The Path to SNAP: Supplemental Nutrition Assistance Program Dynamics Among Young Adults

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Abstract

This study investigates young adults' first experience with the Supplementary Nutrition Assistance Program (SNAP), examining the determinants of first program entry and exit. It makes use of the National Longitudinal Survey of Youth 1997 cohort (NLSY97), which follows respondents from adolescence into adulthood. This study estimates discrete-time hazard models of program entry and exit with and without unobserved heterogeneity. Unobserved heterogeneity is modeled using both a parametric approach, in which a gamma distribution is assumed, and a non-parametric approach with two mass points. The results are broadly consistent across models, indicating that, for the cohort in this study, accounting for unobserved heterogeneity does not substantially alter the results from a basic discrete-time hazard model.

The results show that expanded categorical eligibility increased the hazard of SNAP entry in the six years following high school, while the absence of vehicle exclusions decreased the entry hazard. For program exit, however, state SNAP policies had no statistically significant effect. The recent birth of a child, prior participation in WIC and low educational attainment were each strongly associated with an increased "risk" of SNAP entry, and decreased "risk" of exit. Somewhat, surprisingly, higher unemployment rates in the local labor market were not significantly associated with higher entry risk, but were strongly associated with a lower exit risk.

Introduction

Supplementary Nutrition Assistance Program (SNAP) policy and administration benefit from an understanding not only of who participates in the program at a given point in time but also of the factors associated with program entry and exit over time. A dynamic analysis of SNAP entry and exit can illuminate how individual circumstances, economic conditions and program policies affect caseload movements. To inform policymakers and program administrators on this subject, USDA Food and Nutrition Service (FNS) publishes an ongoing series of reports that analyze SNAP dynamics, including the determinants of program entry (Mabli et al., 2011; Cody et al., 2005, 2007; Gleason et al., 1998). These reports employ longitudinal data that follow respondents for a period of about 2-3 years. But this rather brief window of observation gives rise to two shortcomings. One is that many of the program spells observed in the data are left-censored and therefore the beginning of the spell, as well as other events contemporaneous with the start of the spell, cannot be identified. Omitting left-censored spells, which tend to be longer than average, results in a biased sample. Another shortcoming is that researchers cannot determine if the spell observed in the data is in fact an individual's first, or subsequent, spell on the program—an important distinction in analyzing program entry.

This study analyzes first SNAP receipt among young adults using the NLSY97, a longitudinal survey that follows respondents from adolescence into young adulthood, for a period of up to 13 years. Because respondents in the NLSY97 begin the survey as adolescents, their first instance of SNAP receipt after leaving high school is observed during the survey period. This obviates the problems of left-censoring and of identifying first spells.[1] The extended survey period also makes it possible to take into account the influence of long-run factors, such as family background.

A drawback of the survey is that it is of a single cohort, so the analysis is limited to program receipt in early adulthood. Nevertheless young adults comprise an important subpopulation of SNAP participants, and their path to first program receipt is of particular interest. In part, this is because those who first enter the program in early adulthood are more likely to have multiple program spells and to spend more time on the program than those who first enter the program at a later age (Grieger and Danziger, 2011; Rank and Hirschl, 2005).A better understanding of program take up among young adults may therefore shed light on the factors underlying long-term program receipt and recidivism.To date, though, there has been little direct evidence on young adults' path to first SNAP receipt.

Another reason for the interest in young adults is that they represent an economically vulnerable age group for which SNAP plays an important safety-net role. Young workers face greater job market instability—their unemployment rates are the highest of any age group–and they tend to be less insulated against employment shocks than their older counterparts. They have had less time to accumulate precautionary savings to tide them over a jobless spell. And with limited work experience, they may not qualify for much, if

[1] Here an individuals' first spell refers to their first observed spell after leaving high school. As discussed below, because the NLSY97 measures direct receipt by the respondent (or a spouse or child of a respondent), the first observed receipt is likely capturing the first time an individual has applied for benefits on their own (i.e., independently of their parents).

any, unemployment insurance. On the other hand, some young adults may have access to their parents' precautionary savings, or be able to reduce expenses by moving back in with their parents.

In addition to highlighting the determinants of first SNAP receipt, this study contributes to the broader literature on SNAP dynamics in three other ways. First, by using a data source that, to my knowledge, has not previously been used to study SNAP dynamics, it offers fresh evidence on the determinants of SNAP entry decisions. Second, as a long panel survey, the NLSY97 permits analysis of long-run characteristics that have been largely neglected in previous work (Mabli and Ohls, 2012). Third, it extends the empirical methodology employed in most previous studies of SNAP dynamics by estimating discrete-time hazard models that take into account different assumptions on unobserved heterogeneity.

Data and Sample Selection

This study uses data from the NSLY97, a nationally representative survey of individuals born in the U.S. between January 1, 1980 and December 31, 1984. The survey began in 1997 with 8,984 respondents between 12 and 18 years of age.[2] As of the most recent interview round included in this study, administered in late 2009 and early 2010, 7,561 respondents, between the ages of 24 to 30, remained in the survey. Respondents are interviewed every year, with some variation in the time between interviews.[3] Monthly event histories are created for several measures, including labor force participation, marriage and cohabitation, school enrollment and participation in public assistance programs.

In the NLSY97, questions about program participation, such as SNAP, are asked only of "independent youth." In the survey, respondents are considered independent once they reach 18 years of age. Respondents under 18 years of age are also considered independent once they have a child, enroll in a 4-year college, get married (or enter a ''marriage-like" relationship), move out of a household with any parents (or parent-figures) or leave (secondary) school. Receipt of program benefits recorded in the survey refer only to payments made to respondents, their children or their spouses (or partners), and not to anyone else in the household, such as a parent. In the first interview round, parents are also asked to report whether they have received public assistance in adulthood.

Although no study has yet evaluated reporting accuracy in the NLSY97, it likely also suffers from the underreporting of program receipt documented in other household surveys (Meyer and Goerge, 2011; Meyer et al., 2009). To the extent that reporting error is affected by the length of the recall period, the problem may be more severe in the NLSY97 than in the SIPP, in which interviews are conducted every four months, but less severe than in the PSID or NLSY79, in which interviews are now conducted every two years. To

[2]Only 23 respondents were 18 years old at the time of the first interview round. Only about 7.5 percent of first-round respondents were 17 years old, so that over 92 percent of respondents were between the ages of 12 and 16 as of the first interview.

[3]The mean, and median, gap between interviews is 12 months. Excluding the gap between the first and second interview round, 95 percent of interviews occurred within 15 months of the prior one, with the period between interviews ranging from as short as four months to as long as 19 months. For most respondents, the period between the first and second interviews was longer (a median of 20 months). Although this longer gap raises concerns about recall bias, only 7.4 percent of the sample graduated high school between the first and second round interview rounds and are thus affected by these larger gaps.

mitigate the effect of a relatively long recall period, NLSY97 interviewers make extensive use of events across domains as "triggers and prompting cues" that help respondents more accurately date events (Dugoni et al., 1997; Pierret, 2001; Pierret et al., 2007).

The final sample for this study is restricted to respondents who participated in the first 13 interview rounds. Individuals who left high school prior to the first interview round or who were receiving SNAP benefits when they left high school were dropped from the sample, as were respondents who left high school at either an unusually young (under 17) or an unusually old (over 19) age.[4] The sample was further limited to those who left high school prior to spring 1998 or after summer 2003. The upper bound of this restriction ensures that even the youngest respondents in the sample are observed for a period of at least six years after high school.[5] Finally, respondents are considered right censored following their 74^{th} month in the sample, even though many of the older respondents remain in the sample for a longer period. Including the additional observations for older respondents would confound age and duration effects. With these restrictions, about two-thirds of sample (65.7 percent) reach age 24, 20 percent reach age 23, and only 14 percent reach age 25.[6]

The final sample consists of 6,606 individuals (from 5,275 households), of which 11.7 percent (13.7 percent unweighted) took up SNAP at some point in the 74 months after leaving high school. The median time to first entry is three years (36 months), and one quarter of early adult recipients entered in about a year and a half (19 months) after high school.

State SNAP Policies

At the time most of the NLSY97 cohort was entering adulthood, states were implementing a number of important changes to their SNAP policies. The 2002 Farm Bill provided the impetus for these change by allowing States to alter some of their SNAP eligibility requirements. Most of these policy changes were aimed at making the program more accessible to needy families.

A key component of these policy changes was to make income reporting requirement of SNAP recipients less onerous. To this end, States introduced simplified, or reduced, reporting requirements. Prior to simplified reporting, most SNAP households were subject to a periodic reporting (typically on either a monthly or quarterly basis) or an ?incident? reporting requirement, under which households were required to report any changes in income within 10 days.

Under simplified reporting, SNAP households must only report income changes that occur during the reporting if they result in total countable income rising above 130 percent of the poverty level. The 2002 Farm Bill gave States the discretion to extend simplified reporting requirements to households with non-earned income, referred to as expanded simplified reporting. Many States also lengthened reporting intervals to 4,

[4] Eliminating "non-traditional" leavers results in a small reduction in the sample size (290 respondents) and is imposed out of concern that school enrollment was not accurately recorded for these individuals, especially for older leavers.

[5] The lower bound is of little consequence, as very few respondents reported leaving high school prior to the spring 1998.

[6] Less than one percent reach age 26.

5 or 6 months for 12 month certification periods. In general, the period in which most of the NLSY97 cohort was at risk for first SNAP entry saw many States lessening the reporting requirement on SNAP recipients, at the same time that the NLSY97 cohort were entering adulthood. A priori these changes could be expected to keep individuals in the program longer and, if non-recipients are aware of these policy changes and sufficiently forward-looking, they could also encourage program entry.

Another important policy change adopted by many states over this period was the expansion of categorical eligibility rules. Under the narrow definition of categorical eligibility, SNAP eligibility was conferred to anyone currently certified to receive TANF or SSI benefits. Expanded, or broad-based, categorical eligibility conferred eligibility to households which received benefits or services for which at least half of the funding is through TANF or other maintenance of effort (MOE) programs. Under expanded categorical eligibility, states have raised the income limit for eligibility, and asset tests have in most cases been waived.

Although a number of other specific policy changes have been made over this period, this study will only consider, in addition to the two mentioned above, the loosening of vehicle rules and the introduction of online applications. Both of these policies should have the effect of increasing program entry (and decreasing exit). However, the effect of these policies on the participation of young adults, and especially on first program entry among young adults, is not entirely clear. Individuals with no prior SNAP receipt as an adult might be less cognizant of SNAP policy rules.

Descriptive Results

When young adults take up SNAP for the first time, are they the sole recipients, or do they receive benefits as part of a larger SNAP unit? How much is the benefit amount when they first enter the program, and what other public assistance programs have they also taken up prior to entering SNAP? These question are addressed in table 1. The most common "SNAP unit" consisted of the respondent and a child (38 percent), while just over one in four young adults reported being the only recipient of SNAP benefits in the first month of receipt. Twenty-three percent reported that they received benefits with a spouse/partner and child (or that just their spouse/partner and child received benefits). and just 11 percent reported receiving benefits together with a spouse or partner (or that only their spouse/partner received the benefit). Respondents reported receiving $200 or less in a month when they initally entered the program. Remarkably, nearly two-thirds of repondents reported that they or someone in their family (i.e., spouse/partner or child) had already received benefits from the WIC program. Exposure to TANF, SSI and UI was roughly equal at about 15 percent.

Table 2 examines SNAP participation on the extensive margin: who receives any SNAP benefits in the six years after high school and who does not? Females and blacks were more likely to take up SNAP in the six years following high school, as were individuals who married or cohabited, or who had any children. Of those who took up SNAP in the first six years, more than four in ten reported poor (or fair) health during this period, more than twice the incidence of poor health reported by non-participants. Such a large health disparity is surprising given that no one in the sample reaches the age of 30.

Not surprisingly, differences in educational attainment sharply distinguished recipients from non-recipients. Nearly one in five SNAP recipients did not earn a high school degree, compared to fewer than one in twenty non-recipients. And fewer than one in ten SNAP recipients earned a college degree over this period, compared to one-third of non-recipients. However, relative to the proportion who earned a college degree, the proportion of SNAP recipients who attended some college was rather high, in particular relative to the proportion who earned a college degree. Recipients were more likely to be disconnected from the labor market. They were unemployed on average one in every ten months in the sample, and not working about four in ten months; by contrast, recipients spent on average one in twenty months unemployed and three in ten months out of work.

Early participation in SNAP is also strongly associated with participation in other public assistance programs, particularly WIC. Nearly three-quarters of SNAP participants also received WIC benefits over this period, whereas only 16 percent of non-recipients received WIC benefits. Joint participation was lower for TANF and SSI (and other assistance programs), but in each case markedly higher than among non-recipients. The gap was less pronounced for joint receipt of unemployment insurance.

Empirical Methods

In this section, I estimate discrete-time hazard models in which individuals are "at risk" for SNAP entry upon leaving high school. Thus for individual i the probability of starting a SNAP spell at time t is given by

$$\lambda_i(t) = Pr(T_i | T_i \geq t, x_i) = F(\alpha_0 + \alpha_1(t)x_i(t) + \gamma_i(t)), \tag{1}$$

where $F(\cdot)$ denotes the complementary log-log function.[7] The vector $x_i(t)$ contains the explanatory variables of the model and $\gamma_i(t)$ represents duration dependence, or the effect on the SNAP entry probability of time "at risk." The discrete-time hazard model estimates the probability of an individual entering SNAP in a given month conditional on that individual not having entered the program prior to that month.

For single spell per person data, the log likelihood function takes the following form:

$$log\, L = \sum_{i=1}^{N} \sum_{t=1}^{\bar{t}} [(1 - y_{it}) log(1 - \lambda_i(t)) + y_{it} log \lambda_i(t)] \tag{2}$$

where $\bar{t}$ is the longest observed duration, N is the number of individuals in the sample, and y_{it} is equal to one if individual i is observed to enter SNAP in period t and is equal to zero otherwise. With the data arranged in person-period format, individuals who do not enter SNAP during the sample period will have a y_{it} sequence equal to zero for every period, t. Individuals observed to enter SNAP during the period will have a y_{it} sequence equal to zero for every period except for their period in which they enter SNAP, their last period in the sample.

A shortcoming of the basic discrete-time hazard model described above is that it does not account for unobserved individual heterogeneity(Heckman and Singer, 1984). Unlike in linear models, ignoring individual heterogeneity in a (non-linear) hazard model can lead

[7] In discrete time, the complementary log-log function approximates the proportional hazard model.

to biased estimates, *even if the unobserved heterogeneity is uncorrelated with the independent variables in the model* (Abbring & Berg, 2003; Gaure, Roed, & Zhang, 2007; Heckman & Singer, 1984; Meyer, 1991; Nicoletti & Rondinneli, 2006). The bias in the estimates of the duration dependence parameter, γ, is due to a sorting effect whereby individuals who remain in a given state do so partly because of unobserved characteristics that distinguish them from those who exit the state. In the present study, for example, early SNAP entrants may differ from later entrants, and non-participants, in ways that are not fully captured by variables available in the data. Moreover,the potential bias introduced by ignoring unobserved heterogeneity is not just limited to estimates of the duration dependence parameter. Monte Carlo evidence shows it can also substantially affect estimates of the other explanatory variables in the model(Nicoletti and Rondinneli, 2006). Despite these pitfalls, however, few studies of SNAP dynamics have considered the implications of different assumptions on unobserved heterogeneity.[8]

Unobserved heterogeneity can be incorporated into the basic model as follows:

$$\lambda_i(t) = F(\alpha_0 + \alpha_1(t)x_i(t) + \gamma_i(t) + \eta_i), \tag{3}$$

where the hazard rate is now also condition on the term represented unobserved heterogeneity, η_i.

This study estimates models of SNAP entry under different assumptions on the distribution of unobserved heterogeneity. The first assumption is that unobserved heterogeneity is Gaussian, or normally, distributed. A second specification assumes that the unobserved heterogeneity follows a gamma distribution. The gamma distribution has been a popular choice for representing unobserved heterogeneity in large part because it yields a closed form expression for the likelihood function, making estimation more tractable (Nicoletti and Rondinneli, 2006; Meyer, 1991). Besides being computationally convenient, the gamma distribution was more recently put on firmer theoretical ground by Abbring and van den Berg (2007) who showed that in the large class of models with unobserved heterogeneity, the distribution of heterogeneity among "survivors" converges to a gamma distribution.

Despite its theoretical robustness, the gamma distribution remains susceptible to misspecification biases. For this reason, a nonparametric approach to modeling unobserved heterogeneity is often preferred (Gaure et al., 2007; Heckman & Singer, 1984; Nicoletti & Rondinneli, 2006). In the nonparametric approach, the shape of the heterogeneity distribution is approximated by a multinomial distribution with a finite number of mass points. Although in theory additional mass points can provide a better fit to the true shape of the unobserved heterogeneity distribution, in practice adding mass points makes the convergence of the likelihood function more difficult to achieve.[9]

[8]Because this study looks at only a single cohort, the population of interest here is less diverse than the population of SNAP recipients as a whole. It could be argued, therefore, that accounting for unobserved heterogeneity in this context is less important than it might be when considering *all* SNAP recipients.

[9]Some Monte Carlo evidence suggests that the choice of the number of mass points be guided by an appropriate information criteria (e.g., Akaike), although there is some disagreement about whether, and how much, parameter abundance—the result of adding mass points—should be penalized (see Gaure et al., 2007 and Nicoletti & Rondinneli, 2006). The typical implementation of the nonparametric approach has been to add mass points until the model fails to converge, or simply to estimate a model with a pre-specified

A model with two mass points is the most computationally tractable and corresponds to a situation in which individuals can be sorted on the basis of their unobserved characteristics into either a low- or high-risk type. The heterogeneity term in the log likelihood function then takes the following form:

$$\eta_i = \begin{cases} \eta_i^l & \text{with probability } p_i^l \\ \eta_i^h & \text{with probability } p_i^h. \end{cases} \tag{4}$$

Results from Hazard Models

First SNAP Entry

Estimation results for the hazard models of first SNAP entry are presented in table 3.The first column shows results from the complementary log-log model, while the second and third columns show the results from the PGM model with gamma-distributed heterogeneity and the Heckman-Singer model with two mass points. The last column presents results from a complementary log-log model that includes parental background characteristics. Results reported are the exponentiated coefficients of these models, so that coefficient below unit indicate a negative effect on the hazard ratio and those above unity positive effect.

The models control for basic demographic characteristics, including gender, race and ethnicity, marital/cohabitation status, educational attainment, household composition (age and number of one's own children and the number of adults in the household). Participation in WIC, TANF, SSI (a category that also includes "other" assistance programs), and unemployment insurance is also considered.[10] Controls are also included for year of birth, year of graduation and year of first SNAP entry. The latter is meant to capture time-varying macroeconomic and environmental factors other than the local unemployment rate. Parental background characteristics include whether a parent reported ever receiving food assistance as an adult, whether the respondents' parent(s) fell in the first quartile of parents' income ("low income") and wealth ("low wealth") as of the first round of the survey (when the respondent is an adolescent). Finally, the model considers SNAP policy variables measuring the adoption of expanded categorical eligibility, simplified reporting rules, and the (lack of) vehicle exclusions in eligibility determination in the respondents' state of residence. A number of other variables of potential interest, such as income and labor force status, were excluded on the grounds that these would be determined jointly with the SNAP participation decision and hence would be endogenous.

The direction and significance of the effects are broadly consistent across models. However, in a number of instances the PGM model produces larger effects (and larger standard errors). Females are nearly twice as like to enter SNAP in the first six years following high school. Blacks also have hazard ratios in excess of two, and highly significant, in each of the three specifications. Individuals who are cohabiting with a partner, but who have not been married, are significantly more likely to take up SNAP than those who are not

number of mass points. Another practical concern is that it is not always possible to achieve the theoretically desirable aim of modeling both unobserved heterogeneity and duration dependence without imposing strong parametric assumptions.

[10]Note that all time-varying covariates are measured are lagged one month to avoid endogeneity concerns.

married (or have been married) or cohabiting. This is result is likely driven mostly be male respondents who rarely raise children as single parents and thus would be less likely to qualify for SNAP benefits on their own.

As expected not having earned at least a high school degree (or GED) substantially raises the hazard of SNAP entry in all specifications. Having at least some college, but not having earned a degree, reduces the entry hazard over just a high school degree alone.[11] Attending college may delay risk for first SNAP entry since students must fulfill additional work requirement in order to receive benefits. However, the effect may also point to the improved job market prospects of some with at least some college education.

Having had a child in the last year is also strongly associated with a higher risk of SNAP entry, as is prior receipt of WIC. Together, these results would appear to suggest that a common path to SNAP entry is through mothers' (or expectant mothers') prior exposure to the WIC program. This may work through two channels: one is that, by their prior participation in WIC, these individuals are demonstrating that they are not averse (e.g., due to stigma) to accepting public assistance. Second, when applying for WIC benefits, they were very likely made aware of their potential eligibility for SNAP program. The effect of TANF on entry is also strong and highly significant but, as shown in the descriptive analysis, affects a much smaller proportion of participants. Prior receipt of unemployment insurance is also associated with a higher risk of entry, indicating that young adults who suffer a job loss are making use of multiple safety-net programs. It may also be that collinearity in UI receipt and the local unemployment rate means that the former is absorbing much of the effect of the latter.

Surprisingly, perhaps, the coefficient on the local unemployment rate, though positive, is small and not statistically significant. This may indicate that for young adults, not far removed from high school, demographic shocks, such as having a first child, may be a more important trigger for first SNAP entry than local job market conditions. It may also be that the overall unemployment rate, even in the local labor market, may be a relatively poor indicator of the job market conditions for those low educated workers who are at greatest risk for SNAP participation.

The only state SNAP policy variable that is consistently significant across specifications was the expanded categorical eligibility. Hazard ratios for individuals in states that had adopted expanded categorical eligibility were between 1.32 and 1.35. The hazard of entry was lower for individuals in states that did not allow any vehicles to be excluded from the eligibility determination, but these effects were significant at the 5 percent level in the base specification and the Heckman-Singer model. Simplified reporting was also associated with a lower entry hazard, but was only significant in the Heckman-Singer model. This is not unexpected, since one might expect simplified reporting to have less of an impact on first entry to the program than on continued participation once on the program.

Finally, turning to the model that includes parental background characteristics, only parental income as of the first survey round has a significant effect on SNAP entry, raising the hazard ratio relative to those whose parents income was above the first quartile by nearly 50 percent.

[11] The model also controls for currently attending college.

Exits from First SNAP Spell

Results of the discrete-time hazard models of exit from first SNAP spells are presented in table 4. The first column shows results from the complementary log-log model, while the second and third columns show the results from the PGM model with gamma-distributed heterogeneity and the Heckman-Singer model with two mass points. The last column presents results from a complementary log-log model that includes parental background characteristics. Results reported are the exponentiated coefficients of these models.

In these exit models, accounting for unobserved heterogeneity, whether gamma-distributed or discrete mass point, produces results that are generally consistent with the initial specification that does not explicitly account for unobserved heterogeneity. In particular, in each model an increase in local unemployment rate of one percentage point reduces the probability of exit by about 10 percent. This result is significant across specifications at the .01 level. The effect of SNAP policy is also consistently insignificant across models, even though the point estimates for simplified reporting and expanded categorical eligibility suggest that these reduce the probability of exit by about 7-12 percent. The results for participation in other programs is also consistent in terms of statistical significance; however, the models incorporating unobserved heterogeneity reveal somewhat stronger effects. Individuals who reported receiving WIC and TANF in the previous month were about 40 percent less likely to leave SNAP than those who did not. Individuals who reported UI receipt, however, were about 30 percent more likely to leave SNAP, an estimate that was closer to 40 percent for the models with unobserved heterogeneity. Although the effect of UI is marginally significant, this points to the salutary effect of UI benefits on shortening first SNAP spells. The models also consistently show a strong and significant negative effect of the presence of very young children (under a year of age) on the exit hazard.

The PGM model does reveal some marginally significant effects where the other two models do not. Individuals who cohabit and who are married are more likely to exit SNAP than those who are not married or cohabiting (the model with parental characteristics also shows a marginally significant positive effect for being married and cohabiting). The effect of having some college, but not actually earning a degree, was positive in all models, but only significant (at the 5 percent level) in the PGM model.

The lack of significantly different results once unobserved heterogeneity is introduced may support the contention of Meyer (1991) and others that modeling the baseline hazard function in a flexible manner, as is done here, largely obviates the need to include unobserved heterogeneity in the model. It may also be that account for unobserved heterogeneity is less of a concern in a sample of a single age cohort than, say, in a more representative sample of the population.

Adding parental background variables to the basic model also does not dramatically alter the results, although it does appear in some instances to attenuate the effect of certain variables. For instance, the negative effect of being black on the hazard of exit, though still highly significant, is substantially attenuated. The effect of parental characteristics themselves are of the expected sign, but are either insignificant or marginally significant. A parent had reported prior SNAP in adulthood lowered the hazard of exit by about 20 percent. Individuals whose parents who, as of the first round interview, were classified as "low income" (in the bottom quartile of the income distribution in the sample) also had a lower likelihood of exiting SNAP by about 20 percent.

Conclusion

This study examined determinants of first SNAP entry and exit among young adults. It also investigated the effect of failing to account for unobserved heterogeneity in discrete-time hazard models of entry and exit, as well as different assumptions on the heterogeneity distribution. Lastly, the effect of parental background characteristics on SNAP entry and exit were considered.

For this cohort, different assumptions on unobserved heterogeneity did not produce results that differed dramatically from the base model that ignored unobserved heterogeneity. This is not to say, however, that unobserved heterogeneity can henceforth be safely ignored when studying SNAP dynamics. This study focused on a single cohort, and the similar age of this subpopulation may mean that accounting for unobserved heterogeneity is less consequential that it might otherwise be. However, the results do support the contention of some researchers that the flexible modeling of the baseline hazard is more important than modeling unobserved heterogeneity in discrete-time hazard models.

The results of these models suggested that demographic shocks, particularly the birth of a child, appear to play a larger role in explaining first SNAP entry than local economic conditions. However, once on SNAP, stronger local economic conditions hasten program exit. State SNAP policies, especially expanded categorical eligibility, did appear to raise the risk of entry, but had virtually no effect on program exit. Low education attainment, the presence of young children and prior exposure to other safety-net programs, especially WIC, significantly raised the likelihood of SNAP entry and lowered that of SNAP exit.

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Tables

Table 1
SNAP Unit Composition, Benefit Amount and Other Public Assistance Receipt

SNAP Recipient(s)	
R and Child	0.38
Respondent Only	0.26
SP and Child	0.23
Spouse/Partner	0.11
Other	0.02
SNAP Benefit Amount	
$1-100	0.19
$101-200	0.40
$201-300	0.26
$301 or more	0.15
Not reported	0.00
Other Program Receipt	
WIC	0.65
TANF	0.15
SSI	0.16
UI	0.15
Observations	1206

Source: NLSY 1997

Table 2
Demographic Characteristics of Young Adult SNAP Recipients and Non-recipients

	Ever On SNAP?	
	No	Yes
Demographics		
Female	0.47	0.70
White	0.75	0.53
Black	0.12	0.32
Hispanic	0.12	0.14
Mixed Race	0.01	0.01
Ever Married	0.20	0.33
Ever Cohabiting	0.35	0.69
Ever had kids	0.16	0.73
Ever in poor health	0.19	0.44
Education		
No degree	0.04	0.18
GED	0.04	0.11
High School	0.59	0.64
College degree	0.33	0.07
Any College	0.72	0.42
Other Program Receipt		
Any WIC	0.16	0.77
Any TANF	0.01	0.28
Any SSI	0.03	0.21
Any UI	0.18	0.28
Work Experience		
% Unemployed	0.05	0.11
% Not working	0.30	0.43
Observations	5701	905

Source: NLSY 1997

Table 3
Hazard Models of First SNAP Entry

	CLOG	PGM	HS2	CLOG-P
Female	1.741***	2.100***	1.819***	1.690***
	(0.140)	(0.231)	(0.158)	(0.136)
Black	2.111***	2.528***	2.283***	1.906***
	(0.172)	(0.298)	(0.208)	(0.168)
Hispanic	0.898	0.877	0.873	0.851
	(0.0943)	(0.125)	(0.0966)	(0.0921)
Mixed Race	1.465	1.386	1.426	1.502
	(0.516)	(0.732)	(0.580)	(0.508)
Cohabiting	1.508***	1.744***	1.573***	1.523***
	(0.146)	(0.187)	(0.144)	(0.148)
Married	0.864	0.977	0.876	0.881
	(0.112)	(0.152)	(0.107)	(0.115)
Divorced/Separated	0.716	1.092	0.744	0.760
	(0.247)	(0.446)	(0.240)	(0.259)
No degree	1.555***	2.368***	1.680***	1.443***
	(0.149)	(0.361)	(0.174)	(0.141)
College, no degree	0.697***	0.511***	0.625***	0.713***
	(0.0668)	(0.0667)	(0.0680)	(0.0694)
College degree	0.224***	0.128***	0.184***	0.239***
	(0.0535)	(0.0340)	(0.0459)	(0.0575)
No. kids 1 and under	1.519***	1.797***	1.583***	1.546***
	(0.142)	(0.188)	(0.138)	(0.144)
No. kids 1 to 6 years	0.893	1.389*	0.963	0.905
	(0.0835)	(0.189)	(0.0900)	(0.0855)
No. kids 7 to 17 years	1.724*	3.484*	1.891	1.603
	(0.449)	(1.898)	(0.657)	(0.414)
WIC	4.283***	7.119***	5.260***	4.181***
	(0.502)	(0.984)	(0.677)	(0.494)
TANF	2.501***	6.127***	2.816***	2.380***
	(0.398)	(1.790)	(0.425)	(0.384)
UI	1.406**	1.776***	1.494**	1.347*
	(0.174)	(0.295)	(0.188)	(0.172)
SSI	1.829***	2.705***	1.992***	1.711***
	(0.238)	(0.577)	(0.265)	(0.223)
Local Unemp Rate	1.022	1.018	1.013	1.015
	(0.0198)	(0.0231)	(0.0196)	(0.0200)
Any Simplified Reporting	0.848	0.825	0.820*	0.855
	(0.0797)	(0.0917)	(0.0792)	(0.0811)
Expanded Cat El	1.321**	1.321*	1.349**	1.304**
	(0.124)	(0.169)	(0.138)	(0.125)
No vehicles excluded	0.814*	0.812	0.794*	0.803*
	(0.0737)	(0.0921)	(0.0755)	(0.0741)
Parent with SNAP				1.064
				(0.0840)
Parent Low Income				1.472***
				(0.129)
Parent Negative Wealth				0.977
				(0.146)
Parent Low Wealth				1.033
				(0.0997)
Observations	380190	380190	380190	380190

Notes: Control variables also include dummies for year of birth, year of graduation from high school, year of first entry and dummy variables for spell duration.

Table 4
Hazard Models of First SNAP Exit

	CLOG	PGM	HS2	CLOG-P
Female	0.771**	0.859	0.735*	0.794*
	(0.0727)	(0.108)	(0.0881)	(0.0725)
Black	0.592***	0.479***	0.472***	0.674***
	(0.0601)	(0.0634)	(0.0620)	(0.0690)
Hispanic	1.029	0.960	1.025	1.138
	(0.118)	(0.148)	(0.149)	(0.133)
Mixed Race	0.819	0.976	0.797	0.913
	(0.546)	(0.611)	(0.419)	(0.559)
Cohabiting	1.178	1.249*	1.201	1.214*
	(0.112)	(0.138)	(0.133)	(0.114)
Married	1.260	1.425*	1.317	1.266*
	(0.153)	(0.215)	(0.190)	(0.149)
Divorced/Separated	0.732	0.733	0.711	0.693
	(0.253)	(0.275)	(0.259)	(0.229)
No degree	0.644***	0.689*	0.627**	0.668***
	(0.0745)	(0.100)	(0.0921)	(0.0743)
College, no degree	1.170	1.312*	1.285	1.108
	(0.124)	(0.178)	(0.169)	(0.116)
College degree	1.524	2.329**	1.948**	1.430
	(0.350)	(0.643)	(0.446)	(0.335)
No. kids 1 and under	0.779**	0.740**	0.692***	0.791**
	(0.0652)	(0.0694)	(0.0668)	(0.0657)
No. kids 1 to 6 years	0.898	0.878	0.850	0.895
	(0.0677)	(0.0750)	(0.0729)	(0.0666)
No. kids 7 to 17 years	0.658	0.566*	0.580	0.658
	(0.157)	(0.154)	(0.162)	(0.156)
WIC	0.637***	0.604***	0.576***	0.636***
	(0.0693)	(0.0829)	(0.0771)	(0.0683)
TANF	0.607***	0.544***	0.562***	0.619***
	(0.0631)	(0.0736)	(0.0744)	(0.0637)
UI	1.304*	1.377*	1.419*	1.315*
	(0.162)	(0.214)	(0.208)	(0.157)
SSI	0.737*	0.856	0.698*	0.807
	(0.0940)	(0.129)	(0.102)	(0.0959)
Local Unemp Rate	0.891***	0.904***	0.886***	0.901***
	(0.0204)	(0.0227)	(0.0227)	(0.0202)
Any Simplified Reporting	0.882	0.980	0.932	0.927
	(0.0983)	(0.131)	(0.126)	(0.103)
Expanded Cat El	0.985	0.881	0.914	0.933
	(0.105)	(0.121)	(0.123)	(0.0975)
No vehicles excluded	1.068	1.173	1.165	1.090
	(0.104)	(0.144)	(0.147)	(0.104)
Parent with SNAP				0.796*
				(0.0722)
Parent Low Income				0.808*
				(0.0742)
Parent Negative Wealth				0.892
				(0.164)
Parent Low Wealth				0.848
				(0.0888)
Observations	19632	19632	19632	19632

Control variables also include dummies for year of birth, year of graduation from high school, year of first entry and dummy variables for spell duration.