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Title: Did the Great Recession Change SNAP Participation Behavior? A Panel Analysis of Two Oregon SNAP Participant Cohorts

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Bruce A. Weber

This analysis explores potential changes in the behavior of Oregon's Supplemental Nutrition Assistance Program (SNAP) participants after the 2008 recession. I examine this using individual-level administrative data from the State of Oregon in a linear probability model and a duration model. After controlling for a standard set of factors known to affect SNAP participation including personal and household characteristics, geographic indicators, local economic conditions, and policy changes, I found that those in the post-recession cohort were 13.67 percentage points more likely to participate in any given month and were 40 percent less likely to exit in a given month, assuming they had been enrolled up until that point. My analysis suggests that SNAP participants with given demographic characteristics and earnings behaved differently after the recession than before the recession. These changes in participation behavior led to substantial increases in enrollment spell lengths after the recession.

Did the Great Recession Change SNAP Participation Behavior? A Panel Analysis of Two Oregon SNAP Participant Cohorts

by
Joanna M. Carroll

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APPROVED:

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Major Professor, representing Applied Economics

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Head of the Department of Applied Economics

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Dean of the Graduate School

I understand that my thesis will become part of the permanent collection of Oregon State University libraries. My signature below authorizes release of my thesis to any reader upon request.

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Joanna M. Carroll, Author

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Introduction

In late 2007 and early 2008 a devastating recession swept across the American as well as the international economy. Poverty rates rose across the country, unemployment rates skyrocketed, and income fell (Andrews and Smallwood, 2012; Elsby, Hobijin, & Sahin, 2012). Those who were poor became even poorer. Those who sat on the precipice of poverty were shoved over the edge and many who thought themselves immune from the possibility of becoming poor or impoverished had to face the bleak reality that they were now poor.

This increase in economic need and instability put a substantial strain on welfare and social service programs provided at the Federal, State, and local levels. The U.S. government responded to this need by extending and increasing benefits through the American Recovery and Reinvestment Act (Mabli & Ferrerosa, 2010; Andrews and Smallwood, 2012; Ganong & Liebman, 2013). However, most of these provisions have now expired and policy makers are faced with a slow economic recovery and potential enduring changes in the psyche of the American population and labor force (Kallenber, 2009). This slow recovery and the potential change in the population behavior may have serious consequences for public assistance programs. If more people are entering due to economic need and these people are less likely to exit due to feelings of insecurity brought on by the recession, the strain on the system may be compounded.

This analysis explores potential changes in one particular assistance program. Below I will discuss and analyze the effect of the 2008 recession on the participation behavior of Oregon Supplemental Nutrition Assistance Program (SNAP) participants. Specifically I will examine if there have been significant changes in the probability of participation, exit probability, and spell duration. First I will examine the effects of the 2008 recession on the labor force, economy, and general population as well as current research on SNAP participation behavior. I will then lay out my hypothesis, conceptual framework, and empirical model to explore the potential changes in SNAP participation behavior. I will conclude with a discussion of policy implications and recommendations for future research.

The Great Recession

The 2008 recession, commonly referred to as The Great Recession, had a large impact on the labor market. The effects on the U.S. labor market and workers were very similar to the effects of past recessions (Dickens & Triest, 2012; Elsby, Hobijin, & Sahin, 2012) and included increases in unemployment, decreases in labor force participation (Mosisa & Hipple, 2006), and earnings losses. Industries that were more male dominated, such as construction and manufacturing, tended to suffer larger layoffs. Younger workers were more likely to be affected by job displacement and job loss. Low-skilled workers with low levels of education were also more susceptible to displacement and job loss. What has made this recession stand out from others is the magnitude and duration of these effects. Regardless of which of the above labor market indicators one examines, the 2008 recession has been the worst since the 1940's in terms of both magnitude and duration of effects (Elsby, Hobijin, & Sahin, 2010).

Sum and Khatiwada (2010) examine unemployment and underemployment during the 2008 recession by income deciles. Those in the lowest decile (making $12,499 or less annually) had the highest rates of unemployment which were ten percentage points higher than all other income deciles. They also had the highest levels of underemployment at 20.7%. The underemployment rates of the second and third deciles were also large, at 17.2% and 12.7% respectively.

Not only did the rate of national unemployment reach a post-Great-Depression record high of approximately 10%, the length of unemployment experienced by job losers was longer than in previous recessions (Farber, 2011; Dickens & Triest, 2012; Elsby et al., 2010). Elsby et al. suggest that two primary factors are responsible for this trend, a finding supported by other research. First is the compound disadvantage of unemployment. In general, reemployment rates for job-losers in the 2008 recession have been lower than in other recessions (Farber, 2011). Unfortunately, long bouts of unemployment make workers less likely to exit unemployment. Second is the extension of unemployment benefits. These extensions may have moderately increased the unemployment spell lengths by decreasing the short-term cost of remaining unemployed. The labor force participation rate has hit record lows, reaching 63.3% in March 2013. This is the lowest rate since 1979 and accounts for some of the decline in the unemployment rate, leading to more optimistic figures than may be accurate (Sum & Khatiwada, 2010; Nichols & Linder, 2013).

Earnings losses have also been greater in the 2008 recession than in past recessions. In the aggregate, displaced workers who found new employment earned 17.5% less on average in their new job, while full-time job-losers earned 21.8% less on average (Farber, 2011). This pattern seems to be primarily due to the fact that it is much more common for full-time job-losers to become reemployed in part-time jobs, becoming a section of the labor force known as “employed part-time for economic reasons” (Sum & Khatiwada, 2010; Elsby et al., 2010) with roughly 20% of full-time job losers moving to part-time employment (Farber, 2011). Rates of underemployment were particularly large for those in the lower and middle income brackets (Sum & Khatiwada, 2010).

SNAP Policy and Procedures

SNAP, formerly known as the Food Stamp Program, is commonly considered to have first been conceived of and attempted in 1939 under Secretary of Agriculture Henry Wallace. The primary goals of the program were to sell of agricultural surpluses and improve the nutritional intake of America's needy and poor. Participants originally purchased benefits. Those who were eligible could purchase orange vouchers equal to each dollar they spent. For every orange voucher purchased they received a blue voucher worth 50 cents. Orange vouchers could buy any food item, while blue vouchers could only purchase approved food items.

Over the decades the Food Stamp Program grew and adapted to changing needs and political climates. In 1974 the program began operating nationwide. In 1977 the purchase requirement was eliminated. The program began to evolve into the program it is today in 1988 when the Hunger Prevention Act of 1988 called for the establishment of Electronic Benefits Transfer (EBT) pilot programs. This was seen as a more efficient and cost effective way to distribute benefits. Participants' benefits are placed on a debit card that can be used at participating retailers to purchase approved food items.

The next major changes to the program came with the Personal Responsibility and Work Opportunity Reconciliation Act (PRWORA) of 1996. This act not only required that all states implement an EBT program by the end of 2002, but it also placed strict restrictions on eligibility and benefits including eliminating eligibility to most legal immigrants and reducing the maximum allotment of benefits.

In the 2000's several pieces of legislation including the Farm Act of 2002; the Food, Conservation, and Energy Act of 2008; and American Recovery and Reinvestment Act (ARRA) of 2009 were passed in order to give States more flexibility in applying federal SNAP rules and allocating benefits. Benefits were restored to most eligible immigrants and the EBT system was fully implemented in all States and Territories by the end of 2004. The ARRA specifically, also relaxed eligibility requirements, gave additional administrative funding to states to cover the increase in caseloads, and increased benefits to offset the effects of the 2008 recession (USDA SNAP History, 2013; USDA SNAP Summary, 2013).

In April of 2009 the two major SNAP provisions of the ARRA came into effect. First was an increase in benefits. The maximum benefits for each household size increased and nearly every participant saw at least a small increase in benefits. The amount of the increase varied and was determined by many factors including income and household characteristics (USDA, 2010). The second provision loosened eligibility requirements for some jobless adults. Before this provision able bodied working age adults who were unemployed could only receive benefits for 3 months in a 3 year-period. The ARRA gave States the option to rescind this restriction through fiscal year 2010 (USDA, 2010; Nord & Prell, 2011). However, some States, including Oregon, had already sought and won exemptions from this statute.

SNAP eligibility in all states is based on means and asset tests, employment, and immigration status. Generally a household must have a gross income no higher than 130% of the federal poverty threshold for their household size. They must also have a net income no higher than 100% of the federal poverty threshold for their household size. As discussed above, those who are able bodied and of working age either had to be employed or enrolled in some form of job training or workfare arrangement in order to receive benefits (USDAN SNAP Eligibility, 2013).

In addition to being eligible for SNAP benefits based on the above requirements an individual can also be recognized as “categorically eligible.” Categorical eligibility falls under one of two classifications: cash and non-cash. Cash categorical eligibility is commonly referred to as Traditional Categorical Eligibility. This eligibility standard is based on households receiving cash assistance from General Assistance, Public Assistance, or Supplemental Security Income. Households where all members receive at least one of these benefits are eligible for SNAP. All States must participate in this policy.

Non-cash categorical eligibility is optional, but Oregon has opted to participate in this form as well. Non-cash categorical eligibility is based on a household’s receipt of non-cash or in-kind benefits from a program that is funded through TANF or the State or Federal Maintenance of Effort (MOE) fund. Non-cash categorical eligibility has two forms: Narrow Categorical Eligibility and Broad-Based Categorical Eligibility. Narrow Categorical Eligibility extends categorical eligibility to the recipients of certain program benefits, such as child care assistance, transportation vouchers, or parenting classes, which only cover a small portion of the SNAP population. In Oregon, Narrow Categorical Eligibility only extends eligibility to those who qualify for ERDC (child care assistance). Broad-based Categorical Eligibility, which Oregon also participates in, extends to, as the name would suggest, a broader base of the SNAP population. This form extends eligibility to those who qualify for smaller TANF/MOE funded programs such as informational brochures or phone numbers for TANF funded services. All categorically eligible participants must still meet the non-financial requirements (such as immigration status) in order to qualify for benefits (Shahin, 2009; Laird, 2014).

Eligibility is continuously monitored throughout the participation spell. Eligibility is determined initially when the application is first made. Every six months after the initial application a participant must go through a form of recertification. After the first six months they must complete an interim change form. This is a single piece of paper that only updates the household income status and must be accompanied by supporting documentation such as a paystub. Twelve months after the initial application, the second six month period, the participant must complete a new application. Six months after the second application the participant must again fill out the interim change form. Six months after that they must again fill out a new application. This process repeats throughout the entire participation spell. Participants are also required to report if their income rises over a certain amount between these recertification periods.

SNAP Participation

Today SNAP is the largest food assistance program in the U.S. with an average of 44.1 million people receiving benefits each month in FY2011. The majority of SNAP families fall at or below the poverty line even though the program allows participation by those with a gross income up to 130% of the poverty threshold (USDA SNAP Eligibility, 2013; Strayer, Eslami, & Leftin, 2012). This over representation of those in poverty is primarily due to the fact that many families wait until their circumstances become dire (i.e. they wait until they hit poverty levels) before enrolling (Currie, 2004). Also those who have higher incomes (above the poverty threshold) receive much smaller benefits than those who earn below the poverty threshold. This also results in fairly low take-up rates in terms of percentage of eligible participants who actually enroll in the program.

In the literature on SNAP participation behavior a standard set of factors has been found to be influential. There are economic factors such as low-income and poverty status as well as unemployment and underemployment. Those who live below the poverty line are less likely to exit and tend to have longer spell lengths. Bouts of unemployment and underemployment decrease the likelihood of exit from the program and increase spell lengths (Blank & Ruggles, 1994; Heflin, 2004; Lacombe, Michieka, & Gebremedhin, 2012; Mabli & Ohls 2012; Slack & Myers, 2012). Certain individual and household characteristics also affect participation behavior. Low-levels of adult education, a greater number of children in the household, and being unmarried decrease the likelihood to exit the program (Heflin, 2004; Mabli & Ohls, 2012; Blank

& Ruggles, 1994). Those who have not had previous experience with the SNAP program are more likely to exit the program. Also individuals who are unaccustomed to employment instability are more likely to exit SNAP after making a transition from unemployment to employment (Mabli & Ohls, 2012).

Beginning in the 1960s, participation in the Food Stamp Program maintained a steady upward trend through much of the first three decades of its existence. It peaked in the mid 1990's before taking a steep decline. This decline has been primarily attributed to both the booming economic conditions and the many restrictions placed on the program by PRWORA. By the end of the 1990's this trend had reversed and began a steady upward climb again, leveling off again in the early 2000's before increasing dramatically by roughly 56% between 2007 and 2010 at the onset of the 2008 recession (Landers, 2007; Andrews and Smallwood, 2012).

This more recent dramatic increase has been attributed to two primary factors: the increase in economic need due to the recession and the program changes instituted by the ARRA (Mabli & Ferrerosa, 2010; Andrews and Smallwood, 2012; Ganong & Liebman, 2013). Between 2007 and 2010 the number of people in poverty rose by roughly 26% and those in deep poverty (living at or below 50% of the poverty line) increased by roughly 32%. Not only were there increases in the general number of people in need of the program, but the take-up rates increased from 56% to 69% (Andrews and Smallwood, 2012). In response to the changing conditions, the ARRA both increased benefit levels and lessened restrictions on eligibility requirements

(Andrews and Smallwood, 2011; Ganong & Liebman, 2013; Mabli & Ferrerosa, 2010).

This Analysis

I hypothesize that the behavior of SNAP participants has significantly changed since the Great Recession. This change in behavior is hypothesized to be caused primarily by the injection of a new group of poor into the SNAP population due to the large impact the Great Recession had on the middle class. This new group of poor is not used to employment instability and wage instability and thus their SNAP participation behavior may be different than those who are traditionally used to living with economic insecurity, thus changing the overall behavior of the general SNAP participation population. The appearance of significant and substantive changes in SNAP participation behavior holds important policy implications for future SNAP forecasting.

Conceptual Model

To test this hypothesis I use a conceptual model based on the current research on SNAP participation behavior. I explore this using a probability model and a duration model. These are first modeled as dependent on a set of individual and household characteristics, as well as economic and policy indicators. This sets up a standard model of SNAP participation behavior. Once this standard is established I introduce the post-recession cohort indicator to explore the impact of the recession on post-recession participation behavior. This is a binary variable indicating whether the individual belongs to the pre or post-recession cohort. This should give a measurement of the difference in pre and post-recession behavior. Controlling for both individual characteristics, economic, and policy conditions that commonly affect SNAP participation behavior allows this variable to more closely capture the true behavioral effects of the recession on the overall SNAP participant population. Using this conceptual framework, a panel dataset was constructed with a sample of Oregon SNAP participants.

Empirical Model

This analysis uses multiple quantitative techniques to examine the change in SNAP participation behavior. The first method employed is an examination of cross-tabulations in order to determine if there are significant differences in the composition of the SNAP participant characteristics. Significant changes will lend weight to the hypothesis that a new group of individuals has entered the general population of SNAP participants.

To explore SNAP participation behavior I utilize two statistical models. I first utilize a linear probability model to explore SNAP participation probability. The general form of this model is

$$Y_{it} = \beta_0 + \beta_X X_{it} + \varepsilon_{it}$$

where Y_{it} is the probability of participation in a given month, X_{it} is a vector of individual level time-specific characteristics and ε_{it} is the error term. However, to account for unobserved heterogeneity I introduce correlated random effects. This is of particular importance due to the lack of certain individual level indicators within the data, discussed in more detail below.

The correlated random effects method was developed by Mundlack (1978) and Chamberlain (1984) and has been used in SNAP participation analyses (Atasoy, Mills, & Parameter, 2010). Fixed effects are commonly used in time series and panel statistical models to account for unobserved heterogeneity. Fixed effects help reduce bias in coefficient estimations by accounting for unobserved effects that do not vary over time, but do vary across observational unit. In the case of this study the observational unit is the individual participant. There are some missing data for individual level characteristics, discussed in more detail below. For instance it is a reasonable assumption that educational attainment (one of the missing pieces of data) will not vary much, if at all, over time, but will vary between individuals. While fixed effects is not a replacement for these data it can account for some of the variation.

However, using traditional fixed effects methods in a model with time invariant variables can cause these variables to be dropped. This may lead to omitted variable bias. The fixed effects transformation is achieved by subtracting the time-mean of each variable from each observation. This time-demeaning transformation eliminates the unobserved time-invariant effects assumed to be present within the model, along with all other time-invariant variables. This is an important issue for this analysis as many control variables within these models are time invariant and thus at risk of being dropped under fixed effects methods.

Correlated random effects can work around this problem, though, by selectively adding the time averaged variables, $\bar{X}_i$, to the model, where $\bar{X}_i = T^{-1}\sum_{t=1}^{T} X_{it}$ and X_{it} represents some time-variant independent variable. By including $\bar{X}_i$ in the model and running a random effects estimation it can be proven that the resulting coefficient estimation for X_{it} is equal to the fixed effects estimation (Wooldridge, 2013). Including an $\bar{X}_i$ for each time-variant variable within the model transforms the estimates for those variable's coefficients into the fixed effects estimates. Since an $\bar{X}_i$ is not included for the time-invariant variables these coefficient estimates are not fixed effects estimates. However, these time-invariant variables are also not dropped from the model. Thus the model is able to both control for time-invariant characteristics (such as gender and age at entry) while still obtaining fixed effects estimations for the time-variant variable coefficients. The introduction of correlated random effects changes the general model specification to

$$Y_{it} = \beta_0 + \beta_X X_{it} + \beta_{\bar{X}} \bar{X}_i + \delta_i + \varepsilon_{it}$$

where $\bar{X}_i$ is a vector of average values of time-variant variables that are unique to the individual and $\delta_i + \varepsilon_{it}$ is the composite error term which comprises the relationship between observed and unobserved characteristics. The δ_i captures the time-constant unobservable variation, while the ε_{it} captures the idiosyncratic shocks. The composite error term is assumed to be independent of all X_{it}.

This analysis then models participation as dependent on a set of personal and economic characteristics with county level fixed effects to establish a standard model of

$$Y_{it} = \beta_0 + \beta_P P_i + \beta_X X_{it} + \beta_C C_{it} + \beta_{\bar{X}} \bar{X}_i + \beta_T T_{it} + \delta_i + \varepsilon_{it}$$

where Y_{it} is the probability of participation in a given month, P_i is a vector of time-invariant personal and household level observations, X_{it} is a vector of time-variant personal, economic, and policy characteristics, $\bar{X}_i$ is a vector of the corresponding correlated random effects, and C_{it} is a vector of county indicators. A time trend, T_{it}, is also included in the model to account for systematic changes in participation over time. Participation tends to follow the seasonal employment cycle, increasing during winter months when seasonal employment is scarcer.

This analysis explores the differences between two cohorts of participants across two time periods. The first cohort, who was present in the first time period, entered the program before the Great Recession. The second cohort, who was present in the second time period, entered the program after the Great Recession. To identify which time period an observation falls in I include a binary indicator variable that identifies the observation as post-recession. This leads to a final model specification of

$$Y_{it} = \beta_0 + \beta_P P_i + \beta_X X_{it} + \beta_R R_i + \beta_C C_{it} + \beta_{\bar{X}} \bar{X}_i + \beta_T T_{it} + \delta_i + \varepsilon_{it}$$

where R_i is the binary time-invariant post-recession indicator.

The second empirical model utilized in this analysis is a semi-parametric hazard model, which takes the general form of

$$\hbar_i(t) = \exp(\alpha + \beta_X X_{it} + \varepsilon_{it})$$

where X_{it} is a vector of individual level time specific characteristics. This model utilizes the same set of explanatory variables as the linear probability model and thus runs into similar issues. I utilize correlated random effects and county level fixed effects for this model as well. The final empirical model is specified as such

$$\hbar_i(t) = \exp(\alpha + \beta_P P_i + \beta_X X_{it} + \beta_R R_i + \beta_C C_{it} + \beta_{\bar{X}} \bar{X}_i + \delta_i + \varepsilon_{it})$$

where $\hbar_i(t)$ is the hazard of exiting SNAP as a function of time, P_i is a vector of time-invariant personal and household level characteristics, X_{it} is a vector of time-variant personal and economic characteristics, $\bar{X}_i$ is a vector of the corresponding correlated random effects, R_i is the binary time-invariant recession indicator, and C_{it} is a vector of county indicators.

The Data

The data used for this analysis come from the Bureau of Labor Statistics and the State of Oregon's Integrated Client Services Warehouse, which houses data from several different State programs and departments. There are four primary groups of data that are compiled to generate the final sample. The first is SNAP administrative data. This group contains primarily application data for each participant (i.e. individual and household level characteristics). This dataset also includes information on each individual's participation in other welfare and social service programs. The two primary pieces of data that are missing from this dataset are educational attainment and marital status. Correlated random effects and county indicators within the empirical model are used to account in part for the lack of education data.

The next group of data is geographic data. Individuals' home addresses are identified in the final dataset through their census block group number. These data are compiled primarily from the SNAP administrative data. Addresses are reported on the initial application and participants are required to update their address as it changes. Participants have a strong incentive to report their addresses as their recertification paperwork is sent to them in the mail. If they do not update their address they risk not receiving their paperwork and thus losing their benefits. However, in the event that an address observation for a certain time period and/or individual cannot be identified, other social service databanks are searched to find a viable address. In the end 97% of the SNAP participants have address information. The third group of data is employment data. This comes from the Oregon Employment Department. This dataset has employer-reported information that includes North American Industry Classification System (NAICS) codes and quarterly wages.

The final group of data comes directly from the Bureau of Labor Statistics and includes non-seasonally adjusted county-month observations for unemployment rate and county level annual per-capita income in thousands of dollars. Seasonally adjusted figures were not available on a county-month level. Economic indicator observations were matched to address and time observations for each individual.

Together the data represent two populations of Oregon SNAP participants observed over a 37 month period. The first population includes all SNAP participants who entered in fiscal year 2005 (July 2004-June 2005) while the second population represents all participants who entered during fiscal year 2009 (July 2008- June 2009). An examination of the frequency of entrance by month in each population reveals a stark difference in entrance patterns. In FY2005 there is a steady stream of entrants throughout the first part of the year which then drops a bit toward the end of the year. However, FY2009 shows a steady increase through most of the year with a slight drop toward the end. Entrance frequency in any given month of FY2009 is also much higher than nearly any month observed in FY2005. Not only are the monthly entrance observations much higher in

Table 1: Entry Frequencies by Population

Month	**FY2005**	**FY2009**
July	20,377	21,362
August	20,053	21,377
September	21,717	23,560
October	20,041	26,636
November	20,819	25,118
December	20,134	28,061
January	19,828	30,307
February	16,883	33,403
March	18,729	31,913
April	17,245	29,818
May	16,256	24,209
June	16,757	25,313
Total	228,839	321,077

the post-recession population, but as one would expect, the total number of participants who entered during that year is substantially higher, with 228,839 in FY2005 and 321,077 in FY2009 -- an increase of 40%.

Out of the roughly 550,000 total participants, a random sample of 10,000 is taken, 5,000 from each population. These samples are restricted to include only heads of household. The sample is taken from those who entered in January of their respective fiscal year. This approach permits having all participants in each cohort enter in the same month so that the time trend can be utilized. After examining the frequency table above, January appears to be a valid representation of both populations. The end result is two cohorts, a pre-recession cohort and a post-recession cohort, of SNAP heads of household.

Statistical Model Measurements

The data provided by the State of Oregon is raw administrative level data. Each of the four data sets is structured very differently. This requires some reshaping and disaggregation of data to fit them all together in panel form. Below I will discuss the different variables utilized in the statistical models and their meanings. I will discuss the few cases where variable meaning changed between the raw data and the final dataset. Some variables are not included within the statistical models, but are explored in cross-tabulations alone. These variables and the reasons for their exclusion from the statistical models will be discussed in more detail in the results section.

<u>Dependent Variable</u>

In the linear probability model the dependent variable, *snap*, is a monthly indicator which equals one if the individual is in an open SNAP case that month. Because one month lapses in participation are primarily due to administrative blockages as opposed to actual disenrollment/nonparticipation, individuals are not coded as "not participating" (i.e. *snap* = 0) until they have experienced two consecutive months of nonparticipation. For instance, if a person is enrolled for three months, then experiences a one month lapse in participation before participating for another two months, they will be coded as having six continuous months of enrollment. However, if the person participates for three months, then experiences a two month lapse in participation before participating for another two months, they will be coded as having being enrolled for four months, a one month break in participation, and then two months of enrollment. This same variable is used to construct the dependent variable, exit hazard, in the hazard model. Once the person has a value of zero for their SNAP variable they are considered to have experienced the "event" (i.e. exited SNAP) and their spell is over.

Independent Variables

The primary independent variable in both models, which was discussed above, is a binary indicator for an observation belonging to the post-recession cohort. If the observation for that individual and month belongs to the cohort entering after the recession then the variable, *post-recession*, equals one.

The control variables are selected based on previous research of SNAP participation behavior to establish a standard model of influence on SNAP participation behavior. There are three basic groups of control variables: personal, geographic, and economic (both individual and macro level). The personal characteristics are observed on both the individual and household level. These variables include time-invariant observations such as age at entry, as well as its quadratic term; gender, which equals one if the individual is female; household size, which is the number of people on the individual's initial SNAP case; and finally the number of children in the household under the age of six.

Past experience with SNAP has been a significant factor in predicting SNAP participation behavior (Mabli & Ohls, 2012; Atasoy, Mills, & Parameter, 2010). To account for this, a count variable, *previous snap*, which indicates the number of SNAP spells the individual experienced between January 2000 and their initial observation spell in the data is included. This is a simplistic measure of SNAP experience as it does not give a complete picture of experience. For instance, an individual may have only experienced one SNAP spell before their initial observation within this dataset, but during that spell received SNAP benefits for 3 or four years. On the other hand someone may have experienced two or three SNAP spells, but only received benefits for a total of one year. Which individual qualitatively has "more experience" is a question to keep in mind when interpreting this variable. Unfortunately the data does not include a more detailed measure of previous SNAP use.

Participation in multiple welfare programs has also been shown to affect SNAP participation behavior (Heflin, 2004; Andren, 2007; Malbi & Ohls, 2012). Enrollment in these programs may also be indicative of multiple challenges facing a household. To account for this I build an index, *other participation*, which measures participation in other welfare and social service programs. A group of count variables indicating welfare and social service use is utilized to construct the index. These variables are counts of the number of people within the individual's household who participated in a given program at some point during the current calendar year. Using a count of the number of people in the household receiving services is meant to account for the fact that while a head of household may not be on record as receiving a service or benefit they may still be affected by others in their household receiving them. The programs that are included in the index measure are Temporary Assistance for Needy Families (TANF), medical assistance programs (MAP), mental health programs (MH), drug and alcohol programs (AD), Employment Related Day Care (ERDC), domestic violence survivor services (DV), developmentally disabled services (DD), and foster care (FC).

These variables are standardized (i.e. converted into z-scores), added together, and then averaged. This process puts these measurements in standard deviation units and transforms them into a continuous measure of multiple program participation. This is an important process because while these variables are all count variables and thus already in the same unit of measurement it cannot be said that the difference between having one person in the household on TANF and having two people in the household on TANF and the difference between having three and four people on

TANF is the same. Similarly it cannot be said that having one person in the household on TANF is equivalent to having one person in the household receiving domestic violence services. Adding them together as they stand would essentially infer these equivalences. Standardizing and averaging them converts them into comparable units of measurement.

The variable *adult move* is a binary indicator that equals one if an adult in the same household as the head has a different address than the head in a given month. Essentially it tracks the movement of other adults in and out of the household. The loss of an additional income earner and the general financial hardships of divorce, single parenthood, or caring for a dependent adult can often force people into bouts of SNAP use (Andren, 2007; Bruce, Barbour, & Thacker, 2003; Mabli & Ohls 2012).

The final personal characteristic variable is a binary indicator for those who appear in both time periods. There is a small group of individuals who have a set of observations in both time periods. Since this model is seeking to explore the potential shift in behavior due to the introduction of new participants it is important to account for those who are not new participants (i.e. those who entered SNAP in both January of 2005 and January of 2009 and are known for sure to have had a pre-recession SNAP spell). This is somewhat captured in the *previous snap* variable, but as discussed above the *previous snap* variable does not capture when the SNAP spells took place and thus is not an accurate indicator for pre-recession SNAP use. According to the National Bureau of Economic Research the 2008 recession began

December 2007 and ended June 2009. Thus those in the post-recession cohort with previous SNAP spells may not have actually experienced a pre-recession spell. They may have simply experienced a spell some other time during the recession. Those who appear in both time periods are the only ones known for sure to have experienced a pre and post-recession SNAP spell and thus are not “new users”.

The set of geographic variables indicates both census block group and rural/urban status. Each individual has a monthly census block group observation. This block group observation is based on the individual’s current address, which is not included within the data. If the address belongs to a rural census block, based on U.S. Census classifications, the census block group observation is coded as rural. As certain block groups may contain both rural and non-rural areas, two individuals with the same block group observations could have differing rural codings.

I use the monthly block group observations to construct an indicator variable that equals one when the individual changes address from the previous month. Moving has also been found to be a significant predictor of SNAP and welfare program participation due to both the financial burden of moving as well as the economic reasons that motivate some address changes (Bruce, Barbour, & Thacker, 2003; Irving, 2008). Since the individual addresses are not included within the data there will be a slight amount of error in this measurement as individuals could have experienced a move within the same block group area, which would not be detected by the data.

The first individual level economic variable is a monthly value of wages in hundreds of dollars. This measure also acts as an employment indicator since those with no reported wages are considered not employed. The interpretation of this variable is more complex than this, however. The dataset from which this variable originates came from the Oregon Employment Department and is reported by employers on a quarterly basis. This holds two implications. First is that not all employment sectors, including certain agriculture sectors and self-employment, are required to report to the Employment Department. Second is that since the data only states whether a person is employed in a given quarter there is no way of knowing if the person is employed and earning a wage in a specific month. Monthly wage observations are created by taking the total quarterly earnings and averaging them over the three month period. While this will introduce bias into this measurement, wages earned in one month may be spent in other months. Thus the average monthly wage observation should still closely capture actual monthly income.

The final set of control variables are intended to account for current economic conditions and policy changes. These variables are intended to allow the *post-recession* variable to better capture the true underlying behavioral changes that were not induced by the changes in incentives and need caused by the economic downturn directly or the ARRA. The first macro-level economic variable is county-level monthly unemployment rates. This measure is the non-seasonally adjusted rates that are matched with the individual's current block group observation. Using county unemployment is intended to account for the steep increase in unemployment rates brought on by the recession. The second variable is county-level annual per-capita income measured in thousands of dollars. While the model already controls for individual wages this variable is meant to capture the macro-level decreases in income brought on by the recession.

Finally a variable indicating the benefit increase due to the ARRA is introduced. An approximate benefit increase based on household size ranging from \$11 to \$89 was instituted through the ARRA. These benefit increase numbers were supplied by the Oregon Department of Human Services (DHS, 2013). Each month after March 2009 is coded with the corresponding benefit increase that matches the individual's household size. While this is not a perfect measurement it closely captures the benefit increase experienced by most SNAP participants and allows me to control for changes in participation behavior induced by these benefit changes.

Table 2: Pre-Recession Cohort Descriptive Statistics				
	Mean (SD)	N	Min	Max
Dependent Variables				
SNAP	0.481(0.500)	185,000	0	1
Control Variables				
Age	32.448(11.046)	185,000	9	72
Female	0.543(0.498)	185,000	0	1
Household Size	1.932(1.341)	185,000	1	11
# of children under 6	0.325(0.658)	185,000	0	4
Previous SNAP	2.158(1.198)	185,000	1	9
Other participation	0.033(0.562)	185,000	-0.215	9.473
Both	0.0068(0.082)	185,000	0	1
Rural (indicator)	0.161(0.368)	114,457	0	1
Moved	0.048(0.214)	182,558	0	1
Adult move	0.003(0.053)	185,000	0	1
Monthly wage ($100)	7.536(9.881)	185,000	0	117.628
Unemployment rate	5.951(1.256)	114,475	3	13.9
Per-capita income ($1,000)	34.972(5.036)	114,475	24.178	46.728
ARRA	0(0)	185,000	0	0

Table 3: Post-Recession Cohort Descriptive Statistics				
	Mean (SD)	N	Min	Max
Dependent Variables				
SNAP	0.644(0.479)	185,000	0	1
Control Variables				
Age	32.866(11.439)	185,000	0	69
Female	0.511(0.500)	185,000	0	1
Household Size	1.862(1.317)	185,000	1	11
# of children under 6	0.273(0.602)	185,000	0	4
Previous SNAP	2.483(1.618)	185,000	1	11
Other participation	-0.033(0.402)	185,000	-0.215	5.793
Both	0.0068(0.082)	185,000	0	1
Rural (indicator)	0.168(0.374)	129,372	0	1
Moved	0.064(0.245)	182,669	0	1
Adult move	0.079(0.270)	185,000	0	1
Monthly wage ($100)	6.712(9.896)	185,000	0	310.548
Unemployment rate	11.024(2.136)	129,372	4.8	21
Per-capita income ($1,000)	34.821(4.414)	129,372	23.944	55.468
ARRA	16.866(11.566)	185,000	0	89

Results

Participant Changes Across Cohorts

Before estimating the empirical models I explore the data for significant differences between the two cohorts of participants. Since the data set is in panel form the tables discussed in this section represent observation frequencies. There are 5,000 individuals in each cohort with 37 observations each. This means that the total number of observations in each cohort is 185,000 person-months. Table 4 shows trends in race and ethnicity between the cohorts, retaining person-months as the unit of anlaysis. There does not seem to be any substantive difference between them. However, this could also be due to the fact that many people did not answer the race or ethnicity question on their application, which is the reason it is excluded from the statistical models. The inclusion of these variables would have substantially decreased the number of observations.

Table 4: Race and Ethnicity Frequencies by Cohort

	Pre-Recession	Post-Recession
Race		
Asian	2,775 1.50%	2,664 1.44%
Black	6,401 3.46%	6,475 3.50%
Native American	3,885 2.10%	3,108 1.68%
White	139,786 75.56%	141,266 76.36%
Other	1,295 0.01%	1,369 0.01%
Missing/Unknown	30,858 16.68%	30,118 16.28%
Total	185,000 100%	185,000 100%
Ethnicity		
Hispanic	10,323 5.58%	10,767 5.82%
Non-Hispanic	5624 3.04%	34,817 18.82%
Unknown/Missing	169,090 91.40%	139,416 75.36%
Total	185,000 100%	185,000 100%

Frequencies taken from final cohort samples

The cohorts begin to differ substantially when gender and household composition are examined. While the majority of SNAP heads of household are female there is a significant difference in the share of women heads between the two cohorts (Table 5). The percentage of female heads decreases by 3.18 percentage points, while the share of male heads increases by 3.54 percentage points between the cohorts. This finding is evidence of the particularly large effect the recession had on men.

Table 5: Gender Frequencies by Cohort		
Gender	**Pre-Recession**	**Post-Recession**
Female	100,492	94,609
	54.32%	51.14%
Male	84,508	90,391
	45.68%	48.86%
Total	185,000	185,000
	100%	100%

Surprisingly, the majority of SNAP households in both cohorts are adult only households (Table 6). This trend becomes significantly more prominent after the Great Recession. The percentage of adult-only households increases between 2 and 6 percentage points depending on the number of adults, while other household compositions tended to decrease. Not only are the majority of cases adult only cases, but the majority of those are single adult cases. Of the households with only one adult the majority of those are adult only cases, as opposed to single parent households. This general trend does not change across the cohorts, but as observed in Table 6 the percentage of adult only cases increases in the post-recession cohort, while all other single adult household compositions decrease. Another place that this trend can be observed is the total number of household members (Table 7). The percentage of single person households increases by 4 percentage points in the post-recession cohort, while the percentages of all other sized households decrease. These changes are statistically significant with a p-value less than 0.001.

Table 6: Household Composition by Cohort						
Number of Children	**Number of Adults**					
	1		2		3+	
	Pre-Recession	*Post-Recession*	*Pre-Recession*	*Post-Recession*	*Pre-Recession*	*Post-Recession*
0	105,006 71.96%	111,037 77.73%	9,509 28.21%	11,322 30.03%	999 27.55%	1,295 29.17%
1	21,312 14.60%	17,316 12.12%	9,102 25.08%	10,286 27.28%	1,073 29.59%	1,147 25.83%
2	12,987 8.90%	9,583 6.71%	8,843 25.08%	9,213 24.44%	777 21.43%	1,110 25.00%
3+	6,623 4.54%	4,921 3.44%	7,992 21.63%	6,882 18.25%	777 21.43%	888 20.00%
Total	145,928 100%	142,857 100%	35,446 100%	37,703 100%	3,626 100%	4,440 100%

Table 7: Total Household Size by Cohort		
Total Household Size	**Pre-Recession**	**Post-Recession**
1	105,006 56.76%	111,037 60.02%
2	30,821 16.66%	28,638 15.48%
3	22,977 12.42%	20,683 11.18%
4+	26,196 14.16%	24,642 13.32%
Total	185,000 100%	185,000 100%

Trends within employment also vary significantly between cohorts. Generally those in the post-recession cohort experienced more months of non-employment in a UI covered industry and/or unemployment. The pre-recession cohort spent the majority of their months employed (59%), while the post-recession cohort spent closer to half of their months employed (51%) in a UI covered

Table 8: Employment Sector Frequencies by Cohort and BLS NAICS Aggregation Titles					
			NAICS Code	**Pre-Recess**	**Post-Recess**
Goods-Producing	**Natural resources and mining**	*Agriculture, Forestry, Fishing and Hunting*	11	3,282 2.99%	1,321 1.40%
		Mining, Quarrying, and Oil and Gas Extraction	21	132 0.12%	34 0.04%
	Construction	*Construction*	23	6,892 6.29%	1,980 2.09%
	Manufacturing	*Manufacturing*	31	2,587 2.36%	968 1.02%
		Manufacturing	32	3,411 3.11%	1,691 1.79%
		Manufacturing	33	4,822 4.40%	1,617 1.71%
Service Providing	**Trade, transportation, and utilities Information**	*Utilities*	22	115 0.01%	55 0.06%
		Wholesale Trade	42	2,889 2.64%	935 0.99%
		Retail Trade	44	11,821 10.78%	4,845 5.12%
		Retail Trade	45	7,106 6.48%	2,916 3.08%
		Transportation	48	1,945 1.77%	723 0.76%
		Warehousing	49	601 0.55%	273 0.29%
	Information	*Information*	51	996 0.91%	589 0.62%
	Financial activities	*Finance and Insurance*	52	2,039 1.86%	669 0.71%
		Real Estate and Rental and Leasing	53	1,912 1.74%	1,078 1.14%
	Professional and business services	*Professional, Scientific, and Technical*	54	2,081 1.90%	1,431 1.51%
		Management of Companies and Enterprises	55	883 0.81%	34 0.04%
		Administrative and Support and Waste Management	56	16,687 15.22%	14,415 15.24%
	Education and health services	*Educational Services*	61	2,721 2.48%	2,549 2.70%
		Health Care and Social Assistance	62	12,837 11.71%	13,253 14.01%
	Leisure and hospitality	*Arts, Entertainment, and Recreation*	71	1,268 1.16%	2,212 2.34%
		Accommodation and Food Services	72	16,586 15.13%	26,343 27.86%
	Other services	*Other Services*	81	3,484 3.18%	7,435 7.86%
	Public administration	*Public Administration*	92	2,116 1.93%	4,342 4.59%
	Unclassified	*Other*	99	405 0.37%	2,859 3.02%
Total				109,618 100%	94,567 100%

industry. An exploration of the SNAP participant employment shares in varying NAICS industry classifications reveals trends similar to national patterns of layoffs and reemployment (Table 8). In cases where individuals are employed in more than one job during a quarter/month, the NAICS industry classification for the highest wage earning job is used as the primary classification for each person-month observation. The industries with the largest drop in employment shares from the pre to post-recession cohort are agriculture/forestry/fishing (1.5 % points), construction (4 % points), manufacturing (5 % points), wholesale trade (1.5 % points), and retail trade (8 % points). Conversely the industries that saw the largest gains (greater than 1 percentage point increase) between the cohorts are healthcare and social assistance (2 % points), accommodation and food service (13 % points), other services (5 % points), public administration services (2.5 % points), and unclassified industries (2.5 % points).

A change in wages is also evident between the two cohorts. The post-recession cohort spent more person months at zero average wages, 90,475 (48.91%) person-months, compared to the pre-recession cohort with 75,471 (40.80%) person-months. The average and median wages for the post-recession cohort are also substantially different than the pre-recession cohort. While those in the pre-recession cohort experienced an average monthly wage of $753 and a median wage of $280 those in the post-recession cohort experienced and average monthly wage of only $671 and a median wage of $32.

Table 9: Welfare and Social Service Program Usage by Cohort

Program	**Number of Participating Household Members**				
	0	1	2	3+	Total
TANF					
Pre-Recession	173,600 93.84	4,163 2.25	4,283 2.32	2,954 1.60	185,000 100%
Post-Recession	172,644 93.32	4,440 2.40	4,432 2.40	3,484 1.88	185,000 100%
MAP					
Pre-Recession	132,652 71.70	22,646 12.24	16,109 8.71	13,593 7.35	185,000 100%
Post-Recession	131,482 71.07	28,441 15.37	14,552 7.87	10,525 5.69	185,000 100%
MH					
Pre-Recession	171,132 92.50	12,234 6.61	1,296 0.70	338 0.18	185,000 100%
Post-Recession	175,867 95.06	8,456 4.57	603 0.33	74 0.04	185,000 100%
AD					
Pre-Recession	163,421 88.34	19,685 10.64	1,536 0.83	358 0.19	185,000 100%
Post-Recession	172,668 93.33	12,135 6.56	197 0.11	0 0.00	185,000 100%
DD					
Pre-Recession	183,989 99.45	963 0.52	36 0.02	12 0.01	185,000 100%
Post-Recession	184,337 99.64	626 0.34	37 0.02	0 0.00	185,000 100%
ERDC					
Pre-Recession	176,848 95.59	2,195 1.19	3,707 2.00	2,250 1.22	185,000 100%
Post-Recession	179,704 97.14	1,880 1.02	2,325 1.26	1,091 0.59	185,000 100%
DV					
Pre-Recession	181,378 98.04	1,147 0.62	1,265 0.68	1,210 0.65	185,000 100%
Post-Recession	182,421 98.61	1,142 0.62	898 0.49	539 0.29	185,000 100%
FC					
Pre-Recession	183,475 99.18	1,186 0.64	237 0.13	102 0.06	185,000 100%
Post-Recession	184,307 99.63	479 0.26	127 0.07	87 0.05	185,000 100%

TANF= Temporary Assistance to Needy Families; MAP= medical assistance programs; MH= mental health programs; AD= alcohol and drug programs; DD= services for the developmentally disabled; ERDC= Employment Related Daycare; DV= services for domestic violence survivors; FC= foster care placement

As discussed above a count variable for the number of people in the household receiving other welfare and social services is included in the dataset. A closer look at these variables, also measured in person-month observations, reveals some unexpected results (Table 9). First, the vast majority of SNAP participants do not actually utilize many other social services and welfare programs. Recall that these variables are counts for the number of people within the household that received benefits from the specified program within that calendar year. The most common program, with roughly 30% of person-months with participating families, is the medical assistance programs. The next most common programs, with between 7% and 12% of person months with participating families, are TANF, mental health programs, and alcohol and drug programs. All other programs have 5% or fewer heads with participating families.

SNAP Participation Probability

Two linear probability (LP) models are estimated with robust standard errors (Table 10). The first model is the standard model discussed above. This model includes the set of covariates that have been established in previous research to affect SNAP participation behavior. The standard model behaves as expected, based on current research. Age has a significant quadratic relationship with a concave shape. The effect of age is initially significantly positive, meaning that as age at entry increases by one year the probability of participation in any given month increases. After the inflection point, approximately 34 years of age, the relationship becomes significantly negative. This means that for each additional year after a person passes

Table 10: Linear Probability Results for SNAP Participation		
Variable	Standard Model	Full Model
Age	0.0101*** (0.0016)	0.0103*** (0.0016)
Age^2	-0.0001*** (0.0000)	-0.0002*** (0.0000)
Female	0.0318*** (0.0048)	0.0316*** (0.0048)
HH size	0.0059 (0.0026)	0.0061** (0.0026)
Children under 6	0.0174*** (0.0048)	0.0173*** (0.0047)
Previous SNAP spells	-0.000 (0.0015)	-0.0018 (0.0014)
Other participation	0.0252*** (0.0048)	0.0247*** (0.0048)
Both	-0.0460 (0.0339)	-0.0472 (0.0306)
Rural	-0.00014 (0.0083)	-0.0022 (0.0083)
Move	0.0425*** (0.0027)	0.0426*** (0.0027)
Adult move	-0.0082 (0.0094)	-0.0094 (0.0094)
Wage	-0.0064*** (0.0003)	-0.0064*** (0.0003)
Unemployment rate	0.0047*** (0.0012)	0.0022* (0.0012)
Per-capita income	-0.0134 (0.0028)	-0.0120 (0.0029)
ARRA	-0.0010*** (0.0002)	-0.0011*** (0.000)
Post-Recession		0.1367*** (0.0159)
Trend	-0.0041*** (0.0002)	-0.0044*** (0.0002)
Constant	0.6938*** (0.128/2)	0.8838*** (0.1278)
Stats		
N	240,159	240,159
Wald	2,964.01	3,038.08
R-Sq	0.1254	0.1314

Dependent variable of both models is SNAP monthly participation. Robust standard errors reported in parenthesis. *, **, and *** indicate beta significance at a 90%, 95%, or 99% confidence level, respectively. Outputs for county dummies and correlated random effects not reported. R-Sq obtained using standard OLS model.

the age of 34, the probability of participation in any given month decreases by about 0.01 percentage point.

Females are 3.18 percentage points more likely to participate in any given month compared to their male counterparts. Increases in the number of children under the age of six within the household also increase the probability of participation. The addition of one more child under the age of six into the household increases probability of participation by 1.74 percentage points. General household size has a small but significant effect on participation probability. For each additional person within the household the probability of participation in any given month increases by 0.59 percentage points.

The standard model shows that higher levels of participation in other welfare and social service programs increases the probability of participation in a given month by 2.4 percentage points. However, number of previous SNAP spells do not appear to significantly affect participation probability. This finding may be due to the simplistic nature of the measurement.

The geographic variables generate somewhat unexpected results. Experiencing a move causes participation probability to increase by 4.25 percentage points compared to months where the individual did not experience a move. This is what the current research would suggest. However, an adult moving out of the household does not appear to have significant effects on participation probability. This is perhaps due to the diverse nature of what the *adult move* variable is measuring. Marital status and marital disruption are the common measurements within the literature (Bruce, Barbour, & Thacker, 2003; Heflin, 2004; Mabli & Ohls, 2012). However, I am tracking movement of adults in and out of the household (adults other than the head). Thus some of these adults are not romantic partners nor spouses. The different relationships this variable captures may each have different directional effects. For instance one may expect a positive effect of cohabitation changes (romantic partners moving out of the house) on participation probability, as the research would suggest. If, however, the adult was a non-income earning resident (such as an adult child or elderly parent), their movement out of the house may lessen the financial burden or negatively affect eligibility and thus have a negative effect on participation probability. Within the *adult move* variable these different directional effects may simply cancel each other out, rendering the variable insignificant.

Surprisingly, rural status is insignificant. This finding is somewhat unexpected because recent studies suggest that rural status plays a significant role in welfare program participation (Irving, 2008; Bean & Mattingly, 2010). However, this observation may simply be due to the inclusion of the county dummy variables absorbing the effects of rural status. Rurality is often measured on a county level, but this data measures it on a census block level. Thus small moves within the same county, though technically out of rural blocks, may not cause large enough changes in economic conditions to detect significant effects.

Monthly wage behaves as expected. Increases in monthly wage decrease the probability of participation in a given month. For each additional $100 per month a person earns their probability decreases by 0.64 percentage points. However, per-capita income does not appear to have any significant effect. Unemployment rates have the expected positive effect on participation probability. For every 0.01 percentage point increase in the county unemployment rate the probability of participation in any given month increases by 0.47 percentage points.

The ARRA policy variable has a small, but unexpected effect on the probability of participation. Increases in benefits actually appear to decrease the probability of participation in a given month. However, this effect is small, only decreasing probability by 0.10 percentage points with each dollar increase. This is likely due to measurement error as only approximate maximum benefit increases were used to account for the benefit increases.

The Full Model is where the explanatory variable, *post-recession*, is introduced. The Standard Model coefficients do not qualitatively or substantively change between the two models. The largest change in coefficient happens to the unemployment variable. Once the post-recession variable is included, the unemployment coefficient drops both in magnitude, from 0.47 to 0.22 percentage points, and in significance, from the 99% confidence level to the 90% confidence level. This is likely due to the correlation between unemployment rates and the recession.

The *post-recession* coefficient is highly significant and has a substantial effect. It appears that being in the post-recession cohort compared to the pre-recession cohort increases an individual's probability of participation in any given month by 13.67 percentage points. This finding is significant at the 99% confidence level while controlling for both individual, geographic, economic, and policy factors.

SNAP Exit Hazard

Just like the LP model, two hazard models are estimated, the Standard Model and the Full Model. The hazard ratios with robust standard errors are reported in Table 11. The hazard ratios, which are the marginal effects of the covariates, are assumed to have a consistent effect across time. In other words the effect size is assumed to be the same in all time periods. For instance females are 21% less likely to experience their first SNAP exit in any given month, assuming they had been enrolled up to that point.

This assumption is important as it requires that the variables within the model meet the proportional hazard assumption. Essentially the proportional hazard assumption states that the hazard ratios do not vary over time. The common test for this assumption is a test for nonzero slope by running a linear regression of the hazard model's residuals on time (Gram and Theneau, 1994). This test can be done on both individual variables within a model and globally on the entire model. An examination of this test revealed that the Standard Model does not meet the proportional hazard assumption. In order for this model to meet the proportional hazard assumption the quadratic term for age, *arra*, and the time-averaged correlated random effects variables had to be excluded from the model originally outlined in the Empirical Model section. The implications of these changes will be discussed in more detail below.

Table 11: Proportional Hazard Results for SNAP Exit Probability		
Variable	**Standard Model**	**Full Model**
Age	1.0028* (0.0016)	1.0016* (0.0016)
Female	0.7592*** (0.0272)	0.7578*** (0.0272)
HH size	0.9529*** (0.0177)	0.9529*** (0.0177)
Children under 6	0.8584*** (0.0347)	0.8560*** (0.0346)
Previous SNAP spells	1.0213* (0.0120)	1.0256** (0.0121)
Other participation	0.6872*** (0.0353)	0.6838*** (0.0353)
Both	1.2111 (0.2026)	1.2049 (0.2037)
Rural	1.0162 (0.0489)	1.0210 (0.0489)
Move	0.3646*** (0.0494)	0.3657*** (0.0496)
Adult move	1.3205*** (0.1087)	1.3502*** (0.1107)
Wage	1.0360*** (0.0020)	1.0364*** (0.0020)
Unemployment rate	0.9035*** (0.0060)	0.9828 (0.0181)
Per-capita income	0.9753 (0.0242)	1.0020 (0.0252)
Post-Recession		0.6078*** (0.0627)
Stats		
N	152,093	152,093
Wald Chi2	986.16	986.16

Dependent variable of both models is constructed from monthly SNAP participation. Robust standard errors reported in parenthesis. *, **, and *** indicate beta significance at a 90%, 95%, or 99% confidence level, respectively. The Breslow method for ties was utilized. County dummy outputs are not reported.

The hazard model may seem very similar to the LP model, but there are some distinct differences. The LP model estimates changes in the probability of participating in SNAP in any given month. The hazard model calculates the probability of experiencing an event (a SNAP program exit) at a given point in time, assuming that the individual had been enrolled up until that point. Plotting the hazard function and the resulting survival function, which is done below, gives a representation of spell duration after controlling for a set of covariates.

The Standard Hazard Model yields different results than the Standard LP Model. The personal characteristics are all significant in the hazard model, though some only at the 90% confidence level. They also have the expected directional effect. For instance females are 24% less likely to exit SNAP in a given month, assuming they have been enrolled up until that point, than their male counterparts. This corresponds to the LP model which shows that women have an increased likelihood of participation in a given month of 3.18 percentage points compared to their male counterparts. This makes intuitive sense. If a woman is less likely to exit she should be more likely to participate.

Previous SNAP spells gain significance in the hazard model. For each additional previous SNAP spell a person experienced they are 1.03 times more likely to exit in a given month, assuming they had been enrolled up until that point. Participation in other welfare and social service programs is also significant. A one unit increase in this variable decreases the probability of exit by 31%.

The geographic variables behave similarly in the hazard model as they do in the LP model. The biggest difference is that the *adult move* variable gains significance in the hazard model. Those who experience an adult moving out of their household in a given month are 1.35 times more likely to exit SNAP, assuming they have been enrolled up until that point, compared to months where they did not experience an adult moving out of the household. As discussed above this variable likely captures multiple differing directional effects due to the varied relationships between the heads of household and the adults moving in and out of the household. It appears that the positive directional effects on exit probability outweigh any negative directional effects that may be present within the variable.

As in the LP model, per-capita income is not significant in either hazard model. The unemployment rate is significant in the Standard Model and shows a negative relationship with exit hazard, meaning that as the unemployment rate increases the probability of exit, assuming enrollment up until that point, decreases. However, this variable loses all significance once the explanatory variable is introduced. The loss of significance is somewhat shocking, but much like the drop in significance in the LP model is likely due to the correlation between the recession and the unemployment rates.

The *post-recession* coefficient shows significant negative effect on exit probability. Those who belong to the post-recession cohort are 40% less likely to exit in a given month, assuming enrollment up until that point. This is a very large effect, though the size may reflect some of the effects of the unemployment rate. The big difference here from the LP model is that this estimation does not control for the benefit increase caused by the ARRA. The *arra* variable had to be excluded from this model because it did not meet the proportional hazard assumption. Thus the *post-recession* coefficient estimation may include those effects and become inflated. However, if the ARRA increase behaved in the hazard model similarly as it did in the LP model this is likely a very small effect.

To explore the change in exit probability across time and cohorts I estimate and graph a series of hazard functions across the observation period. To explore first spell duration I estimate a series of survival functions across the observation period. First I estimate the general hazard function of the Full Model (Figure 2). This function shows the relationship between exit probabilities and time, controlling for the covariates within the model. As time progresses the likelihood that a given individual will exit SNAP, assuming they have been enrolled up until that point, changes. Exit probabilities peak around the 12^{th} month of enrollment, for those who have remained in the program up to this point. After that they steadily decline to practically zero. This indicates that individuals' probability of exit increases until the 12^{th} month of enrollment at which point it begins to steadily decline.

The survival function tells a similar story (Figure 3). This graph shows the ratio of predicted survivors across time. In this function individuals who are still enrolled in the SNAP program are considered "survivors". The graph begins with a survival rate of 1 or 100% survival. The curve drops at each time point as people exit the program. These drops represent a proportion of individuals exiting the program at

Figure 1: Full Model Hazard Function

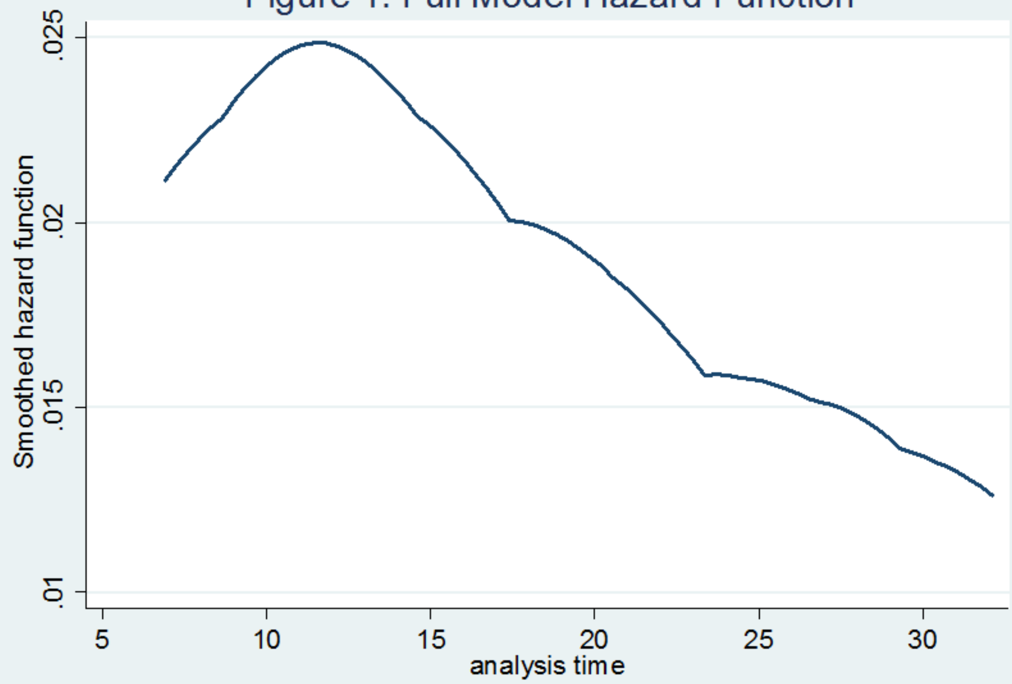
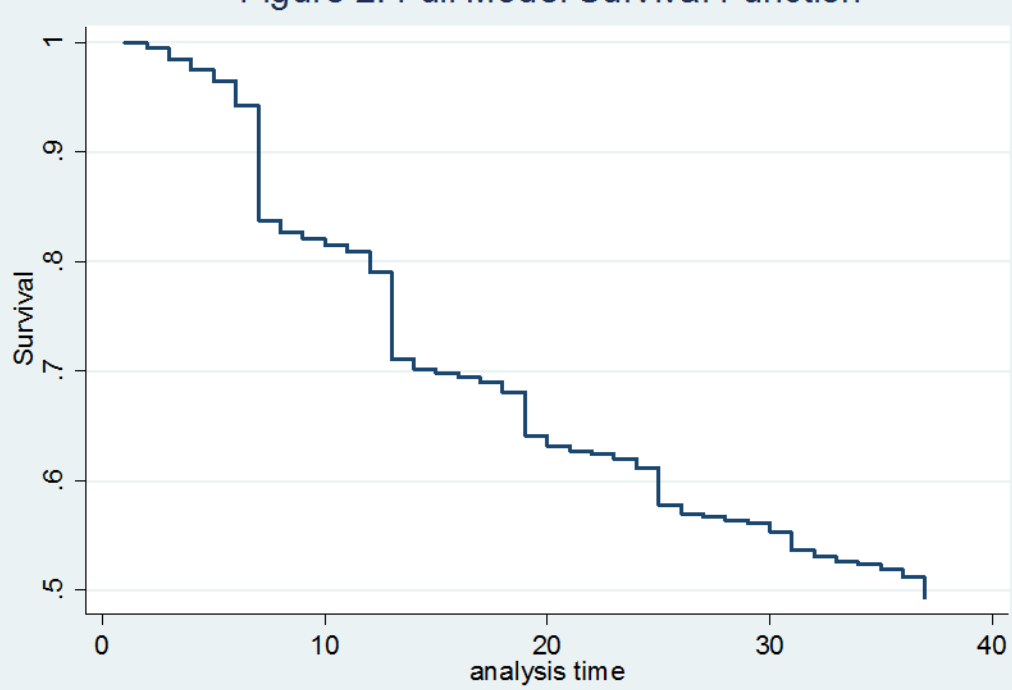


Figure 2: Full Model Survival Function



each time point. For instance a drop from 1 to 0.8 at time point two would indicate 20% of initial participants dropping out at time point two. Another way of expressing this would be to say that time point two has a survival rate of 80%, or that at time point two 80% of participants have survived (i.e. are still enrolled). The stair case shape of the curve is indicative of the time measure. Because one cannot exit between time points (i.e. one can only exit at month 2 or month 3, but not month 2.5) the survival rate remains the same across each time point, thus creating the staircase effect. Every step down on the graph indicates a predicted group of individuals exiting the program.

The survival function tells a very interesting story about spell duration. It appears that the median predicted spell duration, the point at which 50% of participants have exited by, is 37 months, which is the end of the observation period. Before the 37 month time point there are also substantial drop outs at the 6 month time point, where 17% of participants are predicted to have exited, and the 12 month time point, where 29% of participants are predicted to have dropped out. This indicates that these are common spell lengths. These are also the points of recertification. Indeed at each 6 month time point the drop in survival is at least slightly larger than those between the 6 month time points. It seems likely then that people are either failing to recertify or when they do recertify they are no longer eligible.

Both the hazard and survival functions can be predicted at specific levels of covariates. This allows me to predict these functions for each of the cohorts (*post-*

recession=1 and *post-recession*=0). By doing this I can examine the differences in the functions by cohort. First I estimate the hazard function of the Full Model for each cohort (Figure 4). Each of them is shaped similarly to the general hazard function, as well as each other. As expected the hazard function for the post-recession cohort lays below the hazard function of the pre-recession cohort at all points, showing a lower "hazard" of departing SNAP. This is the graphical representation of the significant hazard ratio, reported above, that predicts, assuming enrollment up until that point, individuals are 40% less likely to exit compared to those the pre-recession cohort. This effect is present after controlling for conditions such as the unemployment rate, monthly income, and personal characteristics. Thus this change in exit probability is above and beyond the change induced by the wage losses and the unemployment rate. The peak point of exit probability is still the 12 month marker at which point in both graphs the probability of exit begins its steady decline.

The survival functions reveal some more intricate differences between the two cohorts (Figure 5). The first and possibly the most striking difference between the two cohorts is the median spell length. For the pre-recession cohort the median spell length is 24 months. At 24 months 50% of those in the pre-recession cohort are predicted to have exited the program. However, the observation period of this study is not long enough to predict the median spell length for the post-recession cohort. At 37 months the survival rate is approximately 56% so I can only say that the predicted median spell length for the post-recession cohort is greater than 37 months.

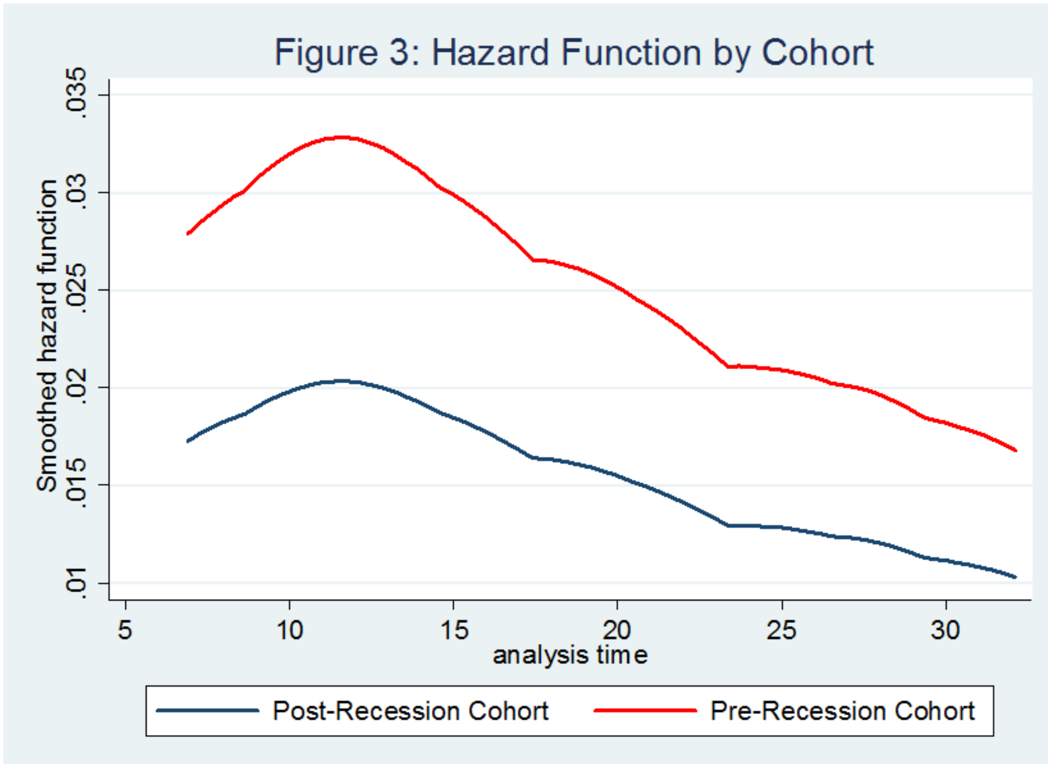


Figure 3: Hazard Function by Cohort
Smoothed hazard function
.01
.015
.02
.025
.03
.035
5
10
15
20
25
30
analysis time
Post-Recession Cohort
Pre-Recession Cohort

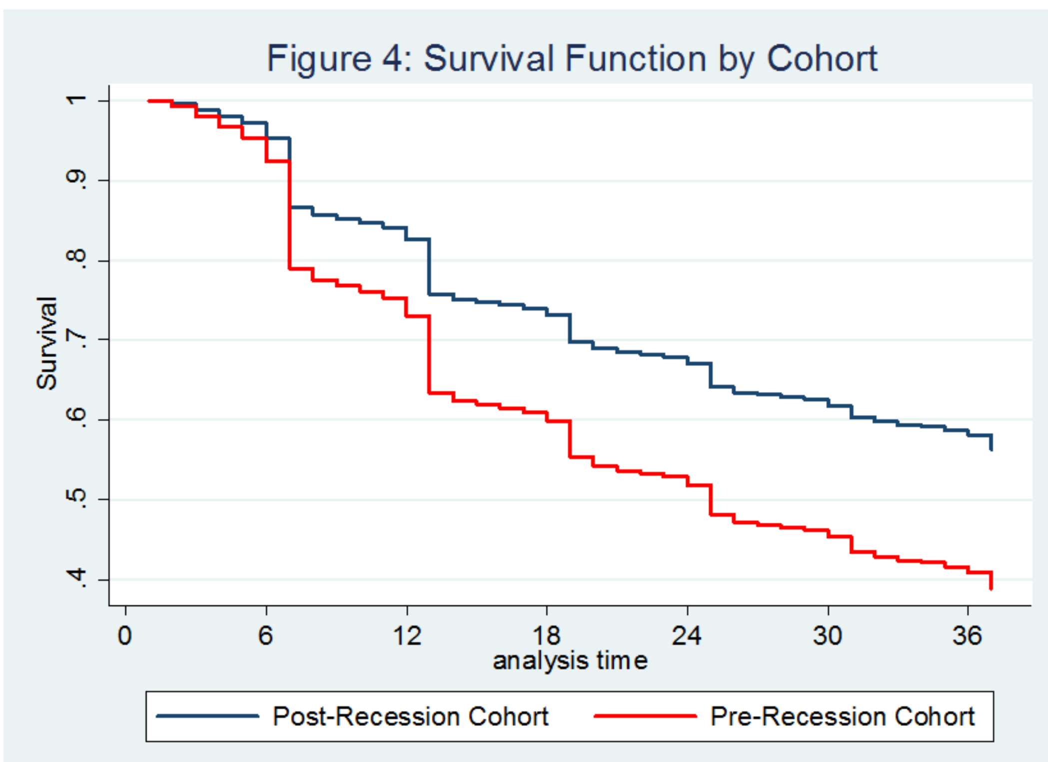


Figure 4: Survival Function by Cohort
Survival
.4
.5
.6
.7
.8
.9
1
0
6
12
18
24
30
36
analysis time
Post-Recession Cohort
Pre-Recession Cohort

Looking back to the first 24 months of the survival function, another striking difference between the cohorts appears. For the first 6 months the functions are very similar, nearly overlapping each other. At the 6 month time point, the first initial substantial drop in survival, the two functions take markedly different paths. The drops in the survival rates for the post-recession cohort at 6 months and 12 months appear to be roughly half the size of the drops at those points for the pre-recession cohorts. After the 12 month point the difference becomes smaller in magnitude, but the drops in the 6 month interval for the post-recession cohort remain smaller than those in the pre-recession cohort.

The proportional hazard model and the resulting hazard ratios, hazard functions, and survival functions show that not only did exit probability significantly decrease in the post-recession cohort, but spell lengths increased as well. The pre-recession cohort generally sees higher exit probabilities and shorter spell lengths, but the two cohorts appear to diverge primarily in the first 12 months. While 6 months (17% predicted exits) and 12 months (29% predicted exits) appear to be common spell lengths in the pre-recession cohort they are less common in the post-recession cohort. Substantially fewer people are predicted to exit the program at 6 and 12 months after the recession. This appears to be the primary driver of the difference between the two survival functions as well as the median spell length.

Discussion and Conclusion

The findings in this analysis hold important implications. Those with higher levels of participation in other welfare and social service programs have an increased likelihood of SNAP participation in any given month of 2.50%. They are also 22% less likely to exit in a given month assuming they have been enrolled up until that point. These findings show that participants with multiple barriers or needs are likely to need longer periods of SNAP support.

Another unexpected finding was that those with more previous SNAP spells were actually less likely to participate by 0.18% in any given month. They were also 1.026 times more likely to exit in any given month assuming they had been enrolled up until that point. This finding may seem counter intuitive, but it is suggestive of an interesting pattern amongst more habitual users. It appears that there is a group of participants who participate frequently, but for shorter periods of time, cycling on and off the program. It seems that the quality of the program exit is particularly important. If participants exit, but are not economically stable enough to remain off the program, SNAP will continue to experience high enrollment rates as those who exit simply cycle back into the program. This continued reenrollment process could potentially mean higher administrative costs for the State. Also the time and money from missed work and transportation costs could be negatively impacting these participants.

After controlling for the standard set of factors that are known to affect SNAP participation as well as for worsening economic conditions it seems that SNAP participation behavior has changed substantially since the Great Recession. Not only has the composition of those who participate in the program changed, but the general behavior of SNAP participants has changed. Generally those in the post-recession cohort were 13.67 percentage points more likely to participate in any given month after controlling for personal, household, economic, and policy factors. At the same time those in the post-recession cohort were roughly 40% less likely to exit in a given month, assuming they were enrolled up until that point, after controlling for personal, household, and economic conditions.

Median spell lengths have seen dramatic increases. More than 50% of those in the post-recession cohort are predicted to remain enrolled for more than 3 years, so the median spell length is more than 37 months. The data for this analysis did not cover a long enough time period to generate an estimate of median spell length for post-recession cohort. At more than 37 months, the median spell length post-recession is more than one year longer than the pre-recession median spell length, which is a larger than 50% increase.

These changes have important implications for both future SNAP forecasts and policy. General trends show an increased need for SNAP benefits (e.g. increased total enrollment and coverage), which has already been putting a strain on the program (Porter & Edwards, 2010; Andrews and Smallwood, 2012). To examine the potential compounded impact of the increase in enrollment and increase in spell length on entrant survival an examination of the yearly time points of 12, 24, and 37 months is very telling. Recall that 12 months was a common spell length and the time point with the highest probability of exit for both cohorts. The 24 month time point was the median spell length for those who entered the program before the recession and 37 months is the end of the observation period.

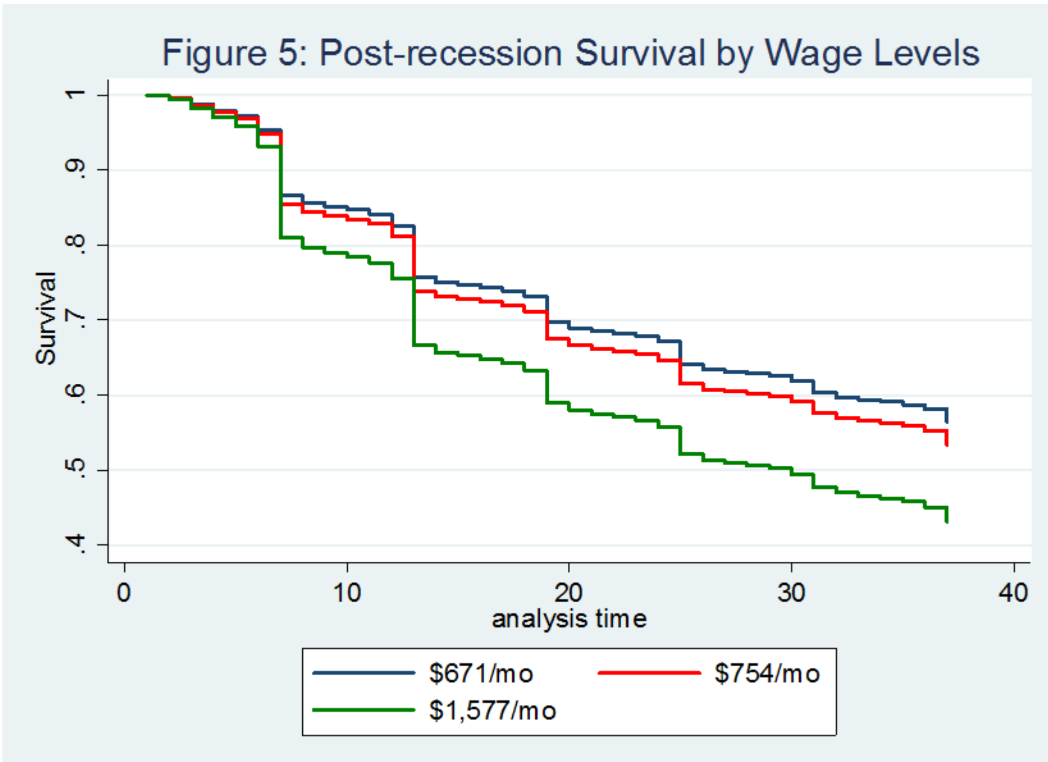
Using the predicted survival rates estimated in this analysis I can calculate the approximate impact of increased spell length coupled with increased enrollment on SNAP entrant survival across the observation period. In Table 12 using an initial enrollment level of 100 participants for those entering before the recession I calculate the anticipated caseload, assuming no other participant entrance, at each time point. Then using an initial enrollment level of 140 participants for those entering after the recession I have simulated a 40% increase in enrollment seen in our data. Then at each time point I multiply the initial enrollment total by the survival rate to get an approximate number of entrant survivors at that time point. I then calculate the percentage increase between the survivors of the pre and post-recession groups to paint a picture of what the compounded effect of the enrollment and spell length increases are over time. The results are quite shocking.

It is important to remember that these are simply survival estimates and do not capture the dynamics of the inflow of new enrollees each month. However, it appears that not only is the estimated increase in entrant survivors substantially larger than the general increase in enrollment or median spell length, but it actually increases in magnitude over time. This shows that the impact of the recession on SNAP program participation is much more complex and dynamic than a simple increase in enrollment and spell length.

Table 12: Estimated Impact on SNAP Entrant Survival			
	Time Points		
	12 Months	*24 Months*	*37 Months*
Pre-Recession (100 participants)			
Survival Rate	0.62	0.50	0.39
Estimated Entrant Survivors	62	50	39
Post-Recession (140 participants)			
Survival Rate	0.75	0.65	0.58
Estimated Entrant Survivors	105	91	81
Percent Change in Caseloads	69%	82%	108%

Another predictive application of these findings is to examine how survival and spell length may change based on changes in other covariates. I can also examine if and how these changes vary across the cohorts. Unfortunately, the coefficient for the unemployment rate was insignificant in the full model and thus I cannot effectively examine changes in the unemployment rate on the survival rates. I can, however, examine changes in survival rates based on changes in wages.

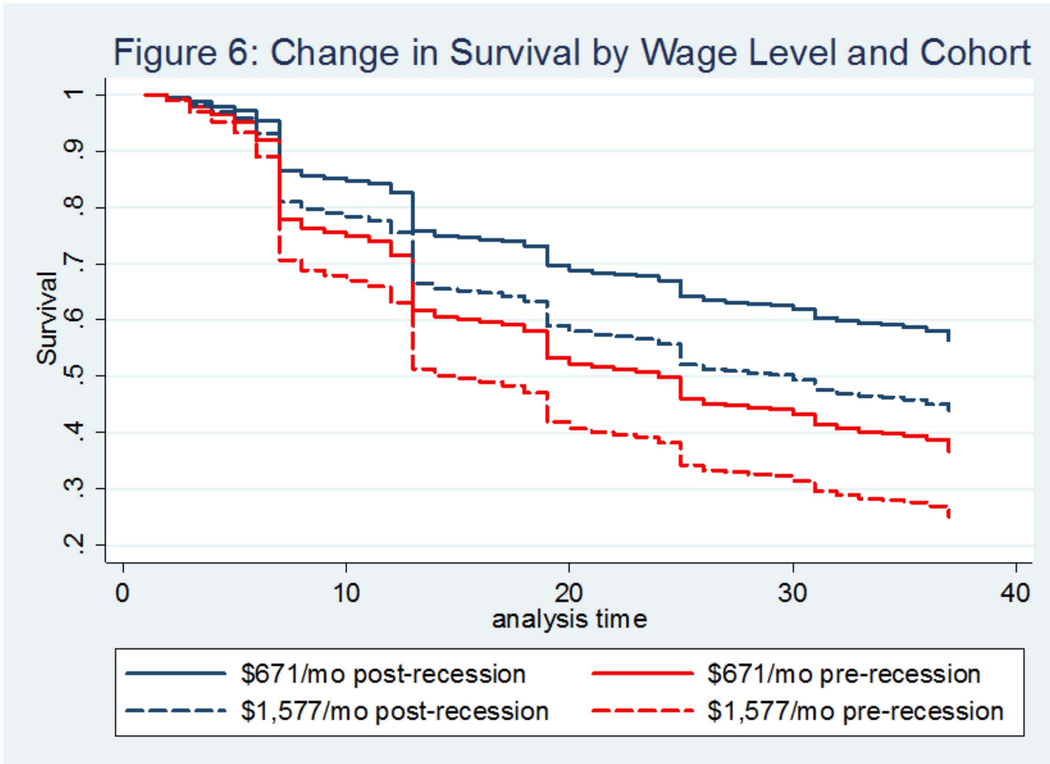
I begin by estimating the survival function for the post-recession cohort at varying levels of wages. I chose three wage points. The first is $671 per month. This is the average wage for those in the post-recession cohort. The second is $754 per month, which is the average wage for those in the pre-recession cohort. The third and final level is $1,577 per month which is the equivalent gross wages for a person working full time, 40 hours a week for 52 weeks a year, at the current Oregon minimum wage of $9.10 an hour.



There is not a very large change in the survival rates or spell lengths between the $671 and $754 monthly wage levels. While the curve for the $754 wage level does sit slightly below the $671 curve, neither curve reveals a medial spell length. This is actually not particularly shocking. While an increase in wages from $671 to $754 is substantial, an 11% increase, both wages are still very meager. A gross monthly wage of $754 amounts to a gross annual income of $9,048 which is 78% of the poverty line for a single individual and is not enough of an increase in wages to raise anyone out of poverty or eligibility for the program. However, the increase to a full time minimum wage job does have a substantial impact on survival rates and spell lengths. The minimum wage curve sits well below the other two curves. The median spell length for an individual making a full time minimum wage income has a median spell length of roughly 30 months.

This is a particularly striking finding. It implies that even if those in the post-recession cohort gained fulltime minimum wage employment it is not enough to drop their median spell length below the median spell length of those in the pre-recession cohort. That means an increase in wages of 135% is not enough to make up for the effects of the recession.

This begs the question: How would the pre-recession cohort respond to a similar increase in wages? How would the magnitude of their response differ? To answer this question I estimate the survival function for the pre-recession cohort at a monthly wage value of $671 per month (the average wage for the post-recession cohort) and $1,577 and combine it with the above survival functions for the post-recession cohort. The differences are remarkable.



As noted above the post-recession cohort experiences a change in median spell length from >37 months to 30 months by increasing wages to fulltime minimum wage. The pre-recession cohort experiences a change in median spell length from 24 months to 14 months by increasing wages to fulltime minimum wage. The change in median spell length for the post-recession cohort is unknown as I was unable to obtain an estimate of median spell length. The change in median spell length for the pre-recession cohort is a 42% decrease. In order for the change in the median spell length for the post-recession cohort to be a 42% decrease the median spell length for the post-recession cohort would have to be 52 months.

A different way to examine the difference in effect size would be to compare the change in the survival rates at different points in time. Table 13 shows the change in the survival rates based on the increase in monthly wages from $671 to $1,577. These changes are calculated at 12, 24, and 37 months. The cohorts start out with similar response sizes, but as time persists the difference between the cohorts increases from 3 percentage points to 10 percentage points. It is now clear that the pre-recession cohort was more responsive to a similar increase in monthly wages than the post-recession cohort.

Table 13: Change in Survival Rates Between Cohorts Based on Wage Levels

	Pre-Recession Survival Rates			**Post-Recession Survival Rates**		
	$671/mo	*$1,577/mo*	*% Change*	*$671/mo*	*$1,577/mo*	*% Change*
12 months	0.61	0.51	16%	0.75	0.65	13%
24 months	0.46	0.34	26%	0.65	0.52	20%
37 months	0.37	0.25	32%	0.58	0.45	22%

What remains unclear are how long this trend will persist and what unobserved factors may be contributing to the observed changes in participation. It would be beneficial to run this analysis on an additional group of SNAP participants who entered in 2012 to see if the pattern has indeed persisted. If these trends persist they hold serious implications for the cost of running the SNAP program. Additional studies that examine more dynamic program participation trends such as entry and exit patterns and participation rate patterns would also shed light on the impact of the recession on participation behavior. A survey analysis that can match personal experiences, feelings, and knowledge with the administrative data of this analysis would give a better understanding of what precise factors are causing the large change in participation behavior.

The recession placed a substantial economic burden on the American public, especially those already in poverty and those in the lower middle class (Elsby et al., 2010; Sum & Khatiwada, 2010; Farber, 2011). Enrollment in SNAP drastically increased during this time. These increases alone placed a substantial burden on the program. However, this analysis revealed that in addition to increases in enrollment there have been substantial and significant increases in the length of time entrants remain enrolled in the program. Now not only does Oregon have more hungry mouths to feed, but it must feed them for much longer.

References

Andren, Thomas. (2007). The Persistence of Welfare Participation. IZA Discussion Paper Series, No. 3100

Andrew, M., Smallwood, D. (2012). What's behind the Rise in SNAP Participation? Economic Research Service Amber Waves. March

Atasoy, S., Mills, B.F., and Parmeter, C.F. (2010) The Dynamics of Food Stamp Program Participation: A Lagged Dependent Variable Approach. Agricultural and Applied Economics Association 2010 AAES, CAES, & WAEA Joint Annual Meeting.

Bean, J.A. & Mattingly, M.J. (2010). More than one in ten American households relies on Supplemental Nutrition Assistance Program benefits. *The Carsey Institute at the Scholars' Repository*. Paper 126.

Blank, R. M. & Ruggles, P. (1994). Short-Term Recidivism Among Public-Assistance Recipients. American Economic Review, 84:2, 49-53.

Bruce, D., Barbour, K., & Thacker, A. (2003). Welfare Program Reentry Among Post-Reform Leavers. University of Tennessee.

Chamberlain, G. (1984). Panel Data", in Griliches, Z. and Intriligator, M. D. (eds.). Handbook of Econometrics, Volume IL Amsterdam: Elsevier Science Publishers.

Currie, J. (2004). The Take Up of Social Benefits. NBER Working Paper Series. WP# 10488.

Department of Human Services. (2013). ARRA Reduction to Monthly SNAP Benefits Talking Points. Oregon Department of Human of Human Services.

Dickens, W. T., Triest, R. K. (2012). Potential Effects of the Great Recession on the U.S. Labor Market. The B.E. Journal of Macroeconomics, 12:3

Elsby, M.W, Hobijin, B., Sahin, A. (2010). The Labor Market in the Great Recession. National Bureau of Economic Research, Working Paper #15979.

"Farber, Henry (2011) : Job loss in the Great Recession: Historical perspective from the displaced workers survey, 1984-2010, Discussion paper series //orschungsinstitut zur Zukunft der Arbeit, No. 5696, http://nbn-resolving.de/urn:nbn:de:101:1-201105173328

Ganong, P., Liebman, J. B. (2013). Explaining Trends in SNAP Enrollment. NBER.

Grambsch, P. M., and T. M. Therneau.(1994). *Proportional hazards tests and diagnostics based on weighted residuals*. Biometrika 81: 515–526.

Heflin, C. M. (2004) Who Exits the Food Stamp Program after Welfare Reform? Institute for Research on Poverty, Discussion Paper no. 1279-04.

Irving, S. K. (2008). State Welfare Rules, TANF Exits, Geographic Context: Does Place Matter. Rural Sociology, 73:3, 605-630.

Kallenber, A. L. (2009). Precarious Work, Insecure Workers: Employment Relations in Transition. American Sociological Review, 74:1, 1-22.

Kim, M. (1998). The Working Poor: Lousy Jobs or Lazy Workers? *Journal of Economic Issues*, 32:1 , 65-78

Lacombe, D. J., Michieka, N. M., Gebremedhin, T. (2012). A Bayesian Spatial Econometric Analysis of SNAP Participation Rates in Appalachia. JRAP, 42:3, 198-209.

Laird, E. & Trippe, C. (2014). Programs Conferring Categorical Eligibility for SNAP: State Policies and the Number and Characteristics of Households Affected. *Mathematica*, Final Report 40202-90

Landers, P.S. (2007). The Food Stamp Program: History, Nutrition Education, and Impact. Journal of the American Dietetic Association, 107:11, 1945-1951.

Mabli, J. & Ferrerosa, C. (2010). Supplemental Nutrition Assistance Program Caseload Trends and Changes in Measures of Unemployment, Labor Underutilization, and Program Policy from 2000 to 2008. Mathematica Policy Research Inc. Final Report.

Mabli, J. & Ohls, J. C. (2012). Supplimental Nutrition Assistance Program Dynamics and Employment Transitions: The Role of Employment Instability. Applied Economic Perspectives and Policy, 34:1, 187-213.

Mosisa, A. & Hipple, S. (2006). Trends in Labor Force Participation. Monthly Labor Review, US Department of Labor.

Mundlack, Y. (1978). On the Pooling of Time Series and Cross Section Data. Econometrica, 46:1, 69-85.

Nichols, A. & Lindner, S. (2013). Why are Fewer People in the Labor Force during the Great Recession? Urban Institute, Brief #16.

Nord, M. & Prell, M. (2011). Food Security Improved Following the 2009 ARRA Increase in SNAP Benefits. USDA Economic Research Service, Economic Research Report Number 116.

Shahin,Jessica. (2009). Improving Access to SNAP Through Broadbased Categorical Eligibility. USDA Food and Nutrition Services Regional Administrators communication. http://www.fns.usda.gov/sites/default/files/093009_0.pdf

Slack, T., Myers, C. A. (2012). Understanding the Geography of Food Stamp Program Participation: Do Space and Place Matter? Social Science Research, 41, 263-275.

SNAP Eligibility. (2013). U.S. Department of Agriculture Food and Nutrition Service. http://www.fns.usda.gov/snap/eligibility. Accessed January, 2014.

SNAP History. (2013). U.S. Department of Agriculture Food and Nutrition Service. http://www.fns.usda.gov/snap/rules/Legislation/about.htm. Accessed January, 2014.

SNAP Summary. (2013). U.S. Department of Agriculture Food and Nutrition Service. www.fns.usda.gov/pd/SNAPsummary.htm. Accessed January, 2014.

Strayer, M., Eslami, E., & Leftin, J. (2012). Characteristics of Supplemental Nutrition Assistance Program Households: Fiscal Year 2011. Supplemental Nutrition Assistance Program Report No. SNAP-12-CHAR.

Sum, A. & Khatiwada, I. (2010) Labor Underutilization Problems of U.S. Workers Across Household Income Groups at the End of the Great Recession: A Truly Great Depression Among the Nation's Low Income Workers Amidst Full Employment Among the Most Affluent. Center for Labor Market Studies Publications. Paper 26.

USDA. (2010). USDA Food and Nutrition Service Supplemental Nutrition Assistance Program (SNAP) American Recovery and Reinvestment Act Plan Update. U.S. Department of Agriculture Food and Nutrition Service.