error attributable to that source.

Bridges, Del Bene, and Leonesio (2002) perform a similar analysis using data from the 1992 and 1993 SIPP panels to the DER. Their findings are similar, and also show SIPP earnings to be higher than DER earnings for lower earners and lower for higher earners.

Later in the appendix, we compare our findings to Pedace and Bates's; more detail on their paper is included in that discussion.

C. Data

The public-use data from the 1996 SIPP panel include monthly information on households, families, and individuals over 48 months, including detailed monthly demographic, program, employment, and health characteristics for a nationally representative sample. SSA and Census have matched these SIPP public use files to administrative records on earnings (including self-employment earnings) using Social Security Numbers (SSNs).

The bulk of our analysis looks at individuals in this matched data set and compares the annual earnings reported for these individuals in the SER with their annual earnings from the 1996 SIPP panel.¹⁰ However, it is not possible to make comparisons for every individual in the data set for each year. As a result, we constructed an analysis sample for each year consisting of just those individuals where such a comparison is possible. We generally focus on working-age individuals, which we define as ages 18 through 65. However, where we compare our findings to past papers – primarily Pedace and Bates (2000) – we instead follow their convention of looking at individuals 15 and older.

Availability of annual earnings data. One factor limiting our sample is that earnings data from the SER are only available on an annual basis, while the SIPP contains monthly earnings data. To make a comparison between the two, we construct annual earnings variables for the SIPP by summing over the 12 months of each year. This is only possible when there are 12 months of data. As a result, we do not include an individual in our analysis for a given year unless 12 months of SIPP earnings data are available for that individual.

There are several reasons why there may not be 12 months of data for an individual in a year. Some are related to the SIPP's interview structure. An original sample of households is selected to participate in the SIPP, and these households are interviewed periodically at the end of several four month "waves." (There was a total of 12 waves for the 1996 SIPP.) However, households may not be stable from wave to wave: individuals originally in a SIPP household may move out (for example, due to divorce or a child leaving for college) or new individuals may move in (for example, due to marriage or the birth of a new child). A substantial portion of individuals who participate in interviews at the beginning of each SIPP panel do not participate in some or all of later interviews, a situation known as attrition. Further, in 1996 and 1999 many individuals lack at least one month of data due to the SIPP's interview schedule: only two of the four staggered rotation groups, representing approximately 50 percent of SIPP participants, were first interviewed early enough that the time period they asked about (i.e., the previous four months) included January 1996. Similarly, for one of the four staggered rotation groups,

¹⁰ Earnings data include earnings from self-employment. It is possible that there are larger discrepancies between the two data sources with regards to self-employment earnings than with regards to wages and salaries, due to differences in how the two data sets classify income types as self-employment earnings.

the last interview occurred in December 1999, too early to report the earnings they had received in that month.¹¹

The 1996 SIPP panel includes about 116,000 individuals that were included in the survey at least once. On average, for each year we drop about half of these individuals from our sample because they do not contain earnings in at least one month of the year. (See *Exhibit C.1*.)

Exhibit C.1: SIPP Participants With Less Than 12 Months of Earnings Data, By Year

	1996	1997	1998	1999
Total individuals in SIPP	115,996	115,996	115,996	115,996
# individuals with <12 months earning data	76,200	44,973	49,483	44,631
% of individuals in SIPP with <12 months earning data	65.7%	38.8%	42.7%	38.5%
Remaining individuals	39,796	71,023	66,513	71,365

Non-match with SER. As discussed above, for many records in the SIPP, SSA was not able to make a successful match to the SER. This primarily occurred for two reasons. First, in many cases no valid Social Security Number was provided during a SIPP interview. Second, the SIPP-SER match provided to us for analysis only contained a match of individuals who were present in SIPP households during the first interview. Thus, no SER record was available to us for sample members who entered households after the first interview. As shown in *Exhibit C.2*, dropping the non-matched individuals reduces the remaining sample size by between 5,700 and 13,000 each year.

¹¹ See Bureau of the Census (2001) for more information.

Exhibit C.2: SIPP Participants Not Matching to SER, By Year

	1996	1997	1998	1999
Total individuals remaining from Exhibit C.1	39,796	71,023	66,513	71,635
# individuals not matching to SER data	5,734	12,060	12,957	10,710
% of individuals not matching to SER data (as percent of total individuals in the SIPP)	4.9%	10.4%	11.2%	9.2%
Remaining individuals	34,062	58,963	53,556	60,925
Addendum: Remaining individuals as a percentage of total individuals in the SIPP (115,996)	29.4%	50.8%	46.2%	52.5%

There are on an average nearly 52,000 individuals matching to the SER each year, leaving 207,506 person-year observations (i.e., repeats of individuals across the different years). These observations serve as the analysis sample for most of the analysis in this appendix. Of these, 114,927 observations are of working age individuals between 18 and 65 years of age.

D. Analysis of Reciprocity Match

The first question we address is whether SIPP and SER match in identifying earners and non-earners. *Exhibit C.3* shows a cross-tabulation of working-aged (18-65) individuals identified in the 1996 SIPP as having or not having earnings (including self-employment earnings) in the two data sets.

Exhibit C.3: Comparison of Earners and Non-Earners as Identified in the SIPP and SER

	Positive earnings in SER	Zero Earnings in SER	Total
Positive earnings in SIPP	75.5%	7.0%	82.5%
Zero earnings in SIPP	3.3%	14.2%	17.5%
Total	78.9%	21.1%	100.0%

Notes: 114,927 person-year observations in total. Sample includes working-age (18-65) individuals in the 1996 SIPP panels (covering 1996-1999). Individuals are included for each year where 12 months of earnings data are available in the SIPP and where matches were made to the Summary Earning Records data set.

In 89.7 percent of observations, the SIPP and SER match in whether their data show an individual as having any earnings in the year; in the other 10.3% of cases, one of the data sets shows the individual as having earning in a year while the other shows the individual as having no earnings in the same year. About two-thirds of the non-matching cases (or 7.0 percent of cases overall) are cases in which the SIPP shows the individual as having earnings in the year but the SER does not. In the other third of non-matching cases (or 3.3 percent of cases overall) the SER shows earnings for the individual but the SIPP does not.

There are several potential explanations for the mismatched cases. Where the SIPP shows earnings not present in the SER, some individuals worked jobs not covered by the Social Security system, such as some state or local government workers and some long-term federal government workers, domestic workers who do not get paid substantial amounts by any particular household, and some agricultural workers. Others likely had “off-the-books” earnings that were not reported to the IRS, but that they nonetheless reported to SIPP interviewers. Another possible cause is survey error, where respondents mistakenly reported earnings for themselves or a household member where no earnings actually existed. Where earnings were present in the SER but nothing was reported in the SIPP, the most likely explanation is that the individual had earnings, but these earnings were not reported during the SIPP interview.

While we are unable to directly identify which of these sources were at play, data in the SIPP do allow us to look at the characteristics of individuals for whom the two data sources do not agree. *Exhibit C.4* compares the demographic characteristics of working-aged adults with zero earnings in only one or the other data source to those with zero earnings shown in both and to the whole sample of working-aged adults.

Exhibit C.4: Descriptive Demographic Statistics of Individuals With Zero Earnings Shown in the SER or SIPP – Working Aged Adults, 1996-1999

	Individuals with zero earnings in the SER but positive earnings in the SIPP	Individuals with zero earnings in the SIPP but positive earnings in the SER	Individuals with zero earnings in both the SIPP and SER	Full sample
Number of individuals in the sample	7,998	3,821	16,301	114,927
Age				
Average age	42.3	36.2	46.3	40.0
18-25	10.6%	38.2%	10.1%	15.5%
26-35	18.8%	15.4%	14.7%	22.9%
36-45	28.2%	15.9%	20.1%	27.1%
46-55	27.7%	13.1%	21.4%	20.9%
56-65	14.7%	17.4%	33.7%	13.6%
Race				
White	82.8%	71.4%	80.7%	84.3%
Black	12.8%	21.2%	14.5%	11.4%
American Indian	1.3%	2.2%	1.3%	1.1%
Asian Pacific Islander	3.1%	5.2%	3.5%	3.2%
Ethnicity				
Hispanic	12.4%	15.5%	10.6%	9.5%
Non-Hispanic	87.6%	84.5%	89.4%	90.5%
Sex				
Female	49.9%	57.7%	68.9%	51.1%
Male	50.1%	42.3%	31.1%	48.9%

	Individuals with zero earnings in the SER but positive earnings in the SIPP	Individuals with zero earnings in the SIPP but positive earnings in the SER	Individuals with zero earnings in both the SIPP and SER	Full sample
Relationship to Reference Person				
Reference Person	48.4%	30.6%	45.0%	51.0%
Spouse	29.6%	24.2%	36.2%	28.8%
Child	12.0%	36.6%	12.3%	14.4%
Grandchild	*	*	*	0.4%
Parent	*	*	1.0%	0.4%
Sibling	1.2%	*	1.1%	0.8%
Other relative	1.0%	2.1%	1.4%	1.1%
Foster child	*	*	*	*
Unmarried partner	1.8%	*	1.3%	1.7%
House/roommate	1.0%	*	0.6%	0.9%
Roomer/boarder	*	*	*	*
Other non-relative	*	*	0.5%	0.5%
Type of Household				
Stable household				
Married family	66.5%	66.4%	66.1%	67.0%
Family, male head of household	3.9%	3.5%	2.9%	3.1%
Family, female head of household	10.3%	19.4%	14.2%	11.4%
Non-family, male head of household	8.4%	3.3%	6.3%	7.0%
Non-family, female head of household	6.2%	3.1%	6.4%	5.9%
Group quarters	*	*	*	0.2%
Change in household type				
Married family	1.6%	*	1.4%	2.0%
Family, male head of household	*	*	0.5%	0.7%
Family, female head of household	1.0%	*	1.0%	1.2%
Non-family, male head of household	*	*	*	0.9%
Non-family, female head of household	*	*	*	0.7%
Group quarters	*	0.0%	*	0.0%

* Results are suppressed when there are less than 75 observations in a cell.

“Head of household” and “reference person” are used interchangeably to refer to the owner or renter on record of the household.

As the table shows, those with zero earnings in the SIPP but with earnings in the SER are on average younger than the other groups shown. More than one-third fall into the 18 to 25 range (38.2 percent, compared to only 15.5 percent in the sample overall and about 10 to 11 percent of those with zero SER earnings). They are more likely to be black (21.2 percent, compared to 11.4 percent in the overall sample), more likely to be Hispanic (15.5 percent compared to 9.5 percent in the overall sample), and are more likely to live in a female headed household than the other groups (19.4 percent lived in female-headed “stable” households compared to 11.4 percent in

the sample as a whole; “stable” here means that the household composition did not change over the course of the year).

In comparison, the demographic characteristics of the group of people with zero earnings in the SER and positive earnings in the SIPP are close to the characteristics of the full sample. Three quarters fall within the middle age categories (74.8 percent are in the 26-55 range, compared to 70.9 percent in the full sample, 56.2 percent of those with no earnings in either source, and 44.4 percent of those with zero SIPP earnings but positive SER earnings). They are somewhat more likely than the overall sample to be Hispanic (12.4 percent versus 9.5 percent).

Those with no earnings shown by either data source also have similar demographic characteristics to the sample as a whole. This group, however, is substantially more likely to be older – they have the highest average age, and 33.7 percent fall into the 56-65 age range, compared to 13.6 percent of the overall sample – and is more likely to be female (68.9 percent compared to 51.1 percent in the sample as a whole).

Individuals for whom the SER showed income but where no income was reported in the SIPP are noticeably less likely to be the SIPP’s household reference person.¹² In cases where the SER shows earnings but the SIPP does not, only 30.6 percent of the individuals are the reference person, compared to 51.0 percent in the overall sample. On the other hand, 36.6 percent of these individuals are children of the reference person, compared to 14.4 percent of the sample overall. Even though all members of the household are supposed to respond to the SIPP questionnaire themselves, this finding is supportive of the idea that one member of the household may be responding on behalf of his or her children and misreporting the children’s earnings.

Exhibit C.5 shows income and earnings statistics for the same groups of individuals.

¹² The SIPP reference person is the owner or renter on record of the household. Other household members are classified according to their relationship to the reference person. When individuals are not available to complete an interview, the household reference person is most often the household member that will complete the interview for them. We use the terms “reference person” and “head of household” interchangeably in this paper.

Exhibit C.5: Descriptive Earnings, Income, and Industry Statistics of Individuals With Zero Earnings Shown in the SER or SIPP – Working Aged Adults, 1996-1999

	Individuals with zero earnings in the SER but positive earnings in the SIPP	Individuals with zero earnings in the SIPP but positive earnings in the SER	Individuals with zero earnings in both the SIPP and SER	Full sample
Number of individuals in the sample	7,998	3,821	16,301	114,927
Job industry				
Agricultural work	2.1%	*	0.9%	1.7%
Domestics	1.8%	*	*	0.5%
Government	12.2%	0.0%	*	4.4%
Annual income, mean (SIPP)	\$26,174	\$4,733	\$6,810	\$26,046
Nonearnings Income	\$2,419	\$4,733	\$6,810	\$2,551
Earnings	\$23,755	\$0	\$0	\$23,495
Earnings as a percent of total income	90.8%	0.0%	0.0%	90.2%
Percent with zero earnings	0.0%	100.0%	100.0%	17.2%
Transfer income	\$160	\$448	\$982	\$216
Percent with zero income from any source (SIPP)	0.0%	40.0%	16.0%	3.6%
Annual earnings, mean (SER)	\$0	\$5,550	\$0	\$20,397
Percent with zero earnings (SER)	100.0%	0.0%	100.0%	20.7%
Years of earnings, mean (SER)	22.6	19.6	22.1	22.9
Total earnings, 1937 to date, mean (SER)	\$107,265	\$163,398	\$115,335	\$307,052
Average annual earnings over lifetime, mean across individuals in sample (SER)	\$4,747	\$8,357	\$5,230	\$13,391
Zero years of earnings (SER)	4.31%	0%	7.33%	1.31%
Quarters covered, mean (SER)	0	2.20	0	2.97
Income and Earnings (SIPP)				
Total Household Income, mean	\$58,136	\$42,447	\$39,873	\$57,016
Household Earnings	\$51,944	\$32,787	\$27,126	\$50,988
Non-Earnings Income	\$6,192	\$9,661	\$12,747	\$6,028
Earnings for receivers	\$51,954	\$43,570	\$40,811	\$53,971
Household Food Stamp Income	\$154	\$392	\$383	\$151
FS Income for receivers	\$1,534	\$2,051	\$1,721	\$1,554
Household AFDC Income	\$138	\$371	\$299	\$111
AFDC Income for receivers	\$3,290	\$3,302	\$3,302	\$2,752
Household SSI Income	\$209	\$546	\$991	\$272
Income for receivers	\$3,750	\$4,653	\$4,712	\$4,286
Percent of households with public assistance	13.0%	25.0%	31.4%	13.1%
Percent of households with zero earnings	0.0%	24.2%	32.8%	5.4%
Percent of months in which household had earned income	90.7%	68.1%	58.6%	88.2%
Percent of households with zero income	0.0%	*	0.8%	0.2%

* Results are suppressed when there are less than 75 observations in a cell.

As with the demographic patterns, earnings and income patterns appear to be much closer to the general sample for the group with no earnings in the SER than for the group with no earnings in the SIPP. *Exhibit C.5* shows that for individuals for whom no earnings appear in the SER, but for whom earnings do appear in the SIPP, the SIPP shows annual income of \$26,174 on average, very close to the \$26,046 average income for the full sample. Earnings are also similar, with average annual earnings of \$23,495 shown by the SIPP for the entire sample and \$23,755 for those with earnings in the SIPP but not the SER. In contrast, while the SER shows average annual earnings of \$20,397 in the overall sample for those with earnings, for those with no earnings shown in the SIPP the SER shows average annual earnings of only \$5,550. This appears consistent with the generally younger age of this group.

Interestingly, the similarities between the group with no SER earnings and the overall sample even holds when looking at years of earnings identified in the SER; despite having no SER earnings in the year of the match, individuals in this group have 22.6 other years of earnings recorded in the SER on average, compared to 22.9 years of earnings in the SER for the sample as a whole. Unsurprisingly given that they are on average younger, the group with no SIPP earnings has fewer years of SER earnings on average (19.6).

Exhibit C.5 also shows average non-earnings income identified in the SIPP for individuals and the households they reside in. Again, the SIPP earnings but not SER earnings is very close to the general sample, with \$6,192 in non-earnings household income on average compared to \$6,028 on average in the sample as a whole. Those with no SIPP-reported earnings but with earnings in the SER have \$9,661 in average non-earnings income reported in the SIPP. Those with no earnings shown in either data source have the most non-earnings income on average, \$12,747. A similar pattern is seen among the share of households the SIPP identifies as receiving public assistance income.

Data in the SIPP allows us to look at the industries in which people with earnings shown in the SIPP but not the SER work. There are three general industries where we might expect to see a number of people working in jobs not covered by the Social Security system: agriculture, domestic services, and government jobs. As *Exhibit C.5* shows, these industries are more highly represented among workers with no SER earnings than among the sample as a whole. In total, 16.1 percent of these workers work in these three broad industries, as compared to only 6.5 percent in the sample as a whole.

E. Comparison to Past Papers

As mentioned in the discussion of literature, several recent papers have made similar comparisons between the SIPP and Social Security Administrative data. *Exhibit C.6* shows a comparison between our findings and the findings of two such papers. Pedace and Bates (2000) looked at a match between the 1992 SIPP and the SER. Bridges, Del Bene, and Leonesio (2002) perform a comparison between the 1993 SIPP panel and the DER. The biggest difference between the SER and the DER relevant to the analysis of earnings reciprocity is that the DER includes earnings not covered by the Social Security system while the SER does not.

Both of these papers look at the population age 15 and above, instead of the working-aged population. As a result, we reran the comparison for this population and show the results in the table below.

Exhibit C.6: Comparison of Earners and Non-Earners as Identified in the SIPP and SER Among Individuals 15 Years or Older; Findings from Three Papers

Pedace and Bates (2000)			
1992			
	Positive earnings in SSA data	Zero earnings in SSA data	Total
Positive earnings in SIPP	61.0%	6.4%	67.4%
Zero earnings in SIPP	3.6%	29.0%	32.6%
Total	64.6%	35.4%	100.0%

Bridges, Del Bene, and Leonesio (2002)			
1993			
	Positive earnings in SSA data	Zero earnings in SSA data	Total
Positive earnings in SIPP	65.4%	5.4%	70.7%
Zero earnings in SIPP	3.2%	26.1%	29.3%
Total	68.5%	31.5%	100.0%

Elkin and Turner (2007)			
1996-1999 ¹³			
	Positive earnings in SSA data	Zero earnings in SSA data	Total
Positive earnings in SIPP	63.4%	6.4%	69.8%
Zero earnings in SIPP	3.8%	26.4%	30.3%
Total	67.1%	32.9%	100.0%

The table shows that the three studies are quite consistent. Pedace and Bates found disagreement in the identification of earnings between the two sources in 10.0 percent of cases, while the current study finds disagreement in 10.2 percent of cases. A conclusion is that we do not find any evidence that changes in SIPP methodology in 1996 panel notably improved identification of earnings recipients in the SIPP.

Bridges, Del Bene, and Leonesio found discrepancies between the two data sources in 8.6 percent of cases. The lower number may be largely due to the DER's inclusion of non-covered jobs. Indeed, most of the difference occurs in the category where the SIPP showed income but the SSA data did not; Bridges, Del Bene, and Leonesio's figure is one percentage point lower than that found in Pedace and Bates and our own analysis. It is interesting to note that this one percentage point difference is consistent with our industry analysis above. We found that 16.1 percent of working-aged people with earnings in the SIPP but not the SER work in industries

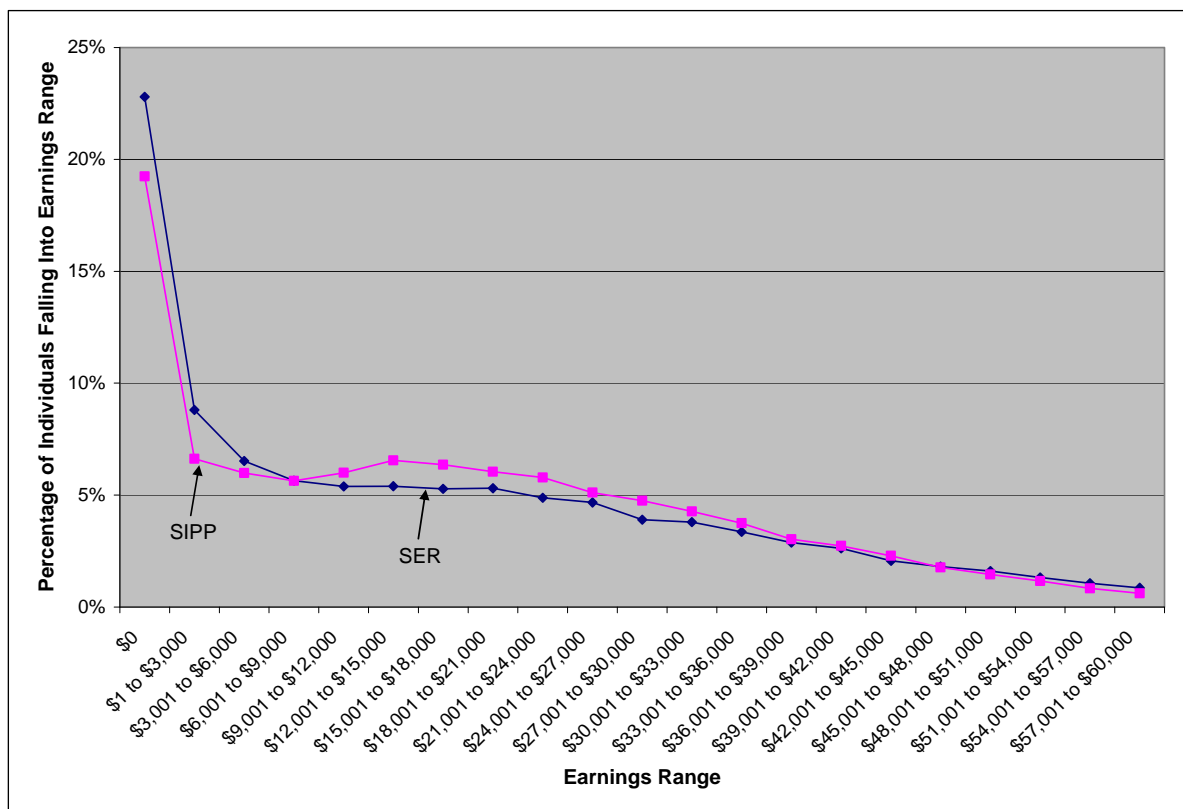
¹³ By combining the four years of data, our figures essentially represent a (weighted) average over the 4 years. Background data shows that there is a small amount of variance across years – e.g., the portion of the sample with earnings in the SIPP but not the SER ranges from 6.1 percent in 1998 to 7.0 percent in 1996 – but the overall pattern is relatively consistent.

with a disproportionate number of uncovered jobs (agriculture, domestic services, or the government sector). If we assume the same proportion holds for the 6.4 percent of those over age 15 identified in the same category in *Exhibit C.6*, and we further assume that for people with no earnings shown in the SER all jobs in these industries were indeed uncovered, that would account for one percentage point, leaving 5.4 percentage points unaccounted for – the same percentage Bridges, Del Bene, and Leonesio found. This is not to say that all such jobs are uncovered, but rather that our findings from the SER are consistent with the implication from Bridges, Del Bene, and Leonesio’s findings that about 16 percent (one-sixth) of cases where the SIPP shows earnings but the SER does not are due to uncovered jobs.

F. Analysis of Differences in Earnings Measures

Exhibit C.7 shows the distribution of earnings amounts among the analysis population as measured in the two data sources. For each data source, only individuals with earnings of \$60,000 or less are included in the distribution shown in the chart. (Given that the chart includes only these individuals, the percentage of individuals with zero earnings may not match what was shown in earlier table.)

Exhibit C.7: Distribution of Individuals By Earnings Reported in the SIPP and the SER (Individuals with less than \$60,000)



The pattern evident from *Exhibit C.7* is that a higher percentage of SER cases have no earnings or earnings less than \$9,000, while a higher percentage of SIPP fall into the range of roughly

\$9,000 to \$36,000 range.¹⁴ Above that range, the two are roughly similar, not differing by more than 0.3 percentage points in either direction.¹⁵ In other words, the SER shows more individuals at very low annual earning levels, while the SIPP shows more individuals with middle-range (and lower-middle range) earnings. This is consistent with prior research that found that among lower-end earners the SIPP showed more earnings than the SER.

Exhibit C.8 looks at discrepancies between earnings reported in the SER and earnings reported in the SIPP. Only individuals for whom both the SER and SIPP show earnings are included. It follows a table from Pedace and Bates, who assumed that the SER administrative data represented truth, and used ranges defined by earnings as measured by the SER. The left-hand columns show that there is a high frequency of substantial discrepancies. In only 62 percent of cases overall is the SIPP earnings amount within 25 percent of the SER earnings amount, and in only 21 percent of cases is it within five percent of the SER earnings amount. In general, accuracy increases as SER earnings rise; in about three-quarters of cases between \$20,000 and \$50,000 in SER earnings, the SIPP value is within 25 percent of the SER value, and in close to half of the cases in this range it is within 10 percent. (The top category, showing SER earnings above \$50,000 is most likely anomalous because of upper limits on covered earnings in the SER and top-coding in the SIPP.) These findings generally mirror Pedace and Bates's although we find somewhat smaller frequencies of the larger discrepancies. (For example, in the \$15,000 to \$20,000 range, we find 43 percent of cases where earnings are within ten percent of each other and 72 percent where they are within 25 percent of each other; Pedace and Bates found 48 percent and 78 percent respectively.) This may suggest a small increase in accuracy of the earnings amounts in the 1996 SIPP panel as compared to the 1992 previous panel.

The right-hand columns, showing means and medians, provide a sense of the directionality of misreporting. The positive medians show that individuals with up to \$15,000 in SER earnings more often report earnings in the SIPP that are higher than what is shown in the SER, but that pattern flips above \$15,000 where individuals more often report lower earnings in the SIPP than in the SER. However, in all categories up to \$45,000, the means are greater than the medians, showing that on the whole the discrepancies tend to be bigger in cases where SIPP earnings are higher than SER earnings. The differences between means and medians are particularly stark in the lower earnings ranges, which may reflect earnings in jobs not covered by Social Security and/or "off-the-books" jobs. These findings are somewhat different from Pedace and Bates; the averages we found were greater in all categories; and the absolute value of the median discrepancies they found were in most categories greater than the absolute values of the discrepancies we found.

¹⁴ As found earlier, there are more cases with zero earnings shown in the SER than cases with zero earnings shown in the SIPP. Removing the zero earning cases from the distribution emphasizes more strongly the pattern that a higher share of cases in the SER show earnings less than \$9,000, and a higher share of cases in the SIPP show earnings between \$9,000 and \$36,000.

¹⁵ The pattern does not change notably if the individuals with zero earnings in each data source are omitted.

Exhibit C.8: Distribution of Discrepancies, SER as Base (Individuals 15 Years Old and Above)

SER EARNINGS CATEGORY	Percent within:			Difference (SIPP-SER)		N
	5% of SER	10% of SER	25% of SER	Mean	Median	
\$1 to >\$4,999	7.75%	14.23%	30.16%	4,799	579	14,524
\$5,000 to >\$9,999	13.63%	24.46%	48.52%	3,404	375	10,634
\$10,000 to >\$14,999	20.87%	36.90%	64.50%	2,309	68	9,704
\$15,000 to >\$19,999	24.44%	43.08%	72.02%	1,466	-336	9,438
\$20,000 to >\$24,999	26.60%	45.14%	74.17%	673	-708	8,668
\$25,000 to >\$29,999	27.67%	47.13%	76.83%	-201	-1,167	7,359
\$30,000 to >\$34,999	28.06%	48.12%	77.70%	-1,264	-1,813	6,421
\$35,000 to >\$39,999	27.59%	47.54%	78.20%	-2,259	-2,399	5,164
\$40,000 to >\$44,999	27.80%	47.82%	76.61%	-2,306	-2,625	4,015
\$45,000 to >\$49,999	28.07%	47.64%	77.56%	-3,837	-3,628	3,142
\$50,000 and above	19.31%	33.09%	61.36%	6,921	-2,375	12,985
Total sample	20.62%	35.80%	62.12%	2,121	-258	92,054

Given the findings of Abowd and Stinson (2003), whose model suggested that earnings data contained within SSA data contains at least as much error as the SIPP's, we also present the same distribution table using the SIPP instead of the SER as the base (*Exhibit C.9*). The left-hand columns, showing the distribution of the frequency of discrepancies of various sizes, show essentially the same pattern. For most earnings categories, and for each threshold, the frequencies are slightly higher when the SER is the base, possibly partially reflecting higher average SIPP earning amounts, which if distributed broadly would provide a larger base against which percent differences are measured. On the other hand, the right-hand columns differ substantially. Median discrepancies are positive for all income categories (again, ignoring the anomalous top category). Mean discrepancies are also positive for all categories up to \$45,000, but for the \$45,000 to \$50,000 category is slightly negative. Mean discrepancies are generally smaller than was found using the SER as the base. Median discrepancies are also smaller at the higher earnings categories.

Exhibit C.9: Distribution of Discrepancies, SIPP as Base (Individuals 15 Years Old and Above)

SIPP EARNINGS CATEGORY	Percent within:			Difference (SER-SIPP)		N
	5% of SIPP	10% of SIPP	25% of SIPP	Mean	Median	
\$1 to >\$4,999	9.45%	17.33%	36.35%	1,575	215	12,011
\$5,000 to >\$9,999	13.95%	24.94%	49.98%	1,150	95	10,351
\$10,000 to >\$14,999	18.69%	33.06%	59.45%	957	229	10,923
\$15,000 to >\$19,999	21.68%	38.05%	64.45%	1,109	543	10,569
\$20,000 to >\$24,999	24.02%	41.01%	67.97%	1,260	743	9,610
\$25,000 to >\$29,999	24.41%	41.47%	69.14%	1,312	961	8,121
\$30,000 to >\$34,999	26.60%	44.54%	70.95%	786	926	6,782
\$35,000 to >\$39,999	27.53%	45.69%	70.83%	484	989	5,176
\$40,000 to >\$44,999	26.80%	45.09%	72.18%	251	1,222	4,127
\$45,000 to >\$49,999	28.70%	46.58%	70.87%	-408	927	3,059
\$50,000 and above	21.62%	36.15%	63.36%	-24,605	-6,263	11,325
Total sample	20.49%	35.17%	60.61%	-2,121	258	92,054

A few observations stand out when comparing this table to the previous one. First, in the lowest earnings categories (\$0 to \$5,000 and \$5,000 to \$10,000) differences are a little more frequent using the SIPP as the base, but in the rest of the categories the opposite is true; differences are more frequent when categorized by SER earnings. In particular, above \$10,000 discrepancies of more than 25 percent are more common by between 4 and 8 percentage points when categorized by SER earnings. Differences are bigger in absolute value among most categories of earnings when the SER is used as the base than when the SIPP is used as the base. Further, when the SER is used as the base, differences exhibit a striking declining pattern in both mean and median differences. When SIPP is used as a base, there is less variance among the mean and median differences, which do not exhibit a clear trend. This suggests errors are more randomly distributed when SIPP earnings are used as the base, though consistently positive by a small amount.

G. Conclusion

The findings of this paper are largely consistent with much of the previous literature. Findings from our analysis of the match in reciprocity between the SIPP and the Social Security administrative data are very close to those in Pedace and Bates (2000) and Bridges, Del Bene, and Leonesio (2002), with all three papers showing the two data sources to match on earnings reciprocity in about 90 percent of cases, and showing that cases where an individual has earnings in the SIPP but not the SER are more common than the opposite. For individuals with earnings shown in both the SIPP and SER, we found that – at least when using the administrative data as the base – the SIPP shows higher earning amounts for the lower end of earners than the administrative data does; this too is consistent with many prior studies, but is not as evident when the survey data are used as the base.

With regards to the analysis of reciprocity, two types of mismatch warrant explanation. First, among cases where individuals reported earnings in the SIPP but did not have earnings in the SER, Pedace and Bates had suggested that “this type of reciprocity error involves a systematic

failure to capture earnings on the SER.” Our findings suggest that this is still the case. Out of the 6.4 percent of cases that fall into this category, about one percentage point appears to be in uncovered jobs, and more accurate data may be found in the DER. Other possible sources of mismatch include misreporting by SIPP respondents, errors in the SER data set (such as failure on the part of the employer to report earnings for some employees), and “off-the-books” earnings captured by the SIPP but not the SER. It is also possible that some SIPP respondents provided incorrect SSNs, either to SIPP interviewers or to employers, leading to an incorrect match. Overall, this group with earnings in the SIPP but not the SER does not differ noticeably in its demographic or income characteristics from the SIPP population as a whole. One interesting finding that may warrant further investigation is that the number of years of earnings contained in the SIPP for this group does not notably differ from the general population, suggesting that whatever factors led to the individual to have no earnings in the SER did not pertain to previous years.

The group with positive SER earnings and no SIPP earnings, on the other hand, differs from the general SIPP population, most notably in that they are younger and less likely to be the reference person in a household. Earnings are also substantially lower among this group. These factors suggest some of this type of mismatch is attributable to a group that has earnings that were reported to Social Security, but who were not directly interviewed for the SIPP. Instead, the reference persons in their households may have responded on their behalf and misreported that they had no earnings or employment. In addition, some SIPP respondents may omit short-term jobs when responding to the survey, which would show up as low earnings amounts on the SER. This group’s lower earnings and higher public assistance reciprocity rates may also support the idea that misreporting on the SIPP may be more common among lower-income households.

Some of the same factors leading to mismatches in identifying earnings reciprocity may also be at play among individuals with earnings shown in both data sources. For example, individuals working in uncovered jobs for part of the year and covered jobs for the rest of the year would show up as having lower earnings in the SER than in the SIPP. This can account for some of the cases where the SIPP shows higher earnings than the SER. Overall, we found that people report lower earnings on the SIPP than are shown in the SER. Categorizing individuals into earnings categories on the basis of SIPP data did not confirm the finding that individuals at the low end of the earnings spectrum report more on the SIPP than on the SER; errors appear more randomly distributed when the SIPP earnings categorization is used.

Given limitations on our access to the data, we were not able to look more closely at the sources of discrepancies. Future research, preferably using the DER instead of the SER, could look separately at how characteristics differ between cases where earnings in the Social Security data are higher and cases where earnings in the SIPP data are higher, broken out by different earnings categories. Such analysis could be run twice – once using SIPP earnings as the basis of the earnings categories, and once using the Social Security earnings data as the basis. If different patterns emerge, it may be informative as to whether discrepancies are more likely attributable to the survey or administrative data.

REFERENCES CITED IN APPENDIX C

- Abowd, John M. and Martha Stinson (2005). "Estimating Measurement Error in SIPP Annual Job Earnings: A Comparison of Census Survey and SSA Administrative Data," working paper. Available at <http://instruct1.cit.cornell.edu/~jma7/abowd-stinson-200501.pdf>, accessed May 9, 2007.
- Bollinger, C. (1998). "Measurement Error in the Current Population Survey: A Nonparametric Look," *Journal of Labor Economics* 16: 576-594. As cited in Bound, Brown, and Mathiowetz (2000).
- Bound, John, C. Brown, and N. Mathiowetz (2000). "Measurement Error in Survey Data," Population Studies Center Report No. 00-450. Ann Arbor, Michigan: Population Studies Center at the Institute for Social Research, University of Michigan.
- Bound, J. and A. Krueger (1991). "The Extent of Measurement Error in Longitudinal Earnings Data: Do Two Wrongs Make a Right?" *Journal of Labor Economics* 12: 345-368. As cited in Bound, Brown, and Mathiowetz (2000) and Moore, Stinson, and Welniak (1997).
- Bridges, Benjamin, L. Del Bene, and M. Leonesio (2002). "Evaluating the Accuracy of 1993 SIPP Earnings Through the Use of Matched Social Security Administrative Data." Paper presented at the 2002 Annual Meetings of the American Statistical Association.
- Bureau of the Census (2001). *Survey of Income and Program Participation Users' Guide: Supplement to the Technical Documentation, Third Edition*. Prepared by Westat and Mathematica Policy Research Inc. Available at www.sipp.census.gov/sipp/usrguide/sipp2001.pdf, accessed May 9, 2007.
- Coder, J. (1992). "Using Administrative Record Information to Evaluate the Quality of the Income Data Collected in the Survey of Income and Program Participation," Proceedings of Statistics Canada Symposium 92: Design and Analysis of Longitudinal Surveys (Statistics Canada, Ottawa): 295-306. As cited in Bound, Brown, and Mathiowetz (2000) and Moore, Stinson, and Welniak (1997).
- Coder, John and L. Scoon-Rogers (1996). "Evaluating the Quality of Income Data Collected in the Annual Supplement to the March Current Population Survey and the Survey of Income and Program Participation," Bureau of the Census, SIPP Working Paper #215.
- Duncan, G. and D. Hill. (1985). "An Investigation of the Extent and Consequences of Measurement Error in Labor Economic Survey Data," *Journal of Labor Economics* 3:508-522. As cited in Bound, Brown, and Mathiowetz (2000) and Moore, Stinson, and Welniak (1997).
- Hendrick, Mark, K. King and J. Bienias (1997). "Research on Characteristics of Survey of Income and Program Participation Non-respondents Using IRS Data," Bureau of the Census, SIPP Working Paper #211.
- Hotz, V. Joseph and J. K. Scholz (2002). "Measuring Employment and Income for Low-Income Populations with Administrative and Survey Data," *Studies of Welfare Populations: Data Collection*

and Research Issues. Washington, DC: U.S. Department of Health and Human Services, Office of the Assistant Secretary for Planning and Evaluation.

Moore, Jeffrey C., L. L. Stinson, and E. J. Welniak, Jr. (1997). "Income Measurement Error in Surveys: A Review," Bureau of the Census, Research Report # SM97/05.

Pedace, Roberto and N. Bates (2000). "Using Administrative Records to Assess Earnings Reporting Error in the Survey of Income and Program Participation," *Journal of Economic and Social Measurement*, 2000 26 (4) 173-192.

Rodgers, W., C. Brown, and G. Duncan (1993). "Errors in Survey Reports of Earnings, Hours Worked, and Hourly Wages," *Journal of the American Statistical Association* 88:1208-1218. As cited in Bound, Brown, and Mathiowetz (2000) and Moore, Stinson, and Welniak (1997).

Roemer, Marc I. (2000). "Assessing the Quality of the March Current Population Survey and the Survey of Income and Program Participation Income Estimates, 1990-1996," Suitland, Maryland: Bureau of the Census, Housing and Household Economic Statistics Division.

Weinberg, Daniel H. (2003). "Using the Survey of Income and Program Participation for Policy Analysis," Bureau of the Census, SIPP Working Paper #240.