CARRA Working Paper Series

Working Paper *#2014-15*

The EITC over the business cycle: Who benefits?

Maggie R. Jones
U. S. Census Bureau

Center for Administrative Records Research and Applications
U.S. Census Bureau
Washington, D.C. 20233

Paper Issued: December 16, 2014

The EITC over the business cycle: Who benefits?

Maggie R. Jones*
U.S. Census Bureau

November 4, 2014

Abstract

In this paper, I examine the impact of the Great Recession on Earned Income Tax Credit (EITC) eligibility. Because the EITC is structurally tied to earnings, the direction of this impact is not immediately obvious. Families who experience complete job loss for an entire tax year lose eligibility, while those experiencing underemployment (part-year employment, a reduction in hours, or spousal unemployment in married households) may become eligible. Determining the direction and magnitude of the impact is important for a number of reasons. The EITC has become the largest cash-transfer program in the U.S., and many low-earning families rely on it as a means of support in tough times. The program has largely been viewed as a replacement for welfare, enticing former welfare recipients into the labor force. However, the effectiveness of the EITC during a period of very high unemployment has not been assessed. To answer these questions, I first use the Current Population Survey (CPS) matched to Internal Revenue Service data from tax years 2005 to 2010 to assess patterns of employment and eligibility over the Great Recession for different labor-force groups. Results indicate that overall, EITC eligibility increased over the recession, but only among groups that were cushioned from total household earnings loss by marriage. I also use the 2006 CPS matched to tax data from 2005 through 2011 to examine changes in eligibility experienced by individuals over time. In assessing three competing causes of eligibility loss, I find that less-educated, unmarried women experienced a greater hazard of eligibility loss due a yearlong lack of earnings compared with other labor-market groups. I discuss the implications of these findings on the view of the EITC as a safety-net program.

Keywords: EITC, labor market, recession

JEL classification: H2; J1; J2; J6

*E-mail: margaret.r.jones@census.gov. Center for Administrative Records Research and Applications, 4600 Silver Hill Rd., Washington, D.C. 20233. The views expressed in this paper are those of the author and do not necessarily represent the views of the U.S. Census Bureau. I thank Steven Martin for helpful comments on an earlier draft and Hilary Hoynes for sharing an early draft of Bitler et al. (2014). Thanks also to the Census Bureau's research lunch participants.

1 Introduction

After the welfare reform era of the 1990s, the Earned Income Tax Credit (EITC) emerged as the largest cash-transfer program in the United States (Bitler and Hoynes, 2010). It is a tax credit that is paid to filers as part of a tax refund, and its receipt is dependent on three key prerequisites: a recipient must have earned income in the tax year; he or she must file a federal income tax return; and he or she must specifically file for the credit. While there are other eligibility requirements that come into play, these three rules must be met before receipt occurs. The first prerequisite—earnings—is strictly outlined in the tax code. Those who file for and receive the EITC are required to have income that was earned in the tax year in question, such as wage and salary earnings from an employer or self-employment earnings.

Thus, both a strength and a weakness of the EITC is its tie to work. While the program has been shown to encourage work among those who formerly made up welfare rolls (Hotz and Scholz, 2006; Meyer and Rosenbaum, 2001), its usefulness as part of the social safety net has been questioned due to its focus on labor force participants (Williams and Maag, 2008). For single earners incapable of finding work over a tax year, the program provides zero assistance. On the other hand, in cases of underemployment—or for families where one spouse has become unemployed but the other remains working—the credit may provide crucial financial help.

Bitler et al. (2014) identify key features of the social safety net that an important social program should address. One of these features is the ability of a program to increase protection in times of need. For example, the Supplemental Nutritional Assistance Program (SNAP) expanded over the Great Recession, meeting the needs of more of the population as financial difficulty spread (Andrews, 2013). Whether or not the EITC meets this standard is an open question, and the subject of this and other recent papers (Bitler et al., 2014; Moffitt, 2013).

In the current work, I focus on the dynamics of employment and EITC eligibility over the Great Recession. Previous assessments of the EITC used data covering a period of economic expansion and low unemployment (Bitler and Hoynes, 2010). Moreover, these studies generally focused on a population that was entering the workforce from welfare rolls. With welfare largely a program of the past, the question has changed from whether the EITC induces labor force participation to whether it is a program that can stand in for welfare to some extent in times of need.

Data generated during the recession, which for this work include both survey and tax data, give researchers the opportunity to evaluate the program over a period when jobs were scarce. The survey data used in this study has long been utilized to analyze the EITC and labor force participation: the Current Population Survey Annual Social and Economic Supplement (CPS ASEC). For this study, these data have been linked at the individual level to data from W-2s and 1040s supplied by the Internal Revenue Service. The linked data files are used by the Census Bureau to calculate annual estimates of EITC eligibility for the United States. Having the "true" values for key eligibility parameters—such as earnings, adjusted gross income, and filing status—is an improvement over relying on these same values as reported in the survey data. The survey data, in turn, provide important demographic information for the analysis.

The years I analyze cover the end of the last expansion through the official end of the Great Recession (2005 through 2011). I focus the analysis on all those who worked, according to the tax data, or identified in the survey data as a member of the labor force. The analysis proceeds on groups defined by education, sex, and marital status, with the understanding that labor force experience and thus EITC eligibility differed for these groups (Jones, 2013). Then, using the data set up as a panel, I also examine changes in eligibility status for individuals over time.

The current work contributes to the literature on the EITC, and on transfer programs in general, in several ways. First, the data provide particularly high-quality eligibility estimates due to the inclusion of administrative records. Second, the effect of labor market conditions on EITC eligibility has not been studied, although recent work has been performed on caseloads (Bitler et al., 2014; Williams and Maag, 2008). This lack of research may be due to the fact that the major expansions to the EITC, which went into effect in the mid-1990s, coincided with a period of economic expansion and low unemployment rates. Thus the time-series necessary to test any associations has only now become available. Third, the data provide a rare opportunity to examine eligibility changes for individuals over time, allowing for an analysis of the causes of eligibility loss and how these are related to economic forces.

In what follows, I examine eligibility and benefit changes first as functions of the state unemployment rate. Then, using the 2006 panel of the CPS linked with tax data for 2005 through 2011, I examine competing causes of individual eligibility loss using a competing risks framework. Results indicate that eligibility and modeled benefit amounts increased for the full population of earners with children over the Great Recession. Married earners accounted for these changes, while there was no change in either measure for unmarried earners with children. The competing risks analysis captures what happened to eligible earners over time, looking at how eligibility spells ended for earners first identified in the 2006 CPS ASEC. I find that unmarried women with low educational attainment were more likely to lose eligibility due to a yearlong loss of earnings than were unmarried women with high educational attainment. Tests of equivalence of the effect of education indicate that education was a predictor of eligibility loss through zero earnings only for this group.

These results bring into question the effectiveness of the EITC as a substitute for welfare, as has long been trumpeted by policy experts and economists. During the Great Recession, the policy appears often to have failed its main target population—low-skilled single mothers who would otherwise be welfare users. This is not to suggest that the EITC does not “work” as a policy. In fact, the EITC appears to work exactly as intended, and has been instrumental in drawing welfare leavers into the workforce when jobs are available. However, the results have dire implications for the existing focus in policymaking on tying income supports to work. Economic analyses of the EITC have consistently presupposed that jobs are available to welfare leavers; the current work demonstrates what happens when this assumption is not met.

The paper proceeds as follows. Section 2 provides information on the EITC and previous literature. Section 3 goes over the data used in the analysis, describing the sources for the data and the processes by which data sets are linked. Section 4 describes the methods used. Section 5 presents the results and describes some implications of the results. Section 6 provides some sensitivity analyses, and Section 7 concludes.

2 Background and Literature

The EITC is a refundable tax credit that arrives as a lump sum in an earner's tax return. The main original intent of the EITC was to reimburse payroll taxes for low-income earners, for whom these taxes represent a disproportionately high percentage of earnings (Hoffman and Seldman, 2003). Expansions to the credit in the early 1990s occurred in tandem with welfare reform, with the intent of compensating single mothers for the loss of AFDC receipt by creating a wage subsidy that would make work more affordable. While the credit is modest for earners without children, families with children can receive credits as high as 40 percent of their wage and salary earnings. The EITC has been credited with expanding the labor-market participation of single mothers—in effect "making work pay" (Meyer and Rosenbaum, 2001). Use of the EITC as a "safety net" program changed the nature of government assistance to low-income families, from "out-of-work aid (welfare) to in-work aid (EITC)" (Bitler et al., 2014).

The key issue with viewing the EITC as a safety net program is that receipt is a function of earnings. The program provides zero assistance to someone who is unable to find work. A large body of research has demonstrated that the EITC was instrumental in drawing single mothers into the workforce; however, research that assessed the impact of the EITC on labor-force participation of welfare leavers did so over a period when the economy was expanding and unemployment rates were low (Meyer and Rosenbaum, 2001; Grogger, 2003). Even during this period, evidence indicated that many female-headed households fell through the cracks, receiving neither welfare nor wages. For unmarried mothers who did make the transition, employment was often tenuous and unlikely to be covered by unemployment insurance. Thus, although the transition from welfare to work has been well-documented for most low-income women, a non-trivial proportion were unable to make the transition (Turner et al., 2006).

According to the program parameters,[1] a single labor-force participant becomes eligible when his earnings become greater than 0 and less than the maximum allowable income (defined as the maximum of earnings or adjusted gross income). He loses eligibility when earnings drop to 0 or increase beyond the maximum. A married labor-force participant becomes eligible when she and her spouse earn more than 0 and less than the maximum allowable income. Thus, in cases when one earner becomes full-year unemployed, the family may still be eligible if the other spouse has earnings. Therefore, due to the recession's differential effects on low-skilled earners and men, plus the interaction of marriage and education, it is likely that the direction of eligibility change is different between groups.

This belief is supported by research into the effect of recessions on different skill, sex, and race groups. Elsby and Hobijn (2010) found that—similar to earlier recessions—young, male, and less-educated workers and those from ethnic minorities were more strongly affected by the economic downturn than other groups. In examining an earlier time period (1979-1992), Hoynes (1999) found that the labor market outcome of low-skilled workers exhibit greater cyclicality (wider swings between employment and unemployment, for example) in response to economic downturns compared with higher-

[1] The description that follows is simplified. Earnings is the key eligibility requirement, but there are other rules governing eligibility, such as a limit on investment income.

skilled workers. In tandem with labor market outcomes, earners are known to cycle in and out of EITC eligibility as their incomes fluctuate (Horowitz, 2002).

Moreover, the recent recession was marked by two characteristics of importance to EITC receipt. One was the low rate of exit from unemployment to jobs, indicating a higher rate of all-year job loss compared with earlier recessions. The other was the persistence in the reduction of hours for workers who managed to be employed over the period, which would lead to lower household earnings (Elsby and Hobijn, 2010). Together, these effects may conspire to cancel out overall changes in EITC eligibility. Eligibility by group, however, may change depending on which labor market outcome was predominant.

A further issue is the dynamics of eligibility and marriage. While married men are more likely to participate in the labor force than are single men, married women have lower participation rates than single women, and these differences are themselves affected by skill and presence of children (Juhn and Potter, 2006). Much work has been done as well on the issue of "marriage insurance" or "added worker effect"—the extent to which wives (or husbands) change their participation in the labor force to cushion the shock of a spouse's unemployment (for example, Stephens Jr (2002) and Juhn and Potter (2007)).

Thus, EITC eligibility and employment may be simultaneously predicted by race, gender, education, marriage, and childbearing. Jones (2013), for example, found that men, joint filers, and families with children experienced differentially greater increases in EITC eligibility over the Great Recession, while low-skilled workers experienced decreases.

The cyclical nature of both income and transfer programs has been the subject of much work (for example, Blank (2001) and Ziliak et al. (2000)). Unsurprisingly, previous research has shown that caseloads for public assistance rise when the economy turns down, illustrating the countercyclical nature of transfer programs. A contribution of the current work is to determine the counter- or procyclicality of the EITC by group.

3 Data

3.1 Repeated cross-sections

This study uses two related, longitudinal data sets. The first, a repeated cross-section, is the CPS ASEC–IRS matched file for tax years 2005 to 2010. The data and matching process that generates the data used in this analysis is described at length for tax year 2005 in Plueger (2009). The matching process changed little between 2005 and 2010.

IRS data sets include the universe of 1040 filers for years 2005 to 2010 and the universe of W2 records. Census data include the CPS ASEC for years 2006 to 2011 (since the survey provides answers to questions regarding the preceding tax year). Records were linked using a process whereby individuals in each data set are given a unique key, called a Protected Identification Key (PIK). The Center for Administrative Records Research and Applications (CARRA) assigned these unique identifiers via the Person Identification Validation System (PVS), which employs probability record linkage techniques (see Wagner and Layne (2014) for more information).[2] CARRA uses personally identifiable information (PII) such as name, date of birth, and address to assign a PIK. CARRA then removes the PII from the data file to anonymize the data and preserve confidentiality so it can be used for statistical purposes and research. Only those observations that received the unique key are used in the analysis. Furthermore, a match is only used if CPS earnings were not imputed or allocated.[3]

Eligibility for the EITC is modeled based on the program parameters. The Census

[2] Over the time period included, the PVS system was altered to include 1040 observations with Individual Taxpayer Identification Numbers (ITINs). The inclusion of ITINs changes the sample slightly, with more non-citizen tax filers being identified. These observations would, however, only be EITC eligible if they were married to a 1040 filer with an SSN. To check whether this had any influence on my results, I ran all analyses on citizens. The results were unaffected.

[3] There is some bias introduced in who receives a PIK and who does not; see (Bond et al., 2014). To check whether this bias affects my estimates, I ran weighted models where the CPS sample weights had been recalculated based on the probability of receiving a PIK. Estimates were unchanged.

Bureau's estimates of eligibility use the survey responses to questions regarding variables that reflect the program parameters, which are superseded by the "true" value from the tax data whenever possible. Such variables include earnings, adjusted gross income, investment income, and filing status. Problems in determining eligibility largely arise due to uncertainty regarding household formation, since the presence of children is a prerequisite for the higher EITC amounts and the wider range of eligible earnings. Moreover, children must meet certain age and residency restrictions. This work uses the modeled data, which has indicators for estimated eligibility and values for the total EITC amount a family is eligible for.

The repeated cross-section sample is restricted to members of the labor force who have children, mainly because the incidence of eligibility among non-parents is so low that it is difficult to assess changes over time. The data are aggregated into groups defined by sex, skill, and marital status. This aggregation follows similar work by Hoynes (1999), with the exception that marital status is included as an important component in eligibility determination due to the effect of spousal earnings, and race is not included.[4] Skill is defined based on whether the earner has less than a high-school education or more than a high-school education. Marital status is defined by an earner's or family's 1040 filing status, which is augmented using the marital status indicator in the CPS ASEC for those who do not file.

For the regression analysis, the data are further aggregated into cells defined by state and year, such that each cell contains the mean for the dependent variables for each skill/marital group.[5] Each regression is weighted using the underlying population of each cell. The raw count of possible observations is therefore 51 states multiplied by 8 skill groups and 6 years.

[4]Even when grouped into two-year periods, there were not enough observations within certain state-years to also collapse by race.

[5]In this paper, the District of Columbia is treated as a state equivalent.

3.2 Panel data

While cross-sectional data provides a year-by-year snapshot of eligibility rates by skill group, and can be used to examine the relationship between economic conditions and eligibility, such data are not suited to examining the causes of eligibility loss or gain. The cause of loss or gain in one period for an individual can only be determined by observing the individual in the preceding period. Thus the second data set is a panel based on the 2005 linked CPS ASEC–IRS matched file, in which each adult earner in the file is linked to tax data from tax years 2005 to 2011. The panel data allow me to track the eligibility experiences of respondents to the 2006 CPS ASEC for a further 6 years, with some limitations that are explained below.

Eligibility for 2006 CPS ASEC respondents is modeled using further years of 1040 and W2 data. I consider household structure to be fixed at the characteristics reported in the survey, and I then age-out children from qualifying status using the ages reported for them in 2006. The number of children reported for a household is replaced by the number of children claimed on 1040 data in future years. Similarly, I assume that an individual's marital status remains at 2006 reports unless he or she reports otherwise in later 1040 data. I limit the sample to those who report 1040 or W-2 earnings in 2005, since I am not able to track earnings for those who report in the survey that they were self-employed in 2006. Year-by-year self-employment earnings can only be observed using survey data.

Using W-2 earnings, 1040 earnings, 1040 AGI, 1040 interest income, marriage in 2006 superseded by filing status in later years, and children reported in 2006 superseded by children claimed in later years, I run the eligibility modeling for each subsequent tax year. I retain all earners in the file who experienced a spell of eligibility between 2005 and 2011. The eligibility of married persons is treated separately, since joint filers may file separately in a later year. For each earner, I look only at the first episode of eligibility, and the data is right-censored (eligibility spells that do not end).

There are some concerns in using this data as described, some of which can be partially addressed. The first issue is that some respondents to the 2006 ASEC may have left the sample, and their attrition is due to something other than lack of labor-force participation and 1040 filing. Some 2006 survey respondents may have died. Others may have left the labor force due to disability or retirement, although we would expect these respondents to have filed taxes in later years due to sources of income such as Social Security benefits. To address this issue to some extent, I remove any survey respondents if I observe them in a given year, but never in a subsequent year. For example, if I have a W-2 record for a survey respondent in 2009, but I do not have a W-2 or 1040 record for her in 2010 or 2011, I drop her from the sample. The loss of a such a respondent means that the long-term unemployed will be underrepresented in the final sample. Because the relationship between unemployment and EITC eligibility is the focus of the analysis, any coefficients reporting this relationship will be underestimated. I examine the impact of this sample restriction in Section 6.

A second concern is education, as many EITC-eligible respondents may continue their education over the time period. There is no method by which these changes can be captured. As a partial solution to this problem, I restrict the sample to respondents who were 25 or older at the time of the CPS survey, thus retaining those who have more likely finished their education by tax year 2005.

4 Methods

One way to examine an association between economic conditions and changes in EITC eligibility and benefit levels over time is to run regressions of unemployment rate on each dependent variable, controlling for state and time effects. This is the technique employed by Bitler et al. (2014) in their analysis of EITC caseloads, which employs Statistics of Income (SOI) data from 1996 to 2008. It is instructive to look at results from a similar model and compare them. The equation below gives the general model used:

$$y_{ist} = \beta * UN_{st} + \sigma_s + \tau_t + Z_{st}\pi + \epsilon_{ist} \quad (1)$$

The parameter of interest is β, which gives the effect of the state unemployment rate on EITC eligibility or benefit amount. Included are fixed effects for year (τ_t), and state (σ_s), as well as state-level variables that may affect both the demand and supply of labor (state EITC and state minimum wages, expressed in log form). The model is run using the full sample collapsed by labor-market group, state, and year. These groups form a model in which married and unmarried labor-market participants are analyzed separately.

The model above describes the changes experienced by groups in repeated cross sections over the course of the recession, which is useful for making comparisons about similar populations over time. Using the panel data, the key question is how eligibility changed for individuals over time in response to changes in economic circumstances. To answer this question, I run competing risks models that examine how eligibility spells for the EITC end. The different ways a person could lose eligibility were pooled into three risk categories: total loss of earnings, earnings or AGI above the maximum, and family change (including loss of qualifying children and marriage or divorce).

To the extent that eligibility determination is based on EITC rules, these risk categories are exhaustive but not mutually exclusive without making some important assumptions. A person without earnings is, by definition, ineligible. However, a person who chooses not to earn a wage because of high total income would not have been eligible regardless of whether he or she wanted to earn a wage. Thus I categorize the initial risk as due to loss of earnings, but replace the risk category as due to high income if a respondent without earnings fits this definition. Income maximums for eligibility are, however, dependent on family structure, with higher income levels allowed for married couples and those with children. Thus I supersede the high-AGI category with the family-change category for cases in which the respondent reported earnings, had income above the maximum, and in the same period experienced a change in family status.

Anyone who experienced a spell of eligibility over the time period is included in the final sample, and for consistency with the preceding analysis, I also restrict the sample to earners who had at least one qualifying child in at least one tax year. A person is considered as becoming at risk for leaving eligibility when he or she is eligible in any time period, including the first. Meanwhile, eligibility that does not end by 2011 is censored.

The modeling technique I use is that of Fine and Gray (1999). In contrast to a Cox regression analysis, a Fine and Gray competing risk analysis allows a researcher to assess events that compete with failure from the event of interest, rather than having competing events treated as though they were censored. Rather than a survivor function, competing risks models consider a failure function—the cumulative incidence function (CIF), which describes the probability that an event will take place before a certain time ($P(T \leq t$ and event type k)).

Fine and Gray (1999) defined a "hazard of the subdistribution" as

$$\lambda_1(t; \mathrm{X}) = \lim_{\delta t \to 0} \frac{1}{\delta t} Pr[t \leq T \leq t + \delta t, \epsilon = 1 | T \geq t \cap \epsilon \neq 1, \mathrm{X}] \tag{2}$$

where λ_1 is the hazard of interest, while those who fail due to other hazards remain at risk. The cumulative hazard function can be easily calculated from the subdistribution hazard. The baseline subhazard is subsumed in the model, while the effects of covariates, as in a Cox regression, are proportional:

$$\lambda_1(t; \mathrm{Z}) = \lambda_{1,0}(t) \exp[\mathrm{X}^T(t)\beta] \tag{3}$$

I also included time-varying coefficients in the model, since these were seen to be significant upon inclusion. In other words, for a given covariate x_1, the proportion becomes

$$\lambda_1(t; \mathrm{Z}) = \lambda_{1,0}(t) \exp[(\beta_1 + \gamma_1 g(t))x_1] \tag{4}$$

where $g(t)$ is a linear function of time. Thus, γ_1 gives the magnitude of the deviations from the main effect, β_1, over time.

The Fine and Gray model takes the last value of a time-dependent covariate for an observation that fails because of a competing risk. The inclusion of a time-dependent measure may bias the results because later values are not captured. Thus, I use only time-invariant covariates or those measured at baseline (tax year 2005). These include two education levels (defined in the same way as in the cross-sectional analysis), marriage status, race, Hispanic origin, age, number of qualifying children, and the state unemployment rate and EITC. When unemployment rate is included as a time-varying measure, the risk ratios on the variable of interest—education—do not change substantially. Each set of models include the variables from this list interacted linearly with time when the interaction is found to have a significant effect in one of the models.

As in the cross-section analysis, the focus is on the intersection of sex, skill, and marriage in the joint determination of labor-market and eligibility outcomes. Thus I run the analysis on the full sample and four subgroups: unmarried women, unmarried men, married women, and married men. The main independent variable is education, which captures how the two skill groups within each subgroup fared in terms of eligibility over the recession. In Section 6, I provide a similar Cox analysis which allows me to further test the differential effect of education for groups analyzed in different models but sharing overlapping characteristics.

5 Results

5.1 Summary statistics

First, a look at the summary statistics of both the cross-sectional and panel data is in order. Table 1 shows the rates of eligibility for the different marriage/skill/sex groups for 2005 and 2010, showing the manner in which eligibility changed for each group. Also shown are two measures of employment experiences: “Any work," which is an indicator variable equal to 1 when a respondent reports working at all during the tax year; and “Average weekly hours,” which is a continuous variable reporting the number hours the respondent usually worked per week in the tax year. Both employment variables show a decrease for each of the skill groups, with low-skill workers showing the largest decreases. In terms of eligibility, all groups except low-education, unmarried women experienced increases, with the largest increases seen for married, low-education workers. Overall the results give suggestive evidence that eligibility increases were codetermined with poor job market outcomes, but only for those who were married.

It is instructive to look at the changes experienced by each group in the distribution of earnings, which is shown in Figure 1. Each of the 8 labor-market groups are shown. The changes in earnings distributions provides some suggestive evidence of how eligibility might change for these groups in an economic downturn. Each panel shows the kernel density for real family earnings in 2005 and 2010, over a range of earnings between \$0 and \$50,000.[6] Droplines indicate the maximum earnings allowed for those with one child and more than one. Density of earnings for all groups have large increases at 0, but this is more marked for lower-skilled earners. With the possible exception of high-skill married men, there is increased density between 0 and the maximum incomes—this is especially marked for unmarried, high-skill men. Female earners similarly show a greater density in 2010 at 0 for most groups. This appears to be strongest

[6] Earnings for joint filers is the sum of earnings from both spouses. Earnings for 2005 have been adjusted for inflation to 2010 dollars.

for unmarried, low-skill women. Meanwhile, density of earnings in the eligible area appears to be slightly higher for married earners, but unchanged for unmarried earners.

These relationships between unemployment and eligibility in the cross-sectional data are examined more closely in the regression results in Table 3, discussed in subsection 5.2.

Moving to the panel data, Panel A of Table 2 shows the pattern of eligibility spells for the respondents in the 2006 CPS ASEC, with each cell capturing the number who started a spell in the year listed in the row and ending in the year listed in the column. As reported in the table, a total of 20,759 CPS ASEC 2006 respondents were eligible at some point between 2006 and 2011. Of these, 10,745 started the period in an eligible state. Of those who were eligible in the first period, 3,156 (30 percent) retained eligibility for the entire period (reported in Panel B). For those who became eligible after tax year 2005 (12,045 respondents), 3,826 retained eligibility to the end (37 percent). Most spell lengths for those eligible in the first period were seven years, followed by one year. For those starting in period 2 or later, most eligibility spells were one year. As with any duration data, it is impossible to know what eligibility spells would look like if we had everyone's lifetime history. However, it does appear as though EITC eligibility, at least over the recession, was persistent for much of the sample.

Table 3 shows the yearly rate of failure due to the different risk types, defined earlier. The table displays the number of observations and the percent over each of the three risks. Those who do not fail in a given year include those who retain eligibility and those who are not yet eligible. The percentages indicate that there was an uptick in eligibility loss due to total lack of earnings beginning in 2009, the year when the national unemployment rate increased to 10 percent.

5.2 Regression results

Table 4 shows the regressions of unemployment rate on eligibility, benefit, and employment outcomes, both pooled over the entire sample, broken out between married and single filers, and broken out by skill group. These results gives an idea of how aggregate eligibility changed over time for these skill groups in response to changes in the state unemployment rate.

In each case, the results show the coefficient from a regression of the unemployment rate on the dependent variable listed in the column. For all models, data were collapsed into group-state-year cells. Each equation includes state and year fixed effects and measures of state EITCs and minimum wages. All equations are weighted using the cell population as the weight.

The results using the full data show that the state unemployment rate is associated with an increase in EITC eligibility and modeled benefit amount in the population of earners with children. The effect on eligibility is small but statistically significant, with a one percent increase in the unemployment rate associated with an eligibility increase of less than a tenth of a percent. Comparing married with unmarried earners indicates that the change overall is driven by an increase in eligibility for married earners. This is suggestive of a "marriage insurance" effect, implying that as one spouse loses work, the other has income that will keep the family eligible. It may also indicate how married families may be driven into eligibility through lower earnings overall, but an absence of zero earnings due to two workers.

The effect of unemployment rate on eligibility for married earners is larger than that found by Bitler et al. (2014) for caseloads. The authors found an effect of 0.007 for married tax filers with one child and and effect of 0.01 for those with two or more children.

In looking at the results for labor market groups, married men with low educational attainment are the only group to see statistically significant increases in eligibility in response to the unemployment rate (about a 0.01 increase in eligibility for a 10 percent increase in unemployment). The coefficients for all other groups except for unmarried, low-skill women are positive, but not statistically different from 0. This may be due to the small samples available when running the models separately by group.

Table 5 shows the results of the competing risks analysis when the full panel is used. Hazard ratios are reported for each of the risks in separate columns. Each hazard ratio indicates the main effect of the variable on the probability that an eligibility spell ended through the given risk. The main effect for each time-invariant covariate is shown.[7]

As in any hazard analysis, the ratios report the additional likelihood that an observation with the given characteristic (or higher value) failed for the reason specified. Results show that women were less likely than men to lose eligibility by any means, and that the hazard ratio was fairly similar across risks. In general, women had about a 30 percent lower risk of any type of eligibility loss compared with men. Compared with the more highly educated, those with a high school education or less had a 35 percent lower risk of loss due to high income, and a 21 percent lower risk of loss due to family change. Those who were unmarried at baseline were about 40 percent less likely than those who were married to lose eligibility due to total earnings loss or high income, and 19 percent more likely to lose eligibility due to family change. Those who reported Black alone as their race were about a quarter less likely as those reporting White alone to experience eligibility loss due to earnings loss, about half as likely to lose eligibility due to high earnings, and about 40 percent less likely to lose eligibility due to family change. Those reporting their race as "other" were less likely than those reporting White alone to lose eligibility due to high income or family change (27 percent and 26 percent, respectively). Those identifying as Hispanic were about a quarter less likely to lose eligibility due to high income or family change compared with non-Hispanics. Older respondents were slightly more likely to lose eligibility through any risk. Those with more qualifying children at baseline were less likely to lose eligibility through high income or family change,

[7]I do not show time-varying coefficients, but they are described in the footnote to each table.

with a further child translating into a 5 percent lower risk of loss due to high income and an 10 percent lower risk of loss due to family change. Finally, the baseline unemployment rate in the state was associated with an increased risk of eligibility loss due to high income (8 percent, respectively), but a lower risk of loss due to family change. This last finding is surprising, although it could be capturing earnings growth over the period for those who manage to stay in the workforce in high-unemployment areas. This earnings growth may reflect a greater number of hours worked for those who retained a job during this period as employers limited hiring.

While the preceding analysis gives an idea of how different groups fared during the recession, it does not capture the interactions between characteristics that might lead to different outcomes in terms of eligibility. To explore further how gender, education, and marital status may predict how an individual loses eligibility—and to coordinate the panel data results with those from the cross-sectional analysis—I separately examine four groups defined on gender and baseline marital status. The main independent variable of interest for these subsamples is low-education.

Table 6 shows the competing risks analysis for women who were unmarried at baseline and men who were unmarried at baseline (separate models). In contrast with the full model, compared with more highly educated unmarried women, unmarried women with low education were 22 percent more likely to experience eligibility loss due to lack of earnings, and about half as likely to lose eligibility due to high income. In contrast, low-education unmarried men were no more likely to lose eligibility due to lack of earnings than their more highly educated peers. They were, however, about 30 percent less likely to lose eligibility due to high income. Unmarried women who reported their race as Black did not differ in their risk profile compared with the full sample, with the exception that the hazard ratio on loss due to lack of earnings is not precisely estimated. Black unmarried men did not differ from White unmarried men except for the risk of loss due to high income, with Black men 61 percent less likely to lose eligibility due to this risk (the same pattern was seen for women who reported their race as "other"). Women who reported their race as Asian alone were 2.7 times as likely than White alone, unmarried women to experience eligibility loss due to family change. These results may be driven by a small number of observations, since there are few Asian women who were unmarried at baseline but have children at some point during the sample period. For unmarried women, having more children at baseline translated into a lower risk of eligibility loss due to high income or family change. An increase in one qualifying child was associated with a 37 percent decrease in loss due to high income and a 34 percent decrease in the risk of loss due to family change. For men, a one-child increase was associated with a 41 percent lower risk of loss due to high earnings.

Table 7 shows the same analysis for women and men who were married at baseline. Because I am looking at individual trajectories, it seems important to point out that the subsamples shown in these tables include observations who were married to one another at baseline. If many of these couples remained married, their failure from a particular risk would have occurred concurrently. Thus, it is not be surprising that the risk profile for married women and men look more similar to one another than the profiles for unmarried women and men. Both men and women with low educational attainment were less likely than their better-educated counterparts to experience loss due to high income (38 percent less for women and 32 percent for men) and family change (29 percent less for women and 26 percent for men). Married women who reported their race as Black alone were less likely than married White women to lose eligibility due to lack of earnings or family change. Both men and women who reported Asian alone were less likely than married whites to lose eligibility due to family change. Hispanic men were less likely than non-Hispanic men to lose eligibility due to high earnings. For married men and women, a one-year increase in age at baseline was associated with a 1 to 2 percent increase in eligibility loss for any reason; however, the ratios were not statistically significant for the lack of earnings risk for women and the family change risk for men.

Baseline number of children and unemployment rate were, for married men, associated with an increase in eligibility loss due to high income.

6 Sensitivity analyses

The creation and analysis of the panel data required some assumptions that may have affected the results just discussed. The first issue is attrition: observations for whom we do not have a further record in the tax data after a given year. Among the many reasons why we would not have data for these observations is withdrawal from the labor market. Dropping these observations may thus significantly underestimate the effect of the Great Recession on eligibility, since one of the distinguishing features of the latest recession was long-term unemployment and the discouragement of workers (Elsby and Hobijn, 2010). To test the effect of attrition, I ran models that retained the missing observations and coded the failure type for these observations as due to a lack of earnings. The results are reported in Table 8.

The table shows the results for unmarried and married respondents when those who attrit from the data are retained and their risk is coded as "no earnings." For unmarried women, the risk of eligibility loss due to lack of earnings is intensified (36 percent versus 22 percent), which fits the hypothesis that workers with less skill are more likely to withdraw from the labor market due to discouragement. The corresponding risk ratios for the other groups are not different. For loss due to lack of earnings, age now appears to have a positive relationship for all groups, with older ages associated with a higher risk. This positive effect may reflect loss that has been coded as lack of earnings but is not due to discouragement, but rather a withdrawal from the workforce due to death, disability, or retirement (although we would expect this last group to still file 1040s to reflect retirement income).

A second issue of possible concern is the use of the Fine and Gray model. The justification for using the model depends on how the question is framed. The preceding analysis presented hazard ratios when the comparison groups were retained as still at risk rather than censored. Using data duplication (such as the technique outlined in Putter et al. (2007), among others), similar models can be run using Cox regressions where the hazards for each risk are modeled simultaneously.

Table 9 shows the results of running Cox models. The results are similar to the main models, with certain hazards slightly greater and others diminished. Specifically, the risk that unmarried women lose eligibility due to a lack of earnings is again 18 percent greater if she has low educational attainment. Also of interest are the hazard ratios for unemployment rate, none of which are statistically significant in the Cox models.

Using Cox models also allows for tests that the effect of education on the risk of loss due to lack of earnings is statistically different between groups that share an important characteristic. For example, we might want to know whether the effect of education, which is significant only in the models restricted to unmarried women, truly differs between married and unmarried women (or unmarried women and unmarried men). Such an analysis is possible with a Cox model that has been stratified by the variable of interest to estimate the separate baseline hazard rates. Currently, there is no similar test available with the Fine and Gray model (Putter et al., 2007).

Each Cox model is run with the variable of interest—education—interacted with each independent variable and then used to stratify the model. When looking only at women, the coefficient on married times education provides a test of whether the effect of education is the same for unmarried and married women. The Chi-squared value for this test was 5.7, allowing for a rejection of equality. Similarly, when looking only at those who were unmarried at baseline, the coefficient on sex times education provides a test of whether the effect of education is the same for men and women. The Chi-squared value in this case was 5.5, again allowing for a rejection of equality. These tests reinforce the interpretation that unmarried women whose educational attainment was low faced a greater risk of eligibility loss due to zero earnings than did other groups who shared a common characteristic (female or unmarried).

7 Conclusion

Considering the EITC's importance in bolstering the income of low-wage earners, any evaluation of the program needs to take into account what happens when incomes are threatened by an economic downturn. An inspection of the distribution of earnings from before and after the recession revealed that labor force participants experienced a spike at 0 earnings, which would, by construction, make them ineligible for the EITC. This is true for single filers and for married filers who do not have a spouse's earnings to rely on. Many skill and marital groups experienced a slightly higher density of earnings in the eligibility range, but this effect was concentrated among married earners.

Results from plotting the data, as well as regressions of state unemployment on eligibility, indicate that married earners saw increases in eligibility, while eligibility was flat for single earners. The only explanation for this in light of almost-universal negative job market experiences is that the presence of spousal earnings retained eligibility, or drove families into eligibility when their previous earnings had been too high. Clearly, marriage has a protective effect when it comes to the EITC.

The results of a competing-risks analysis support and extend this hypothesis. Unmarried women experienced a higher risk of loss due to zero earnings when their educational attainment was low. This result is troublesome, since it indicates that, at least in a downturn, the EITC fails to reach the target population for whom it was specifically expanded during the welfare reform era. Looking at the outcomes for individuals over time indicates that marriage, gender, and skill were each important factors in how individuals transitioned out of eligibility.

The effectiveness of the EITC in meeting its policy goals is not in question. During times when employment opportunities are widely available, there is no doubt that the EITC is strong enticement for labor force participation. There is also no doubt that it has provided a substantial boost in income for those who can find work, especially married families where one spouse remains employed. However, all of the excellent aspects of the policy become irrelevant for single earners when no jobs are available. Between the difficulty of enrolling in TANF or remaining in the program, a lack of coverage of unemployment insurance and curtailment of benefits, and cuts to the Supplemental Nutrition Assistance Program, many female-headed households may soon find themselves without a safety net program to assist them in times of need.

References

Andrews, M., 2013. Usda economic research service-more americans relied on food assistance during recession.

Bitler, M., Hoynes, H., Kuka, E., 2014. Do in-work tax credits serve as a safety net? Tech. rep., National Bureau of Economic Research.

Bitler, M. P., Hoynes, H. W., 2010. The state of the social safety net in the post–welfare reform era. Brookings Papers on Economic Activity.

Blank, R. M., 2001. What causes public assistance caseloads to grow? Journal of Human Resources 36 (1), 85–118.

Bond, B., Brown, J. D., Luque, A., O'Hara, A., 2014. The Nature of the Bias When Studying Only Linkable Person Records: Evidence from the American Community Survey. Tech. rep., U.S. Census Bureau, Center for Administrative Records Research and Applications.

Elsby, M. W., Hobijn, B., 2010. The labor market in the great recession. Brookings Papers on Economic Activity.

Fine, J. P., Gray, R. J., 1999. A proportional hazards model for the subdistribution of a competing risk. Journal of the American Statistical Association 94 (446), 496–509.

Grogger, J., 2003. The effects of time limits, the EITC, and other policy changes on welfare use, work, and income among female-headed families. Review of Economics and Statistics 85 (2), 394–408.

Hoffman, S. D., Seldman, L. S., 2003. Helping Working Families: The Earned Income Tax Credit, w Edition. W.E. Upjohn Institute for Employment Research, Kalamazoo, MI.

Horowitz, J. B., 2002. Income mobility and the earned income tax credit. Economic Inquiry 40 (3), 334–347.

Hotz, V. J., Scholz, J. K., 2006. Examining the effect of the Earned Income Tax Credit on the labor market participation of families on welfare. Tech. rep., National Bureau of Economic Research.

Hoynes, H., 1999. The employment, earnings, and income of less skilled workers over the business cycle. Tech. rep., National Bureau of Economic Research.

Jones, M. R., 2013. Changes in EITC eligibility and participation: 2005–2009. IRS Research Bulletin.

Juhn, C., Potter, S., 2006. Changes in labor force participation in the united states. The Journal of Economic Perspectives 20 (3), 27–46.

Juhn, C., Potter, S., 2007. Is there still an added-worker effect? FRB of New York Staff Report (310).

Meyer, B. D., Rosenbaum, D. T., 2001. Welfare, the Earned Income Tax Credit, and the labor supply of single mothers. Quarterly Journal of Economics 116 (3), 1063 – 1114.

Moffitt, R. A., 2013. The great recession and the social safety net. The ANNALS of the American Academy of Political and Social Science 650 (1), 143–166.

Plueger, D., 2009. Earned Income Tax Credit participation rate for tax year 2005. IRS Research Bulletin.

Putter, H., Fiocco, M., Geskus, R., 2007. Tutorial in biostatistics: competing risks and multi-state models. Statistics in medicine 26 (11), 2389–2430.

Stephens Jr, M., 2002. Worker displacement and the added worker effect. Journal of Labor Economics 20 (3), 504–537.

Turner, L. J., Danziger, S., Seefeldt, K. S., 2006. Failing the transition from welfare to work: Women chronically disconnected from employment and cash welfare*. Social Science Quarterly 87 (2), 227–249.

Wagner, D., Layne, M., 2014. The Person Identification Validation System (PVS). Tech. rep., U.S. Census Bureau, Center for Administrative Records Research and Applications.

Williams, R., Maag, E., 2008. The recession and the Earned Income Tax Credit. Tech. rep., The Urban Institute.

Ziliak, J. P., Figlio, D. N., Davis, E. E., Connolly, L. S., 2000. Accounting for the decline in afdc caseloads: Welfare reform or the economy? Journal of Human Resources, 570–586.

Table 1: Eligibility statistics: Cross-section data

	Eligibility			Any work			Average weekly hours (log)		
	2005	2010	change	2005	2010	change	2005	2010	change
Married MTHS men	0.08	0.10	0.02	0.97	0.91	-0.09	3.74	3.66	-0.09
	0.00	0.00		0.00	0.00		0.00	0.01	
Married HS men	0.25	0.35	0.10	0.95	0.80	-0.20	3.68	3.47	-0.21
	0.01	0.01		0.00	0.01		0.01	0.01	
Unmarried MTHS men	0.29	0.35	0.06	0.89	0.87	-0.13	3.58	3.43	-0.16
	0.02	0.02		0.01	0.01		0.03	0.04	
Unmarried HS men	0.53	0.58	0.05	0.90	0.81	-0.19	3.50	3.20	-0.30
	0.02	0.02		0.01	0.01		0.03	0.03	
Married MTHS women	0.17	0.22	0.06	0.94	0.92	-0.08	3.47	3.39	-0.08
	0.01	0.01		0.01	0.01		0.02	0.03	
Married HS women	0.45	0.54	0.09	0.93	0.86	-0.14	3.35	3.23	-0.12
	0.02	0.02		0.01	0.02		0.03	0.04	
Unmarried MTHS women	0.53	0.56	0.03	0.94	0.91	-0.09	3.43	3.23	-0.20
	0.01	0.01		0.01	0.01		0.02	0.02	
Unmarried HS women	0.77	0.74	-0.03	0.92	0.83	-0.17	3.19	2.95	-0.24
	0.01	0.01		0.01	0.01		0.02	0.03	

Source: CPS ASEC-IRS linked file for tax years 2005-2010. Reported are the means for each variable after collapsing into cells defined by skill, state, and year.

Table 2: Eligibility statistics: Panel data

	Exit year							
Panel A	2006	2007	2008	2009	2010	2011	Never	Total
Start year: 2005	3,372	1,449	999	558	524	401	3,156	10,459
2006		1,229	711	295	245	169	997	3,646
2007			707	222	145	116	387	1,577
2008				526	268	152	461	1,407
2009					823	324	604	1,751
2010						542	545	1,087
2011							832	832
Total	3,372	2,678	2,417	1,601	2,005	1,704	6,982	20,759

Panel B	EITC eligibility	
Starting in	Period 1	Period 2 or later
Number	10,459	10,300
percent	50.38	49.62
Number right censored	3,156	3,826
percent	30.17	37.15
Spell length (years)		
1	32.24	42.23
2	13.85	20.10
3	9.55	11.61
4	5.34	7.98
5	5.01	5.40
6	3.83	9.68
7	30.17	-

Source: CPS ASEC 2006 linked with 1040 and W-2 data from 2005–2011. Panel A reports the number of observations fitting into each spell category. Panel B reports the proportion of observations experiencing the spell type described.

Table 3: Risk of failure by year and risk type, panel data

Exit year	2006	2007	2008	2009	2010	2011
No earnings	856	460	455	476	444	298
percent of failure	0.25	0.17	0.19	0.30	0.22	0.17
Income>max	1,152	928	727	582	893	755
percent of failure	0.34	0.35	0.30	0.36	0.45	0.44
Family change	1,364	1,290	1,235	543	668	651
percent of failure	0.40	0.48	0.51	0.34	0.33	0.38
No failure	17,387	14,709	12,292	10,691	8,686	6,982

Source: CPS ASEC 2006 linked with 1040 and W-2 data from 2005–2011. Reported are the numbers and percentages that failed due to the risk listed in column 1. The number who do not experience a failure in a given year includes those who are eligible and do not fail in that year and those who are not yet eligible. Total observations is 20,759.

Table 4: Effect of unemployment rate on EITC eligibility, take-up, modeled benefit amount, and actual amount received

	Eligibility	Benefit (log)	Obs.
All	0.06*	0.45*	2,431
	(0.03)	(0.21)	
Married earners	0.06*	0.43*	1,214
	(0.03)	(0.19)	
Unmarried earners	0.04	0.31	1,217
	(0.04)	(0.23)	
Married men, high education	0.03	0.20	306
	(0.02)	(0.11)	
Married men, low education	0.09*	0.69	306
	(0.04)	(0.29)	
Unmarried men, high education	0.08	0.83	301
	(0.10)	(0.69)	
Unmarried men, low education	0.01	0.24	304
	(0.07)	(0.46)	
Married MTHS women	-0.02	-0.04	306
	(0.07)	(0.51)	
Married HS women	0.07	0.37	296
	(0.08)	(0.55)	
Unmarried MTHS women	0.04	0.28	306
	(0.04)	(0.25)	
Unmarried HS women	-0.02	-0.18	306
	(0.05)	(0.32)	

Source: CPS ASEC-IRS linked file for tax years 2005-2010.
$*p < 0.05, **p < 0.01, ***p < 0.001$.The number of observations reflect the way the data were collapsed: by skill, marriage, sex, state, and year. Each column shows the coefficient on unemployment rate from a regression including state and year fixed effects and state-level EITC and minimum wage. Standard errors clustered at the state level appear in parentheses.

Table 5: Competing risks models, full sample

	No earnings	Income>max	Family change
Main			
Female	0.68***	0.73***	0.65***
	(0.06)	(0.05)	(0.04)
HS or less	0.95	0.65***	0.79***
	(0.09)	(0.04)	(0.05)
Unmarried in 2005	1.00	0.57***	1.19***
	(0.04)	(0.02)	(0.03)
Black alone	0.77*	0.52***	0.60***
	(0.09)	(0.05)	(0.05)
Asian alone	1.05	1.19*	0.69***
	(0.10)	(0.07)	(0.05)
Other race	0.71	0.73	0.74*
	(0.14)	(0.12)	(0.11)
Hispanic	0.85	0.77***	0.79**
	(0.09)	(0.07)	(0.06)
Age	1.02***	1.02***	1.01*
	(0.01)	(0.00)	(0.00)
Number of children	1.03	0.95***	0.90***
	(0.02)	(0.01)	(0.01)
Unemployment rate	0.94	1.08*	0.94
	(0.04)	(0.04)	(0.03)
State EITC	0.79*	1.07	0.88
	(0.08)	(0.08)	(0.06)
Percent failing	14.40	24.26	27.70
Observations		20,759	

Source: CPS ASEC 2006 linked with 1040 and W-2 data from 2005–2011. $*p < 0.05, **p < 0.01, ***p < 0.001$. Reported are the coefficients from a competing risks model in which each risk is modeled separately. For example, leaving eligibility due to no earnings is compared to leaving eligibility either for family change or earnings/AGI above the maximum. All variables reflect status in tax year 2005. Standard errors, clustered on the individual, appear in parentheses. Not reported are time-varying coefficients for sex, education, Black alone, other race, Hispanic, age, and baseline unemployment and EITC. Of the sample, 33.6 percent never lost eligibility after gaining it.

Table 6: Competing risks models, women and men unmarried at baseline

	Women			Men		
	No earnings	Income>max	Family change	No earnings	Income>max	Family change
Main						
HS or less	1.22**	0.50***	0.93	1.02	0.69***	0.93
	(0.08)	(0.03)	(0.04)	(0.11)	(0.06)	(0.07)
Black alone	0.92	0.57**	0.48***	0.63	0.39**	0.81
	(0.18)	(0.11)	(0.07)	(0.21)	(0.13)	(0.16)
Asian alone	3.57	2.91	2.71**	1.10	1.04	1.25
	(2.42)	(1.70)	(1.04)	(0.84)	(0.54)	(0.94)
Other race	0.85	0.48*	0.93	0.58	0.49	0.68
	(0.32)	(0.17)	(0.24)	(0.31)	(0.27)	(0.20)
Hispanic	1.02	1.00	0.81***	1.17	0.96	0.67***
	(0.09)	(0.09)	(0.05)	(0.15)	(0.11)	(0.07)
Age	1.00	1.02*	1.01	1.03*	1.03	1.00
	(0.01)	(0.01)	(0.01)	(0.02)	(0.01)	(0.01)
Number of children	0.99	0.63***	0.66***	0.81	0.59***	0.83
	(0.10)	(0.06)	(0.05)	(0.13)	(0.09)	(0.09)
Unemployment rate	0.91	1.06	0.91	1.00	0.94	0.90
	(0.08)	(0.08)	(0.05)	(0.14)	(0.11)	(0.07)
State EITC	0.82	1.07	0.95	0.84	0.94	0.95
	(0.16)	(0.18)	(0.11)	(0.25)	(0.24)	(0.18)
Percent failing	14.81	15.50	30.76	15.17	21.84	33.88
Observations		5,781			2,267	

Source: CPS ASEC 2006 linked with 1040 and W-2 data from 2005–2011. $*p < 0.05, **\ p < 0.01, ***p < 0.001$.Reported are the coefficients from a competing risks model in which each risk is modeled separately. For example, leaving eligibility due to no earnings is compared to leaving eligibility either for family change or earnings/AGI above the maximum. All variables reflect status in tax year 2005. Standard errors, clustered on the individual, appear in parentheses. Not reported are time-varying coefficients for Black alone, Asian alone, other race, age, and baseline unemployment and EITC. For the subsamples, 38.9 percent of unmarried women and 29.1 percent of unmarried men never lost eligibility after gaining it.

Table 7: Competing risks models: women and men married at baseline

	Women			Men		
	No earnings	Income>max	Family change	No earnings	Income>max	Family change
Main						
HS or less	1.07	0.62***	0.71**	1.05	0.68***	0.74*
	(0.17)	(0.07)	(0.09)	(0.17)	(0.08)	(0.10)
Black alone	0.60*	0.84	0.64*	1.27	0.83	0.88
	(0.15)	(0.19)	(0.12)	(0.31)	(0.18)	(0.17)
Asian alone	1.10	1.16	0.68**	1.00	1.17	0.59***
	(0.17)	(0.11)	(0.09)	(0.17)	(0.11)	(0.09)
Other race	0.88	0.77	1.01	0.67	1.19	0.53
	(0.33)	(0.22)	(0.31)	(0.23)	(0.36)	(0.18)
Hispanic	0.76	0.79	0.79	0.88	0.66**	0.91
	(0.13)	(0.12)	(0.12)	(0.16)	(0.09)	(0.13)
Age	1.01	1.02**	1.02*	1.02*	1.02*	1.01
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Number of children	0.99	1.02	1.06	1.04	1.10	1.02
	(0.09)	(0.07)	(0.07)	(0.09)	(0.07)	(0.07)
Unemployment rate	0.99	1.11	1.00	0.90	1.15*	1.03
	(0.08)	(0.07)	(0.06)	(0.07)	(0.07)	(0.07)
State EITC	0.78	1.13	0.90	0.75	1.08	0.88
	(0.14)	(0.14)	(0.12)	(0.13)	(0.13)	(0.12)
Percent failing	13.52	27.38	24.74	14.67	30.10	25.73
Observations		6,625			6,086	

Source: CPS ASEC 2006 linked with 1040 and W-2 data from 2005–2011. $*p < 0.05, **p < 0.01, ***p < 0.001$.Reported are the coefficients from a competing risks model in which each risk is modeled separately. For example, leaving eligibility due to no earnings is compared to leaving eligibility either for family change or earnings/AGI above the maximum. All variables reflect status in tax year 2005. Standard errors, clustered on the individual, appear in parentheses. Not reported are time-varying coefficients for education, Black alone, other race, Hispanic, age, number of children, and baseline unemployment and EITC. For the subsamples, 34.4 percent of married women and 29.5 percent of married men never lost eligibility after gaining it.

Table 8: Competing risks models: Unmarried and married, full sample with those who attrit retained

	Unmarried						Married					
	Women			Men			Women			Men		
	No earnings	Income >max	Family change	No earnings	Income >max	Family change	No earnings	Income >max	Family change	No earnings	Income >max	Family change
Main												
HS or less	1.36***	0.47***	0.88**	1.09	0.68***	0.93	0.93	0.58***	0.73*	0.91	0.62***	0.72*
	(0.07)	(0.03)	(0.04)	(0.09)	(0.06)	(0.06)	(0.12)	(0.07)	(0.09)	(0.12)	(0.07)	(0.09)
Black alone	1.00	0.57**	0.47***	0.48**	0.37**	0.78	0.61*	0.81	0.68*	1.30	0.72	0.88
	(0.13)	(0.10)	(0.06)	(0.12)	(0.12)	(0.15)	(0.12)	(0.19)	(0.12)	(0.22)	(0.16)	(0.17)
Asian alone	2.70	3.25*	2.67*	0.87	0.92	1.19	1.14	1.13	0.67**	1.11	1.12	0.60***
	(1.52)	(1.90)	(1.04)	(0.43)	(0.48)	(0.75)	(0.14)	(0.11)	(0.09)	(0.14)	(0.11)	(0.09)
Other race	1.08	0.53	0.85	0.96	0.51	0.69	1.19	0.66	1.02	0.87	1.00	0.55
	(0.27)	(0.18)	(0.22)	(0.36)	(0.27)	(0.21)	(0.34)	(0.19)	(0.31)	(0.21)	(0.33)	(0.17)
Hispanic	0.99	1.01	0.81***	1.07	0.97	0.71***	0.86	0.72*	0.77	0.88	0.64**	0.87
	(0.07)	(0.09)	(0.05)	(0.10)	(0.11)	(0.07)	(0.13)	(0.11)	(0.12)	(0.13)	(0.09)	(0.13)
Age	1.02**	1.02	1.01	1.05***	1.02	1.00	1.02**	1.02**	1.02**	1.02**	1.01*	1.01
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Number of children	1.12	0.63***	0.66***	0.90	0.57***	0.83	1.12	1.02	1.07	1.07	1.11	1.03
	(0.08)	(0.06)	(0.05)	(0.11)	(0.08)	(0.09)	(0.08)	(0.06)	(0.07)	(0.07)	(0.07)	(0.07)
Unemployment rate	0.95	1.06	0.90	1.00	0.92	0.94	1.01	1.10	0.98	0.95	1.16**	1.00
	(0.06)	(0.08)	(0.05)	(0.10)	(0.11)	(0.07)	(0.06)	(0.07)	(0.06)	(0.06)	(0.07)	(0.07)
State EITC	0.93	1.10	0.94	1.04	0.93	0.95	0.79	1.12	0.95	0.85	1.07	0.90
	(0.12)	(0.19)	(0.11)	(0.21)	(0.23)	(0.17)	(0.11)	(0.14)	(0.12)	(0.11)	(0.13)	(0.12)
Percent failing	24.26	13.87	28.21	24.27	19.25	31.60	18.34	25.75	24.52	21.02	27.95	24.90
Observations		6,689			2,649			7,161			6,755	

Source: CPS ASEC 2006 linked with 1040 and W-2 data from 2005–2011. $*p < 0.05, **p < 0.01, ***p < 0.001$. Reported are the coefficients from a competing risks model in which each risk is modeled separately. For example, leaving eligibility due to no earnings is compared to leaving eligibility either for family change or earnings/AGI above the maximum. Standard errors appear in parentheses. For the subsamples, 33.7 percent of unmarried women, 24.9 percent of unmarried men, 31.4 percent of married women, and 26.1 percent of married men never lost eligibility after gaining it.

Table 9: Cox proportional hazard models: Unmarried and married, full sample

	Unmarried						Married					
		Women			Men			Women			Men	
	No earnings	Income >max	Family change	No earnings	Income >max	Family change	No earnings	Income >max	Family change	No earnings	Income >max	Family change
Main												
HS or less	1.18*	0.50***	0.92*	0.61	0.47**	0.77	1.06	0.65***	0.94	1.05	0.69***	0.94
	(0.08)	(0.03)	(0.04)	(0.18)	(0.12)	(0.14)	(0.07)	(0.03)	(0.04)	(0.07)	(0.03)	(0.04)
Black alone	0.98	0.57**	0.46***	0.58	0.35**	0.74	1.05	0.60***	0.92	1.32**	0.73***	1.02
	(0.19)	(0.11)	(0.06)	(0.19)	(0.11)	(0.15)	(0.11)	(0.05)	(0.06)	(0.13)	(0.06)	(0.08)
Asian alone	3.73	3.06	2.92**	0.92	1.29	0.54**	1.08	1.10	0.71**	1.00	1.09	0.65**
	(2.59)	(1.88)	(1.20)	(0.27)	(0.24)	(0.13)	(0.17)	(0.10)	(0.08)	(0.16)	(0.10)	(0.09)
Other race	1.29	0.79	0.93	0.55	0.47	0.70	0.88	0.58	0.87	0.66	1.08	0.50*
	(0.17)	(0.12)	(0.09)	(0.30)	(0.26)	(0.22)	(0.33)	(0.17)	(0.28)	(0.23)	(0.36)	(0.17)
Hispanic	1.03	0.99	0.84**	1.17	0.97	0.70***	0.76	0.59***	0.65**	0.82	0.53***	0.79
	(0.09)	(0.08)	(0.05)	(0.14)	(0.10)	(0.06)	(0.13)	(0.09)	(0.10)	(0.14)	(0.07)	(0.12)
Age	1.00	1.02*	1.02**	1.04*	1.03	1.00	1.01	1.03***	1.02**	1.02**	1.02**	1.01
	(0.01)	(0.01)	(0.01)	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Number of children	0.94	0.56***	0.59***	0.72	0.47***	0.72**	1.09	1.06	1.15	1.10	1.16*	1.07
	(0.11)	(0.06)	(0.05)	(0.13)	(0.08)	(0.09)	(0.12)	(0.08)	(0.10)	(0.11)	(0.09)	(0.09)
Unemployment rate	0.92	1.07	0.92	0.99	0.93	0.90	0.95	1.08	0.95	0.89	1.12	0.97
	(0.08)	(0.08)	(0.06)	(0.14)	(0.11)	(0.07)	(0.08)	(0.07)	(0.06)	(0.07)	(0.07)	(0.07)
State EITC	0.82	1.08	0.98	0.83	0.93	0.90	0.77	1.12	0.99	0.75	1.08	0.95
	(0.16)	(0.19)	(0.12)	(0.25)	(0.24)	(0.18)	(0.14)	(0.15)	(0.14)	(0.13)	(0.14)	(0.14)
Percent failing	24.26	13.87	28.21	24.27	19.25	31.60	18.34	25.75	24.52	21.02	27.95	24.90
Observations		6,689			2,649			7,161			6,755	

Source: CPS ASEC 2006 linked with 1040 and W-2 data from 2005–2011. $*p < 0.05, **p < 0.01, ***p < 0.001$. Reported are the coefficients from a competing risks model in which each risk is modeled separately. For example, leaving eligibility due to no earnings is compared to leaving eligibility either for family change or earnings/AGI above the maximum. Standard errors appear in parentheses. For the subsamples, 33.7 percent of unmarried women, 24.9 percent of unmarried men, 31.4 percent of married women, and 26.1 percent of married men never lost eligibility after gaining it.

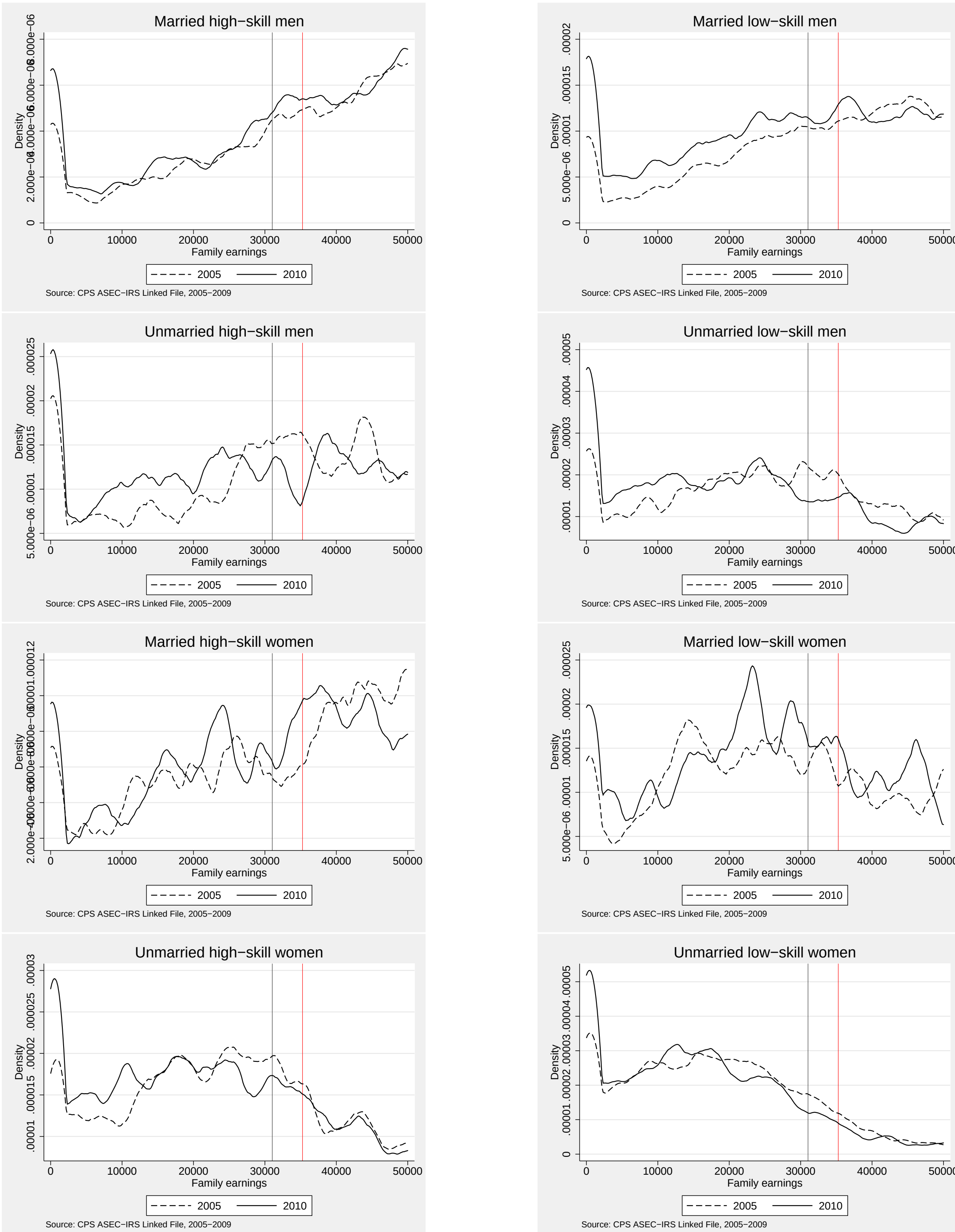

Figure 1. Each graph shows the density of earnings for the specified group. The lighter line is earnings in 2005 (adjusted by CPI), and the darker is earnings in 2010. Two droplines indicate the ending value for EITC eligibility in 2010 (if earnings greater than or equal to adjusted gross income). The sample is restricted to labor force participants and those with children.