CHARACTERIZING RECIPIENTS OF THE EARNED INCOME TAX CREDIT ACROSS TIME – AN EXAMINATION OF SUBSTANCE USE AND ECONOMIC WELLBEING

by
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ABSTRACT

The Federal Earned Income Tax Credit (EITC) is the largest anti-poverty cash assistance program in the United States. The purpose of this dissertation is to identify longitudinal patterns of EITC receipt and examine their association with differential health and economic outcomes, to confirm whether the EITC is a short-term safety net and expand upon current literature through further investigation of individuals that comprise the EITC population. In Chapter 1, I provide an overview of the current literature and problem, as well as an overview of the data source and methods used in this dissertation. In Chapter *2,* I examined the longitudinal impact of the EITC by identifying distinct patterns of claiming EITC benefits and examining the relationship between those patterns and substance use (tobacco, alcohol, marijuana). I performed a longitudinal latent class analysis (LLCA) of individuals who answered a question on claiming the EITC from 2003 to 2010 (n=8,514) to identify longitudinal patterns of EITC receipt. I found that EITC trajectories differed in their reported tobacco and alcohol use but not marijuana or illicit drugs. In Chapter 3, I further explored the relationship between previously identified EITC trajectories and outcomes of economic wellbeing such as material hardship and income-based poverty measures. I found significant differences in reported assets and debts across the EITC trajectories. In Chapter 4, I further examined the co-occurrence between these EITC trajectories and patterns of substance use across time to determine if claiming the EITC may be contributing to differential substance use behaviors. I performed a latent transition analysis (LTA) of EITC trajectories and three substance use trajectories (Tobacco, Alcohol, marijuana), separately. I found that some EITC trajectories were more likely to have a unique substance use trajectory than others. Finally, in Chapter 5, I provided an overview of results and synthesis of finding,

discussed implications for the field of public health, and future directions for this body of research.

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CHAPTER 1. Introduction

1.1. Statement of the problem

The Federal Earned Income Tax Credit (EITC) is the largest anti-poverty cash assistance program in the United States, redistributing approximately $60 billion to low-income households annually, since it was introduced as a refundable tax credit in 1970. Compared to other social welfare programs the EITC has the largest effect, resulting in a 3% reduction in poverty, compared with 1.6% reduction for Temporary Assistance for Needy Families (TANF) and 1.3 % for the Supplemental Nutrition Assistance Program (SNAP) (Falk and Crandall-Hollick, 2018). Low-income individuals are more likely to experience negative outcomes related to health, such as addiction, serious mental illness, increased morbidity/mortality, incarceration, and decreased access to treatment and social welfare benefits (Alexander et al., 2018; Dasgupta et al., 2018; Galea et al., 2004; Iguchi et al., 2002). The U.S. federal government has implemented numerous social welfare programs designed to lift individuals out of poverty by providing cash assistance designed to subsidize the purchase of basic necessities, such as food purchases and temporary assistance for families in need (Lundberg et al., 2010; Shahidi et al., 2019). The federal EITC has been expanded three times in 1993, 2001, and 2008 – each time instituting a higher credit amount to adults with two kids, married couples, and adults with 3 or more kids, respectively (Crandall-Hollick, 2018). In 2018, the average EITC credit received nationwide was $2,476 redistributed across 25 million workers and families (IRS, 2020a). In terms of a conceptual working model, the EITC directly impacts income and employment (i.e. labor force participation)) among recipients of the credit. THE EITC is theorized to impact income poverty through the direct effect on these two factors. Economists use the conceptual theoretical framework of “income” and “substitution” effects to understand the impact tax credits—

including the EITC—have on labor supply. Based on the assumption that the decision to work is about two choices – leisure (i.e., hours of not working) and consumption (i.e., after-tax dollars they can spend on good) (Eissa et al., 1996). Theoretically, the ultimate impact a wage increase has on hours worked depends on which effect is greater. If the substitution effect is larger, an individual will work more hours as their wages increase (Eissa et al., 1996). If the income effect is larger, an individual will work fewer hours as their wages increase and instead consume more leisure (Falk and Crandall-Hollick, 2018). This phenomenon explains why researchers are unable to separate income and labor effects of the EITC. State EITCs have been implemented in 29 states and DC and provide a percentage of the federal EITC credit. State EITCS vary considerably (3-40%) and have been drastically expanded in recent years (Crandall-Hollick, 2018; Williams and Waxman, 2018). While state EITCs serve as an additional source of EITC variation, bivariate regressions of studies that observe consistent EITC participants found that variation in the EITC over time accounts for 67% of variance, number of children accounted for 13%, while state EITCs accounted for 7% (Bastian and Michelmore, 2015). The EITC is used somewhat differently than regular paychecks, often used for investing in housing, car purchase and repairs, paying off bills, childcare and/or children's items (e.g., learning items, clothing, etc.) (Despard et al., 2015; Sykes et al., 2015). The EITC is typically used for debt repayment rather than wealth or asset accumulation, in this way it can improve economic security (Aladangady et al., 2018; Mendenhall et al., 2012; Sykes et al., 2015). The EITC simultaneously impacts two key social determinants of health, income and employment – but the EITC is theorized to indirectly impact health through four key avenues, access to health insurance coverage, reducing stress, decreasing risky behaviors, and increasing nutrition (Rehkopf et al., 2014a; Simon et al., 2018). Although the EITC is not traditionally thought of as an economic welfare policy like

SNAP or TANF, research into the power of these programs to improve poverty and ill-health has increased over the last fifteen years (Crandall-Hollick, 2018).

Growing research into the health effects of the federal EITC have found increases in health insurance coverage, educational achievement among children (Bastian and Michelmore, 2015; Hamad et al., 2018; Strully et al., 2010), improvements in maternal health (Evans and Garthwaite, 2014; Hoynes et al., 2015; Strully et al., 2010), decreased smoking among pregnant women and single mothers (Averett and Wang, 2013; Cowan and Tefft, 2012), and improved well-being (Boyd-Swan et al., 2016). The EITC is theorized to directly impact health through health insurance coverage, reducing stress, decreasing risky behaviors, and increasing nutrition (Simon et al., 2018). To our knowledge, there are no studies that investigate the effect of the EITC on illicit substance use or mental illness. Considering that economic conditions are a major contributor to substance use behavior, and substance use behaviors contribute to the political opposition of economic assistance programs, it is surprising that this research is not widespread (Iguchi et al., 2002; Rhodes, 2009). There is a body of literature devoted to studying the effects of income disbursement on substance use behaviors of recipients of cash assistance programs, finding increases in drug-related harm, unintentional overdose, hospitalizations, ED visits, and treatment interruptions (Dobkin et al., 2007; Krebs et al., 2016; Otterstatter et al., 2016).

The Federal EITC and Substance Use

Aside from the econometric literature on tobacco use, there is no consensus on whether the EITC generally impacts substance use (SU) behavior. To date there has been no comprehensive study of the impact of the EITC on alcohol, marijuana, or illicit substance use, although there has been considerable interest in levels of tobacco use. Current research on the impact of the EITC is characterized by comparative interrupted time series (CITS) studies focused on changes in smoking behavior after the 1993 legislative expansion (Kenkel et al., 2013; Pega et al., 2013). The evidence on smoking after EITC implementation is mixed, one study found no effect five years after the 1993 expansion (Cowan and Tefft, 2012). One study found a very moderate reduction in smoking during pregnancy (OR: 0.95, CI: 0.94-0.96) (Strully et al., 2010). Averett and Wang (2013) found no effect for African Americans, but a large effect for white Americans, two years after expansion. In this study, among women with low education attainment, white women were more likely to reduce their smoking than black women (Averett and Wang, 2013). Researchers may speculate that these mixed results are based on sex, race/ethnicity, or parent status make sense since these factors are significantly associated with claiming the EITC and substance use behaviors (Falk and Crandall-Hollick, 2018; McHugh et al., 2018; Wu et al., 2010). Tobacco studies typically restricted the outcome to women, and used individuals who had one child during the relevant study period as the comparison group (Averett and Wang, 2013; Cowan and Tefft, 2012; Evans and Garthwaite, 2014).

Only one SU study has examined the immediate impact of the EITC on alcohol and marijuana use, including these outcomes in their survey of 30 health behaviors (Rehkopf et al., 2014a). Authors found that during the months of EITC disbursement, there was a slight increase in alcohol use and a decrease in current marijuana use among men and women. The latter result was later ruled inconclusive after sensitivity analyses. The key limitation of this study is potential selection bias. The EITC credit value is directly determined by number of dependents and income level. Authors in this study used the NHANES survey, which does not collect exact income or number of children. As a result, they restricted their sample to individuals between ages 21 and 40, who they assumed would be most likely to have children under the age of 18 (Rehkopf et al., 2014b). Many of these assumptions about eligibility requirement for the EITC are commonly used in other empirical studies. Both previously discussed tobacco studies also restricted their sample to "working age" adults, due to incomplete information on parent status and age of children (Cowan and Tefft, 2012; Strully et al., 2010). Using these assumptions to isolate the group of most likely EITC participants is a concerning practice in the EITC literature.

Methodological Limitations of Current EITC Literature

Current research on the health effects of the EITC are limited by measurement concerns. There are three key issues including restriction to legislative policy expansions, no measurement of the long-term effect of the EITC, and misclassification of the EITC population. A 2012 Cochrane review establishes several methodological flaws that remain pervasive in the current body of work on the health effects of EITC (Pega et al., 2013). The review identified that the comparative interrupted time series studies carried a high risk of bias from misclassification of the EITC exposure, selection bias, unmeasured or unadjusted confounding, bias due to attrition and underlying control for time trends. As a result, the systematic review did not include a meta-analysis.

The first problem EITC researchers face is restriction to legislative policy expansions, all studies were comparative interrupted time series (CITS) studies. Most difference-in-difference analyses of the EITC define the treatment group as EITC-eligible mothers with two or more children, and the control group, as EITC-eligible mothers with one dependent child, restricted to a sample of women with low-educational attainment (Averett and Wang, 2013; Cowan and Tefft, 2012; Pega et al., 2013). However, the crucial assumption that underlying trends in health outcomes are similar between mothers with one child and mothers with two children, is most likely violated. Studies on the number of offspring and health effects have confirmed more offspring is positively associated with CVD risk in women and unhealthy behavior and lifestyle as a consequence of raising more children (Magnus et al., 2016). Lower socioeconomic status is positively associated with having more children, in part because of delayed childbearing in higher income groups (Bhrolcháin and Beaujouan, 2012). There is no consensus on whether number of offspring impacts substance use, but it is reasonable to conclude that socioeconomic status and parental lifestyle would be different between mothers who use drugs with one child versus two or more children. Current methodological limitations of the EITC and health research are also present in the tobacco literature dealing with substance use. For example, Everett and Wang (2013) define EITC eligible individuals had two or more children and a high school degree, while other studies define them as those with some college, but no Bachelor's degrees (Cowan and Tefft, 2012). This can introduce misclassification, because EITC receipt is based on family income, not education. However, educational level has been used by numerous researchers instead of restricting the sample on income, which could introduce selection bias (Baker, 2008; Cowan and Tefft, 2012; Gomis-Porqueras et al., 2011; Pega et al., 2013). Education is commonly used as a proxy for EITC eligibility in many studies that do not wish to use income, due to concerns about confounding and endogeneity bias (Averett and Wang, 2013; Baker, 2008; Baughman and Dickert-Conlin, 2009; Evans and Garthwaite, 2014; LaLumia, 2013). This is a thoughtful decision as the inclusion or omission of income or employment could bias the effect towards or away from a null finding.

Current EITC studies have attempted to observe the longitudinal impact of the EITC policy by studying people who claim the credit consistently for multiple years; however, recent research using IRS data suggests this may not be the case. Based on analysis of federal tax returns, 61% of EITC recipients claimed the EITC for 1 or 2 years (Dowd and Horowitz, 2011). Using restricted IRS data to observe EITC recipients over six years, Ackerman (2009) asserted that "millions more people flow in and out of EITC population than a one-year snapshot reveals". This study also concluded that men are more likely to receive the EITC for 1 year at a time, while women are more likely to be consecutive recipients (Ackerman, 2009). Yet another study using special access IRS panel data found that only 7% claimed the EITC consistently during the study period (Masken, 2006). Theoretically, individuals would no longer claim the EITC for two primary reasons: (1) economic improvement, such as surpassing minimum income requirements or (2) economic decline, such as failing to meet employment requirement or not filing an income tax return. Therefore, measuring the precise longitundinal impact of the EITC would require allowing individuals to naturally change EITC status throughout the life course.

The third concern with the current body of research is the exclusive focus on a subgroup of EITC participants - women with children, specifically those with at least two children. Although most researchers acknowledge that women with children receive the EITC the most often, the articulated goal of the EITC is to help lift families out of poverty (IRS, 2020b). Much less research has been conducted on men, childless adults (Simon et al., 2018). The limitations in the research literature have consequences for political debates, leaving room for opponents of the EITC to speculate that the policy does not have an impact on men and childless adults and federal funding expenditures funding should be reduced (Edwards and de Rugy, 2015; Rachidi, 2015a; Rachidi and Prasad, 2011).

1.2. Overview of Specific Aims

The overall goal of this study was to identify longitundinal patterns of EITC receipt and examine whether they are associated with differential health and economic outcomes, to confirm whether the EITC is a short-term safety net and expand upon current literature through further investigation of individuals that comprise the EITC population. Studies conducted using IRS data suggest that the majority of participants do not receive the EITC consecutively and claim it for shorter periods of time (Ackerman, 2009; Dowd and Horowitz, 2011; Masken, 2006). This creates concern for the current body of EITC studies, which continue to focus on legislative expansions from the 1990s and are unable to examine people who start or stop claiming the EITC. To model longitudinal EITC receipt, we used latent variable modeling to group individuals based on their unobserved heterogeneity in claiming the EITC from 2003 to 2010.

Aim 1: Characterize patterns of claiming the EITC from 2003 to 2010 and measure distal substance use in 2011

The first aim was to identify distinct patterns (i.e., trajectories) of claiming the EITC for a sample of young adults in the 1997 National Longitundinal Survey of Youth. Latent class analysis (LCA) will be used to sort individuals into distinct subgroups based on whether they claimed the earned income credit in the previous year. A latent class regression will be used to examine substance use in 2011. To identify potential predictors of distinct EITC patterns (e.g. sex, parental status, race) covariates will be included as predictors in the model, based on previous literature.

Aim 2: Evaluate whether EITC trajectories are associated with differential indicators of economic wellbeing.

The second aim was to examine if previously enumerated EITC trajectories were associated with different outcomes of economic wellbeing. Rather than focusing on income-based poverty measures alone, I use latent class regression to explore other measures of economic wellbeing, such as material hardships.

Aim 3: Investigate potential co-occurrence between EITC trajectories and substance use trajectories for tobacco, alcohol, and marijuana.

The third aim was to investigate the potential co-occurrence between EITC receipt trajectories and three separate substance use trajectories to further understand whether long-term substance use behaviors are different for different EITC trajectories. I perform a latent transition analysis (LTA) of EITC trajectories and three substance use trajectories (tobacco, alcohol, marijuana), separately. Because sex is significantly associated with greater likelihood of EITC receipt and substance use, I also explored the potential impact of sex as an effect modifier on the transition between trajectory classes.

National Longitudinal Survey of Youth (NLSY97)

Data for this study are from the 1997 National Longitudinal Survey of Youth (NLSY97), which gathers information on the labor force experiences of individuals born between 1980 and 1984. Interviews have been conducted annually from 1997 to 2011, and biannually from 2013 to 2015. The survey consists of a representative cross-sectional sample of 6,748 respondents in 1997, and a supplemental oversample of 2,236 Hispanic or Latino and black respondents. Youth respondents' ages ranged from 12-18 in 1997, and 30-36 in 2015. NLSY97 data are weighted to be representative at the national level and cumulative sampling & panel data weights are provided. The NLSY97 data are collected in 36 states, though data are not representative at the state level. The NLSY97 is the ideal dataset to closely examine the relationship between the EITC and substance use since it conducts follow-up surveys until 2011 with detailed information on income, state identifiers, and provides a nationally representative sample weight.

1.3. Methodological Background

Longitundinal Latent Class Analysis (LLCA)

The goal of LCA is to classify people into distinct groups of classes based on their individual response patterns. The LCA is a person-centered approach that focuses on relationships among people, so that individuals within a group are more similar than individual across different groups (Jung and Wickrama, 2008a). While regression modeling takes a variable-based approach to understand causality, I recognize that variable based approaches are not optimized for situations with information bias or confounding due to unobserved, time invariant factors. On the other hand, a person-centered approach has the opposite goal. Instead of observing the relationships between variables (sex, number of children, EITC exposure), the LCA approach analyzes the latent structure of people, and sorts them into groups (Jung and Wickrama, 2008b; Nylund-Gibson and Choi, 2018). This approach is a unique tool to further understand who EITC participants are through descriptively quantitative methods.

The groups in an LCA are latent, in the sense that they are unobserved, and reflect individual responses to selected indicators. In the current study, the indicators are repeated measures of whether an individual claimed the EITC. This method of using repeated measures is often called the longitudinal latent class analysis (LLCA) (Feldman et al., 2009; Nylund-Gibson et al., 2014). Distal outcomes can be used to examine whether the latent classes display statistically significant mean-level differences in the selected distal outcome variables. In these applications, the latent class variable can be used to describe change over time without having to make any assumptions about the structure or functional form of the change process whereas other longitudinal models do so, such as growth models. LLCA models can thus be specified before a growth model or a growth mixture model as a baseline model to explore heterogeneity in change (Feldman et al., 2009). For distal outcomes, effects across classes are examined by estimating class-specific mean and variance estimates for each distal outcome and then conducting pairwise comparisons to determine where among the classes the distal outcomes are significantly different. Latent Transition Analysis (LTA) is an extension of latent class analyses methods, and regresses one LCA on another latent class model. While LTA traditional measures change in a latent class model at various times points, it can be successfully applied in situations that do not involve LCAs. LTA with non-repeated measures are a useful technique to study developmental changes, and the three-step method can be used to include covariates as predictors in the model (Nylund-Gibson et al., 2014).

Three Step Method. Latent class modeling techniques include the ability to include auxiliary variables (covariates or distal outcome) in the modeling process. While there are numerous methods in use to achieve this, the three-step method is commonly recommended to avoid shifting measurement parameters that occurs with larger sample sizes and predictors of class membership (Nylund-Gibson et al., 2014, 2019). Covariates are included as auxiliary variables in step one, where the latent class enumeration is performed. After this, BCH weights are saved for each latent class in an exported datafile. This datafile is used in Step three, to perform the latent class regression. This regression has two steps, first the covariates are regressed on each latent class, and then the latent class is regressed on the outcome variable (Nylund-Gibson et al., 2019).

Latent Class Enumeration and Fit Statistics

Latent class enumeration typically involves starting with a two-class model and increasing the number of classes and comparing common fit measures. Multiple random starting values were used to ensure estimates did not reflect local maxima, and the best log likelihood value was replicated. Models were compared based on standard fit statistics, the Akaike Information Criteria (AIC), Bayesian Information Criteria (BIC), Lo-Mendel-Rubin (LMR), the Log likelihood (LL), the Bootstrapped Likelihood Ratio Tests (BLRT), and the model entropy (Masyn, 2013; Nylund-Gibson, 2007; Nylund-Gibson and Choi, 2018).

1.4. Public Health Significance

Although the EITC has historically received more bipartisan support as a tax policy than other economic welfare policies, there have been several proposals to change, restructure, or otherwise eliminate the program (Falk and Crandall-Hollick, 2018). The policy's consistent status as the most highly funded social policy, makes it a prime target for critics of welfare spending and tax credit incentives. It is useful to consider how the EITC compares to other forms of economic welfare assistance, such as TANF or SNAP. Categorically speaking, because the EITC is an income shock (i.e., lump sum of money received at one time) as opposed to monthly cash increments, economic theory suggests that people will respond to it differently than SNAP or TANF (Falk and Crandall-Hollick, 2018). The EITC is used for large purchases and debt reduction, rather than accumulating wealth (Despard et al., 2015; Sykes et al., 2015). After receiving the EITC it is difficult to disentangle the labor participation effects (choice to work) from income effects (choice to reduce hours) of the policy, because individual motivation would determine whether people choose to work more to increases their post-tax wages through labor participation or increase their leisure and spend more money through an income effect) (Eissa et al., 1996). Those in opposition to the EITC assert that providing individuals with a refundable tax credit, is essentially welfare assistance and increases the likelihood that they will spend it on non-essential purchases that further harm their health (Edwards and de Rugy, 2015; Prasad, 2011). This is despite the fact that evidence shows EITC recipients spend their refunds on childcare or children's learning items, car repairs and purchases, paying utilities or other bills, and housing (Despard et al., 2015; Sykes et al., 2015)

While single mothers are most likely to receive the EITC, men and childless adults are still encouraged to apply. An example of a key message the IRS provides for promotion and marketing states, “No children? You may still qualify for EITC. Check out the EITC Assistant.” (IRS, 2020b). Opponents of the EITC are aware of this discrepancy, and frequently point out the EITC ends up hurting childless workers who receive no EITC or a small EITC, because it can push down market wages (Edwards and de Rugy, 2015). Other studies assert that expanding the EITC for men would be ineffective, because the EITC has not been helpful for poor women (Marr et al., 2014; Mead, 2014; Rachidi, 2015b). However, many proponents of the EITC are in favor of expanding the credit so that childless men and adults can benefit from the policy (Aviva Aron-Dine and Sherman, 2007; Kapahi and Fellow, 2019; Maag et al., 2019; Marr et al., 2016). In order to fully answer questions about the utility of the EITC for the US population of low-income filers, I must understand more about what type of people are claiming the EITC over time, and whether it appears that their health and economic situation is improving or declining.

This study will contribute to two key areas of literature - the effects of social policies on mitigating substance use and poverty, and further understanding the EITC population and their history of receipt. The current study will provide insights into whether the expansion of non-traditional welfare policies, such as tax policies, have the potential to impact substance use outcomes. If so, policymakers must consider how proposals to restructure the EITC payment system may have unintended consequences if not designed to maximize health impact. If current research continues to exclude men and childless adults, researchers will be unable to offer an evidence-based perspective in policy debates about whether programs like the EITC should be restructured.

CHAPTER 2. Latent Trajectories of Claiming the Federal Earned Income Tax Credit and Substance Use Outcomes

2.1. Abstract

Objective: The Earned Income Tax Credit (EITC) remains the largest anti-poverty program in the US, yet research on its longitudinal health impact among adults is nascent. The EITC is a short-term safety net, often claimed intermittently throughout an individual's life. I aimed to understand the longitudinal impact of the EITC by identifying whether distinct patterns of claiming EITC benefits are associated with varying substance use outcomes. Method: Using data from 8,984 responses to the 1997 National Longitudinal Survey of Youth (NLSY97), which was 51% female and oversampled Black and Latino respondents, we performed a longitudinal latent class analysis (LLCA) of individuals who answered a question on claiming the EITC from 2003 to 2010 (n=8,514) to identify longitudinal patterns of EITC receipt. I also examined sociodemographic correlates of class membership and tested for differences in four substance use outcomes by each latent class. Results: Four EITC classes were enumerated: *Non-claimers* (54%), *Initiators* (23%), *Decliner* (12%), and *Consistent claimers* (11%). EITC *Initiators* (42%) and *Consistent claimers* (39%) had the highest prevalence of tobacco use, while *Non-claimers* and *Decliners* (76%) had the highest alcohol use. There were no significant differences by class in marijuana or illicit drug use. Conclusion: There are distinct patterns of claiming the EITC, and individuals within these trajectories have differential characteristics and substance use behaviors. These trajectories formed two groups which were similar in alcohol and tobacco use, *Consistent claimers/Initiators* and *Decliners/Non-claimers*. Future research should investigate characteristics of individuals in these EITC receipt trajectories, to understand what underlying factors may be contributing to divergent/convergent substance use behavior.

2.2. Introduction

Introduced in 1970 as a refundable credit for low-income, working adults, the Earned Income Tax Credit (EITC) simultaneously impacts two key social determinants of health – income and employment (Falk and Crandall-Hollick, 2018). The EITC is a short-term safety net typically claimed for 1-2 years at a time and used for large purchases (e.g. car) or debt repayment (Ackerman, 2009; Aladangady et al., 2018; Dowd and Horowitz, 2011; Sykes et al., 2015). The federal EITC is associated with improvements in maternal health (Evans and Garthwaite, 2014; Hoynes et al., 2015; Strully et al., 2010), physical and psychological well-being (Boyd-Swan et al., 2016; Gomis-Porqueras et al., 2011; Lenhart, 2019), and educational achievement among children. (Bastian and Michelmore, 2015; Hamad et al., 2018; Strully et al., 2010). While research has demonstrated the effects of the EITC on some aspects of health, research on its substance use effects is limited (Pega et al., 2013). There is no consensus on whether the EITC generally impacts substance use behavior, outside of tobacco research which has shown mixed effects of the EITC (Kenkel et al., 2013; Lenhart, 2018; Strully et al., 2010). There is only one study examining the impact of the EITC on other drugs including alcohol and marijuana, pooling together cross-sectional data to observe the EITC. The authors concluded that during the months of EITC disbursement, there was no significant impact on alcohol use and an apparent, but inconclusive decrease in marijuana use (Rehkopf et al., 2014a). This is surprising, given constant political debates about substance use among welfare recipients in the United States (Hager, 2016). While based on biases rather than fact, concerns about recipients of welfare programs, like the EITC, will use their benefits for drugs is a common argument against expanding these programs to combat poverty. Beyond political arguments, understanding how the EITC impacts substance use is important because economic instability contributes to substance use, and social welfare programs are an important tool to interrupt this cycle (Galea and Vlahov, 2002).

Furthermore, it is well-known that punitive drug laws and bans on social policies (e.g. Food stamps Ban) have disproportionately impacted low-income, communities of color in impoverished neighborhoods (Golembeski and Fullilove, 2005; Iguchi et al., 2002). If federal funding is any indicator, the EITC is the government's primary tool for economic mobility for low-income adults and whether the EITC has an impact on substance use warrants further investigation (Falk and Crandall-Hollick, 2018).

Extant literature on the health impacts of the EITC faces significant methodological concerns, including measurement error and unmeasured confounding (Pega et al., 2013). The majority of EITC literature has used comparative interrupted time series study designs, particularly with difference-in-differences (DD) designs and has not appropriately accounted for changes in policies after the 1993 federal EITC expansion. A difference-in-differences (DD) study is a common technique in policy evaluations and estimates the effect of a policy/intervention by comparing changes in the outcome between a population that received the intervention and a group that did not (control) (Wing et al., 2018). This presents a problem for public health datasets, many of which do not provide exact information on income or tax-eligible dependents, two factors which directly determine EITC eligibility. As a result, EITC studies that use public health datasets must make a number of assumptions to restrict their sample to likely "EITC participants", often based on being of "childbearing age" and income categories that rarely align with EITC cutoffs. (Pega et al., 2013; Rehkopf et al., 2014a). Such assumptions are necessary for DD designs to create a working conceptual model, yet these assumptions about directly measurable EITC criteria introduce considerable measurement error and challenges for replication of results.

The second problem is the exclusive focus of almost all DD studies of EITC on the 1993 expansion, which increased the EITC amount for families with two or more children (Pega et al., 2013). While focusing on a concrete policy change is needed for DD studies, such models are vulnerable to confounding due to secular trends. The early 1990s was a period of widespread and drastic welfare reform in the U.S., increasing the likelihood of confounding. Although some studies that used fixed effects attempt to control other economic welfare policies during that time, these designs cannot adjust for unobserved *time-variant* attitude and behaviors. Furthermore these studies do not account for subsequent EITC expansions that occurred in 2001 and 2009 (LaLumia, 2013). These limitations highlight external validity challenges of EITC studies.

There is a need for research evaluating the impact of EITC receipt on substance use longitudinally that addresses the limitations of DD designs. Particularly, studies are needed that consider how claiming the EITC may change over an individual's life course, which has been absent from existing literature. This is concerning because evidence suggests that the EITC is a short-term safety net. Based on analysis of federal tax returns, 61% of EITC recipients claimed the EITC for 1 or 2 years (Dowd and Horowitz, 2011). Theoretically, individuals would stop claiming the EITC for two primary reasons: (1) increase in economic stability, such as surpassing minimum income requirements or (2) decline in economic stability, such as failing to meet the employment requirement or not filing an income tax return. If existing studies limit their sample to people who do not change EITC status, they prevent themselves from studying long term impact and remove a large segment of the EITC population we are interested in studying. There is much political debate about eliminating the program or restructuring it to maximize its benefit, however research of the long-term effect of the EITC among adults, remains inconclusive (Edwards and de Rugy, 2015; Pega et al., 2013).

The Current Study. The goal of the current study is to use Longitudinal Latent Class Analysis (LLCA) to identify and group common trajectories of EITC receipt from 2003-2010, identify significant demographic correlates of EITC group membership, and examine differences in substance use behaviors in 2011 between latent classes. By examining individual trajectories of claiming the EITC over time, we can identify and observe groups of individuals that may be experiencing economic stability or instability over the years as they claim the EITC. Furthermore, rather than measure the effect of the EITC through a policy expansion, the current study will measure the effect of differential EITC trajectories on substance use behaviors. By studying the effect of the EITC, we are not only studying the long-term effects of the policy but are also observing the developmental trajectory of the EITC target population – low-income adults in the US.

2.3. Methods

Data Source

Data for this study comes from the 1997 National Longitudinal Survey of Youth (NLSY97), a prospective cohort study currently conducted by the Bureau of Labor Statistics which gathers information on the labor force experiences of youth born between 1980 and 1984 as they transition through adulthood (Bureau of Labor Statistics, 2019). These de-identified data were deemed exempt from Institutional Review by Johns Hopkins University. Because detailed information on income and number of children is unavailable for prior EITC studies, the 1997 National Longitudinal Survey of Youth (NLSY97) is the ideal dataset to examine the relationship between EITC and substance use. Interviews have been conducted annually from

1997 to 2011, and biannually from 2013 to the present. The initial NLSY97 survey consists of 8,194 participants, comprised of a representative cross-sectional sample of 6,748 respondents and a supplemental oversample of 2,236 Hispanic/Latino and Black respondents. Youth respondents' ages ranged from 12-18 in 1997, and 30-36 in 2015. NLSY97 data are designed to be representative at the national level and cumulative sampling & panel data weights are provided. Because the goal of the current study is to avoid limitations of prior causal inference EITC studies, I used a model-based approach and did not use study weights (Bureau of Labor Statistics, 2019).

Measures

Claiming the EITC on tax return. Indicators of latent class membership are whether participants claimed the EITC in the past year, from 2003 to 2010. Although, the NLSY began data collection in 1997, I begin the study period in 2003 when all participants were 18 and legally eligible to claim independence on their tax return. All individuals who answer “yes” to having a source of income in the survey are asked whether they claimed an EITC on their tax return last year. For example, in 2007, participants who reported an income source were asked, “Did [*you/you or your spouse/you or your partner*] claim, or are [*you/you or your spouse/you or your partner*] planning to claim, an Earned Income Tax Credit on your [*or your spouse's/or your partner's*] 2006 Federal Income Tax Return?” Individuals who were originally excluded from the question (individuals without a source of income), were coded as not claiming an EITC.

Demographic Characteristics. All demographic characteristics are self-reported and include sex, race/ethnicity, age, educational attainment, marital status, parent status, and health insurance coverage. In terms of race/ethnicity, all NLSY respondents are classified as Hispanic /Latino, Black, Non-black/Non-Hispanic, or Mixed race. Similar to other studies, educational attainment was measured as a binary variable comprised of high school (HS) diploma or less and some college or more (Gomis-Porqueras et al., 2011). We controlled for demographic characteristics in 2011, to adjust for characteristics that may impact substance use in the year we accessed our distal outcome.

Substance Use Outcomes. Substance use outcomes were accessed in 2011, when participants were 28 years old on average. Use of tobacco, alcohol, marijuana, and "other illicit drug" use since the last NLSY interview is assessed at each follow-up visit. Participants were asked, "Since the date of last interview, have you [smoked a cigarette; drank an alcoholic beverage; used marijuana, even if only once, for example: grass or pot; used any drugs like cocaine or crack or heroin, or any other substance not prescribed by a doctor]?" The NLSY also include definitions the interviewer read to participants. An alcoholic drink is defined as "a can or bottle of beer, a glass of wine, a mixed drink, or a shot of liquor", while "other illicit drugs" are "any drugs like cocaine or crack or heroin, or any other substance not prescribed by a doctor, in order to get high or to achieve an altered state".

Statistical Analysis

The goal of a latent class analysis is to classify individuals into distinct groups of categories based on their individual response patterns. The LCA is a person-centered approach that focuses on relationships among individuals, so that individuals within a group are more similar than individual across different groups (Jung and Wickrama, 2008a). While regression modeling takes a variable-based approach to understand causality, we recognize that variable based approaches are insufficient in situation where there is information bias. On the other hand, a person-centered approach has the opposite goal. Instead of observing the relationships between variables (sex, number of children, EITC exposure), the LCA approach analyzes the latent structure of people, and sorts them into groups (Jung and Wickrama, 2008b). This approach is required to further understand who EITC participants are through descriptively quantitative methods. As a result, we explore the impact of sex, race, age, marital status, parent status, parental educational attainment, and health insurance coverage on class membership. Substance use outcomes accessed in 2011 for tobacco, alcohol, marijuana, and other illicit drugs were included as distal outcomes using a three-step approach (Nylund-Gibson et al., 2019). To assess the overall difference between latent classes Wald Test was performed. To compare differences between individuals' classes, added additional "model constraints" were added to include pairwise comparisons between individuals' latent classes. All analyses were performed in Mplus, version 8 (Muthen and Muthen, 2017).

LCA Model Fit. LCA models with 1 to 6 classes were fit. Multiple random starting values were used to ensure estimates did not reflect local maxima, and the best log likelihood value was replicated. Models were compared based on standard fit statistics, the Akaike Information Criteria (AIC), Bayesian Information Criteria (BIC), Lo-Mendel-Rubin (LMR), the Log likelihood (LL), the Bootstrapped Likelihood Ratio Tests (BLRT), and the model entropy (Masyn, 2013; Nylund-Gibson, 2007; Nylund-Gibson and Choi, 2018).

2.4. Results

The prevalence of the latent class indicators, demographic characteristics, and distal outcomes for the full analytic sample are presented in Table 1. The NLSY97 sample is 51% male, 51% white, and on average the highest level of education is some education beyond a high school diploma.

Latent Class Enumeration

Based on fit statistics (Table 2) and substantive interpretation, a four-class model was chosen (Figure 1). Although a 5-class model was initially preferred by some fit statistics (i.e., LMR), the additional class identified was not theoretically meaningful and therefore I chose the more parsimonious model. The first and largest class was composed of individuals who had a probability of less than 9% of claiming the EITC consistently from 2003 to 2010, labeled *Non-claimers* (54% of sample). A second class of those who did not claim the EITC until 2004, labeled *Initiators* (23%). A third class of individuals who claimed the EITC in early years but discontinued after 2007 (12%) and was labeled *Decliner*. Finally, a fourth class was characterized by individuals who had a probability of 80% or higher of claiming the EITC every year, labeled *Consistent claimers* (11%).

Demographic Correlates of Class Membership

For each latent class, the probability of demographic characteristics is presented, and significant associations are bolded (Table 3). Sociodemographic differences are briefly mentioned below, and beta coefficients and odds ratio are presented in the appendix (Supplement Table 1). Compared to those who did not claim the EITC (i.e., *Non-claimers*), significant correlates among EITC classes were sex, age, highest degree, parental status, and marriage status. There were no significant differences in race/ethnicity or health insurance coverage among classes (Table 3). *Consistent claimers* and *Initiators* were both more likely to have children (90%,70%) than *Non-claimers* or *Decliners* (31%, 45%). Compared to *Non-claimers*, all of the EITC trajectories were less likely to have any college education, starting with *Consistent claimer*s (OR: 0.44, $p<0.001$), *Decliners* (OR: 0.53, $p<0.001$) and *Initiators* (OR: 0.56, $p<0.001$) (A-Table. 2-1).

Substance Use Outcomes by EITC Class Trajectory

Tobacco Use. Figure 2 displays the distal outcomes, along with significant pairwise comparisons for each class. Tobacco use since the last survey interview differed significantly by class as indicated by the Wald's test ($\chi = 13.89$, $p = 0.003$). The highest prevalence was among *Initiators* (42%) and lowest among *Non-claimers* (35%). *Initiators* were significantly more likely to use tobacco than *Non-claimers* ($p=0.007$), while *Decliners* were significantly less likely compared to *Initiators* ($\beta=-0.07$, $p=0.003$).

Alcohol Use. Alcohol Use since the last survey interview differed significantly by EITC class ($\chi = 16.62$, $p = 0.0008$), with highest use among *Non-claimers* (76%) and *Decliners* (76%), and lowest use among *Initiators* (71%). *Initiators* had significantly lower alcohol use than *Consistent claimers* ($p=0.02$) and *Decliners* ($p=<0.001$), and marginally lower use than *Non-claimers* ($p=0.06$).

Marijuana Use. Marijuana use since last interview did not differ significantly by latent class ($\chi = 2.08$, $p = 0.56$). However, while the other three groups were similar in prevalence (~17%), the lowest proportion was among *Consistent claimers* (12%).

Other Illicit Drugs. Use of Other illicit substances did not differ significantly by EITC class ($\chi = 1.37$, $p = 0.71$), the prevalence of use across all four classes was 3%.

2.5. Discussion

The goal of this study was to identify patterns of claiming the EITC and observe distal substance use outcomes to examine the longitudinal trajectory of the EITC policy. There were four trajectories of EITC claimers that emerged: *Non-claimers* (54%), *Initiators* (23%), *Decliner* (12%), and *Consistent claimers* (11%). There were significant differences between EITC trajectories in tobacco and alcohol use, but not marijuana or other illicit drug use. Alcohol use was highest among *Non-claimers* and *Decliners* (76%), followed by *Consistent claimers* (73%), and *Initiators* (71%). Tobacco use was highest for *Initiators* (43%), *Consistent claimer* (39%), *Decliner* (37%), and *Non-claimers* (35%). A key pattern emerged from these findings. Among the four groups, *Consistent claimers*/*Initiators* had high tobacco, but low alcohol use, while *Decliners*/*Non-claimers* demonstrated the opposite – low tobacco and high alcohol use.

To identify the cause of these differential substance use patterns and the apparent clustering of the four EITC trajectories into two groups, observing correlates associated with each trajectory can provide context. As illustrated in Table 3, *Consistent claimers* and *Initiators* were both more likely to have children than *Non-claimers* or *Decliners*. Compared to *Non-claimers*, all EITC trajectories were less likely to have a college education or more. Notably, there found no significant differences by class in race or ethnicity. Based on education, parent status, and proportions of female participants, *Consistent claimers*/*Initiators* include the most common population of EITC claimers, single mothers with low education, who are most likely lower income than the other EITC trajectories (*Decliners*, *Non-claimers*).

Disparities in tobacco use remain among vulnerable populations defined by sex, race/ethnicity, socioeconomic status, education, and geography (Cal Ham et al., 2011; Leas et al., 2019; Yu et al., 2010). Although some evidence suggests smoking prevalence is similar across racial groups, other factors such as tobacco outlet density, industry marketing, and gender norms and culture all combine to create a complex picture (Brown-Johnson et al., n.d.; Perkins, 2009). This complexity may partially explains why the body of research on EITC and tobacco use has yielded mixed results (Averett and Wang, 2013; Kenkel et al., 2013; Pega et al., 2013). Although alcohol outlet density and marketing are also higher in low-income communities, alcohol use remains lower among *Consistent claimers*/*Initiators*. These results provide partial support for the assertion that tobacco use is more susceptible to disparities in use and treatment, than alcohol.

Although it remains unclear what specific combination of factors is driving this relationship, these findings suggest that *Consistent claimers*/*Initiators* and *Decliners*/*Non-claimers* are similar to one another and may be similar in other factors that determine the EITC, such as employment or annual income. However, further research is needed to understand whether economic improvement or economic decline is occurring in individuals who change their EITC claiming status over time i.e., *Decliners* and *Initiators*. Examining other indicators of economic status would allow us to observe the key intended policy effect of the EITC, which is to encourage employment and increase income. Unemployment rates are negatively associated with tobacco use, so considering these factors would allow researchers to further explore differences in tobacco and alcohol use (Kenkel et al., 2013; Lenhart, 2019).

Strengths and Limitations. This was the first study to examine individual trajectories of claiming the EITC among young adults (20-30) through a Longitudinal Latent Class Analysis, and the second study to examine the relationship between the EITC and substances other than tobacco. In addition, the NLSY97 is the only national survey with health information that asks participants to report whether they have claimed the EITC and includes information on health, allowing us to decrease potential misclassification bias of prior studies (Pega et al., 2013). Furthermore, the NLSY97 prevents the probable measurement error of prior studies that used cross-sectional data, by allowing us to control for individual time-invariant heterogeneity and providing more detailed demographic information (i.e., marriage and parental status); however, there were a few limitations. The illicit drugs outcome in this study is a crude measure of illicit drug use and prevented us from examining outcomes among different classes by types of illicit drugs. State EITCs were not included in this analysis because the purpose was to examine the longitudinal impact of the federal policy. Gender is not measured in the NLSY97, but sex is ascertained, preventing us from considering how gender may impact these relationships. In addition, we do not know whether individuals who claimed the EITC received it, limiting us to an intent-to-treat interpretation of the results. Aside from IRS data, there are no nationally representative U.S. health surveys that collect information on individuals' EITC receipt (Simon et al., 2018). However, because the majority of EITC-eligible individuals with children (80–86%) receive the credit, this assumption is standard for modelling EITC-health effects (Falk and Crandall-Hollick, 2018; Simon et al., 2018). Finally, this analysis did not determine causality or specific mechanisms that may link the EITC to substance use outcomes. It is reasonable to suspect that such mechanisms are related to econometric theory of individual motivation to maximize income or leisure upon starting a new job, or psychosocial factors such as stress reduction (Eissa et al., 1996).

Conclusion

The current study suggested that there are distinct groups of individuals who claim the EITC over their lifetime and have different sociodemographic characteristics. This study provides support for previous research that concluded that the EITC is a short-term safety net. Thus, excluding individuals who do not have a fixed EITC exposure from the sample, prevents researchers from observing the complete EITC population. This study revealed that two groups of individuals are excluded from the "EITC population" in current studies – those who begin claiming the EITC and those who discontinue claiming the EITC. Future studies should consider using LCA to identify trajectories of claiming the EITC to create an exposure variable that does not require fixed EITC status. These trajectories can then be used in mixture modeling techniques, such as this study, or used as a latent variable in multivariate regression for causal inference studies. Understanding the long-term impact of this short-term income support program will ultimately help researchers identify how tax credits can be utilized as programs to help alleviate poverty and improve health outcomes among low-income, vulnerable populations.

Table 2.1. Prevalence of Latent Class Indicators, Demographic Characteristics, and Substance Use among full NLSY sample (N=8,984)

	Full Sample Proportion or M (SD)
LCA Indicators – Claimed the EITC	
2003	0.19
2004	0.23
2005	0.28
2006	0.30
2007	0.32
2008	0.37
2009	0.36
2010	0.30
Demographic Characteristics	
Male	0.51
Female	0.49
Black	0.27
White	0.51
Hispanic	0.21
Mixed	0.01
Age (2003[a])	20.9 (1.44)
Age (2011)	28.8 (1.45)
HS diploma or less (2003)	0.92
Some college or more	0.08
HS diploma or less (2011)	0.67
Some college or more	0.33
Health Insurance (2003)	0.67
Health Insurance (2011)	0.67
Parent (2003)	0.19
Parent (2011)	0.47
Married (2003)	0.29
Married (2011)	0.31
Baseline SU Prevalence (2003)	
Use Since Last Interview	
Tobacco	0.44
Alcohol	0.70
Marijuana	0.23
Illicit Drugs	0.06
SU Prevalence (2011)	
Use Since Last Interview	
Tobacco	0.37
Alcohol	0.74
Marijuana	0.16
Illicit Drugs	0.03

Notes: [a] Time-varying factors are provided during 2003, the baseline year of the latent class analysis, and 2011, the year distal substance use outcomes are measured. P = proportion; M = mean; SD = standard deviation; LCA = latent class analysis; EITC = earned income tax credit; SU = substance use.

Table 2.2. Model Fit Statistics for Trajectories of Claiming the EITC (N=8,514) [a]

	# OF EITC LATENT CLASSES				
FIT MEASURE	**2**	**3**	**4**	**5**	**6**
# of Free Parameters	17	26	**35**	44	53
LL	-30232.90	-29869.24	**-29643.04**	-29584.40	-29557.26
AIC	60499.80	59790.48	**59356.07**	59256.80	59220.52
BIC	60619.64	59973.76	**59602.80**	59566.97	59594.14
LMR	7274.24 <0.001	718.50 <0.0001	**446.92** **<0.001**	115.85 0.0001	53.14 0.20
Entropy	0.723	0.659	**0.614**	0.614	0.588
Smallest Class	31%	12%	**11%**	8%	6%

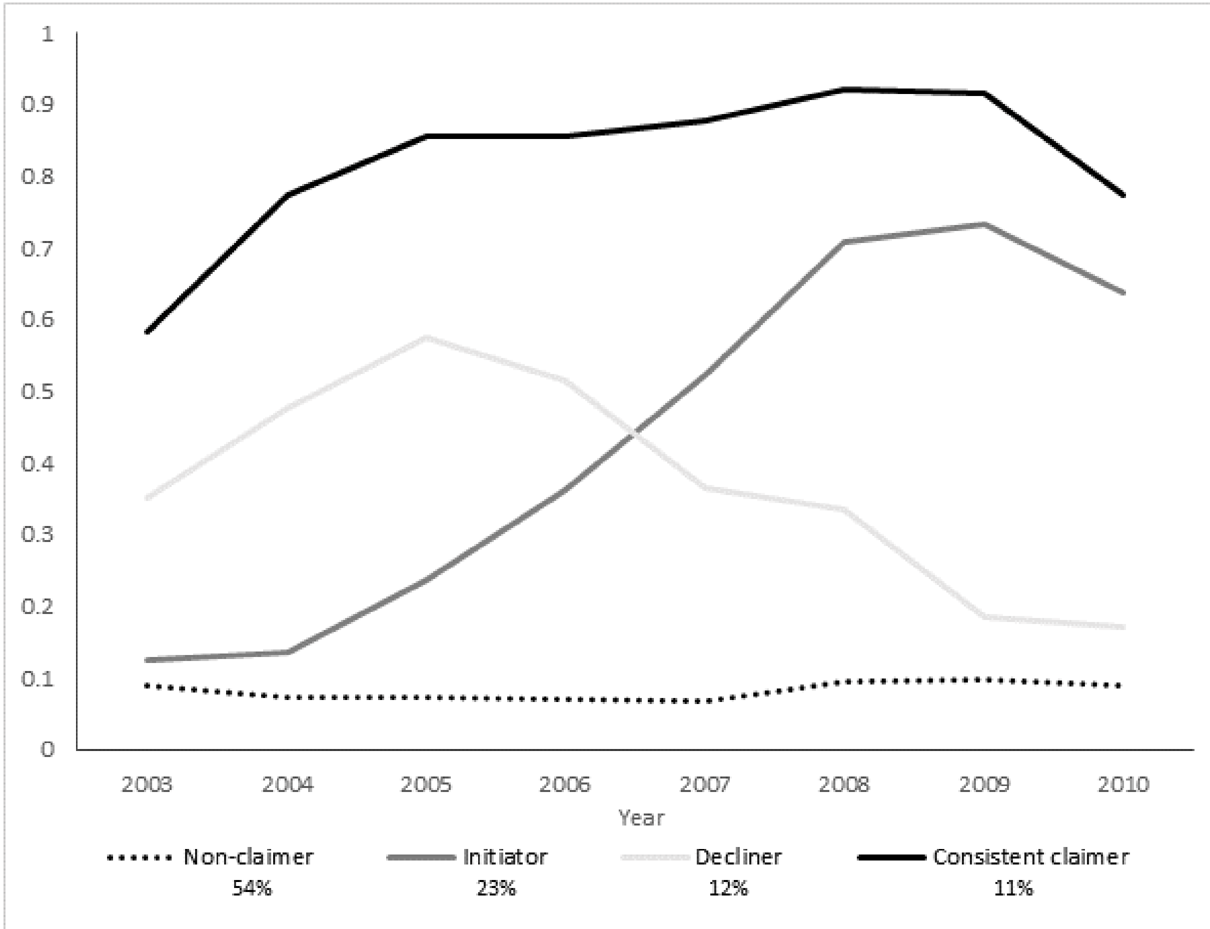
Notes: [a] 470 individuals were excluded from the LCA due to missing data on all indicator variables. LL= log likelihood; AIC= Akaike information criteria; BIC= Bayesian information criteria; LMR= adjusted Lo-Mendell Rubin and p-value.

Table 2.3. Estimated Mean Demographic Characteristics by Latent Class Membership

	Non-claimers **Class 1**	***Initiator*** **Class 2**	***Decliner*** **Class 3**	***Consistent claimer*** **Class 4**
Female	0.44	0.59	0.45	0.77
Race				
Black	0.23	0.32	0.21	0.39
White	0.59	0.37	0.51	0.37
Hispanic	0.17	0.29	0.27	0.23
Age (2011)	28.8	28.6	28.9	29.3
Education				
HS diploma or less	0.55	0.77	0.71	0.80
Some college or more	0.45	0.23	0.29	0.20
Insured (2011)	0.68	0.69	0.69	0.69
Parent (2011)	0.31	0.70	0.45	0.90
Married (2011)	0.36	0.40	0.42	0.48

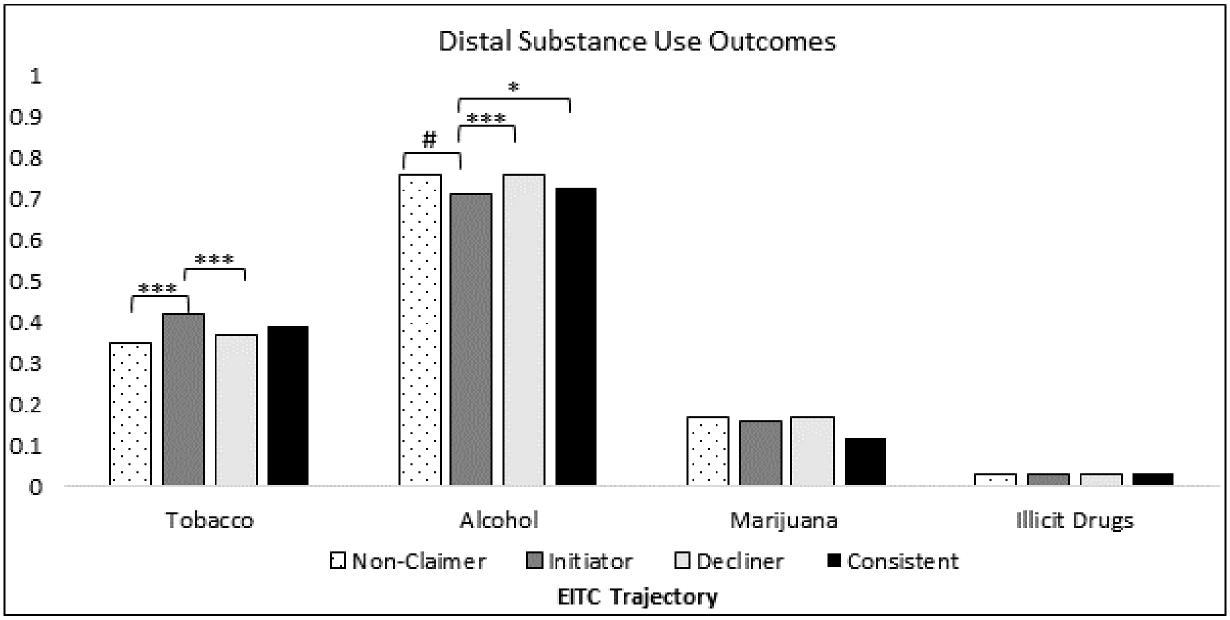
Notes: For relevant statistics (odds ratio) refer to Appendix (A-Table2.1)

Figure 2.1. 4-Class Model of Trajectories of Claiming the EITC



Notes: Y-axis is the probability that individuals in each class would have answered "yes" to claiming the EITC, also called the conditional item probability.

Figure 2.2. Distal Substance Use Outcomes by Latent EITC Trajectory



Notes: Significant pairwise comparisons are displayed by class. #=0.10, *= 0.05, **= 0.01, ***=0.001. EITC=earned income tax credit.

CHAPTER 3. Latent Trajectories of Federal EITC Receipt and Measures of Economic Wellbeing

3.1. Abstract

Objective: In Chapter 2, I intended to understand the longitudinal impact of the EITC by identifying distinct patterns of claiming EITC benefits. In the current study, I aimed to further explore these trajectories by examining their association with measures of economic wellbeing. Method: Using data from 8,984 responses to the 1997 National Longitudinal Survey of Youth (NLSY97), which oversampled Black and Latino respondents, I performed a longitudinal latent class analysis (LLCA) of individuals who answered a question on claiming the EITC from 2003 to 2010 (n=8,514) to identify longitudinal patterns of EITC receipt. I also examined sociodemographic correlates of class membership and tested for differences in eight measures of economic wellbeing outcomes, four income-based poverty measures (household worth, assets, debts, poverty ratio) and four indicators of material hardship (health, life satisfaction, bill collectors, unemployed member). Results: The Income-to-Poverty ratio and value of assets varied by class, but there was no difference in household net worth or value of debts. EITC *Initiators* had lower income-based poverty than *Consistent claimers*, as evidenced by significantly higher assets (~ $1.4k vs $890), marginally less debt (~ $5.9k vs $6.7k). Conclusion: There are distinct patterns of claiming the EITC, and individuals within these trajectories have differential economic health outcomes. These findings suggest that on average, people who stop claiming the EITC (i.e., *Decliners*) stop claiming the credit due to exceeding maximum income levels, rather than failing to meet work requirements or filing an income tax return.

3.2. Introduction

The Federal Earned Income Tax Credit (EITC) was first introduced in 1970 as a refundable credit for low-income, working adults. The EITC is the largest anti-poverty cash assistance program in the United States and directly impacts two key social determinants of health – income and employment (Falk and Crandall-Hollick, 2018). The federal EITC is associated with physical and psychological well-being (Boyd-Swan et al., 2016; Gomis-Porqueras et al., 2011; Lenhart, 2019) and educational achievement among lower-income children (Bastian and Michelmore, 2015; Hamad et al., 2018; Strully et al., 2010). While these health effects are promising, the primary goal of the EITC is to help lift low-income families out of poverty by encouraging work and employment (Falk and Crandall-Hollick, 2018). Some literature on the health effects of the EITC include income as a secondary outcome in the analysis, to measure whether the EITC has had an impact on health by impacting income and employment (Cowan and Tefft, 2012; Kenkel et al., 2013; Rehkopf et al., 2014a).

Previous research has evaluated the EITC's employment effects, concluding that the EITC increases the work force participation of single mothers and leads to corresponding increases in post-tax income. One study found a 34% of the increase in employment for single mothers between 1993 and 1999 was due to the EITC (Falk and Crandall-Hollick, 2018). The bulk of research has focused on unmarried, single mothers, because like the bulk of EITC research, these studies examine how legislative expansions of the EITC influenced previously unimpacted groups through causal inference methods. Studies have not investigated the impact on childless adults, mainly because the EITC has not been expanded for this group and most studies evaluate EITC expansions. Research is less conclusive for married individuals but suggests that married women may reduce the number of hours they work (Crandall-Hollick and Hughes, 2018). Investigating the EITC's impact on equity and poverty reduction, often involves observing poverty rates or tax burden. Because the EITC is not included in the definition of income for the official poverty measure, alternative measures must be used. The Supplemental Poverty Measure (SPM), has been used to assess the effects of social policies. When transfers from government tax programs were included in a broader measure of poverty, refundable tax credits reduced poverty by 3%,compared to 1.6% for food assistance (SNAP) and 0.2% point for temporary welfare assistance (TANF). Research examining if the tax credit improves outcomes related to equity such as health and education outcomes is growing. However, there are not many EITC studies that measure effects in terms of other economic health indicators, such as ability to meet material needs and demands.

Poverty is a multidimensional phenomenon (Isaacs et al., 2004). Poverty can be holistically defined as the extent to which an individual goes without having resources, including financial, emotional, mental, and spiritual resources and support systems (Payne, 2013). However, we often think of poverty only in terms of having the financial resources to purchase goods and services. This is because poverty is often conceptualized in terms of income thresholds, namely throughout the U.S. official poverty measure (OPM). While there are specific criticisms of the OPM, the major problem can be described in two ways, which Fremstad (2010) describes as the “too low, too narrow” problem”. This refers to the fact that the income threshold for the federal poverty line is too low, and what type of income and resources qualify as income are too restrictive to reflect individual’s material reality. Citro and Michael (1995) describe economic poverty as a “low level of material goods or services or a low level of resources to obtain these goods and services”. They describe two forms of economic wellbeing, one based on lack of resources, typically measured by income, and the other on the lack of goods and services, typically thought of as deprivation or hardship. The OPM and the SPM are both income-based poverty measures, meaning they rely on income to determine poverty. Researchers have turned to deprivation poverty measures in recent years, to make up for limitations of income-based measures. Material hardship is a deprivation measure comprised of several indicators and is increasingly being used to understand relative (having less than peers) and subjective (feeling deprived) poverty (Nelson, 2011). While there is no single definition of Material hardship, the definition by Beverly (1999) defines it as “inadequate consumption of very basic goods and services such as food, housing, clothing, and medical care.” Bauman (1998) describes the material hardship approach as using “direct measures of economic well-being to keep track of how people are getting by.” Common measures of economic wellbeing used to assess material hardship include such as food insecurity, difficulty meeting basic needs, lack of consumer durables, housing problems, neighborhood problems, and fear of crime (Nelson, 2011).

Previous longitundinal research establishes that people experience poverty for different durations, some individuals experience generational poverty (lasting for two or more generations), while others experience transient poverty (Currie, 2011; Haveman et al., n.d.). Another limitation of the extant literature on EITC and health, is the inability to observe the long-term impact of the EITC over the years on economic outcomes. Current EITC studies are limited by the inability to observe income-based poverty or deprivation over time among EITC recipients as they claim the credit on and off throughout their life. The bulk of current EITC studies use causal inference study designs to evaluate the effect of legislative expansions of the EITC (Pega et al., 2013). One predominant method is the difference-in-difference policy analysis, which characterizes most methods. A DD study is a common technique in policy evaluations and estimates the effect of a policy/intervention by comparing changes in the outcome between a population that received the intervention and a group that did not (control)

(Wing et al., 2018). The problem is that EITC exposure must be fixed to evaluate the impact of the policy. As a result, the sample of EITC recipients is composed of people that have claimed the credit consecutive years in a row, without interruption. Evidence confirms that the EITC is a short-term safety net typically claimed on and off for one or two years at a time(Ackerman, 2009; Dowd and Horowitz, 2011). Thus, it would yield greater validity if researchers could study low-income individuals across the life course as they change their EITC status every year, since this what IRS record indicate. Theoretically, individuals would stop claiming the EITC for two primary reasons: (1) increase in economic stability, such as surpassing minimum income requirements or (2) decline in economic stability, such as failing to meet the employment requirement or not filing an income tax return. If existing studies limit their sample to people who do not change EITC status, researchers are unable to study a considerable segment of the EITC population or understand long term impact. Because poverty is partially characterized by economic instability and flux (Currie, 2011), current studies unable to assess whether the economic situation of EITC recipients is changing over the years, as they claim the credit sporadically.

In Chapter 2, I identified four trajectories of EITC recipients: *Non-claimers* (54%), *Initiators* (23%), *Decliners* (12%), and *Consistent claimers* (11%). There were significant differences between EITC trajectories in tobacco and alcohol use, but not marijuana or other illicit drug use. This chapter revealed that two groups of individuals are excluded from the "EITC population" in current studies – those who begin claiming the EITC and those who discontinue claiming the EITC.

The Current Study. The current study seeks to understand whether economic wellbeing outcomes vary across individuals with various EITC receipt history. The goal of the current study is to extend the previously enumerated EITC trajectory classes (Aim 1) in order to identify significant characteristics (i.e., correlates) of class membership (e.g., age, sex) and understand if these classes impact economic wellbeing outcomes. One concern with current EITC studies is the inability to look at the impact of longitudinal EITC receipt due to limitations of current EITC study design. The previous study concluded that it is important to consider the impact of different EITC trajectories because they may have a differential effect on health behaviors specifically substance use behavior. By examining individual trajectories of claiming the EITC over time, we can observe groups of individuals that are improving, declining, or remaining consistent in claiming the EITC. Despite its non-inclusion in the official poverty measure, the EITC is the government's primary tool for economic mobility for low-income adults and whether the EITC has an impact on substance use warrants further investigation (Falk and Crandall-Hollick, 2018).

3.3. Methods

The 1997 National Longitudinal Survey of Youth (NLSY97)

Data for this study are from the 1997 National Longitudinal Survey of Youth (NLSY97), a prospective cohort study currently conducted by the Bureau of Labor Statistics which gathers information on the labor force experiences of youth born between 1980 and 1984 as they transition through adulthood (Bureau of Labor Statistics, 2019). Because detailed information on income and number of children is unavailable for prior EITC studies, the 1997 National Longitudinal Survey of Youth (NLSY97) is the ideal dataset to examine the relationship between EITC and substance use. Interviews have been conducted annually from 1997 to 2011, and biannually from 2013 to the present. The initial NLSY97 survey consists of 8,194 participants, comprised of a representative cross-sectional sample of 6,748 respondents and a supplemental oversample of 2,236 Hispanic/Latino and Black respondents. Youth respondents' ages ranged from 12-18 in 1997, and 30-36 in 2015. NLSY97 data are designed to be representative at the national level and cumulative sampling & panel data weights are provided. Because the goal of the current study is to avoid limitations of prior causal inference EITC studies, I used a model-based approach and did not use study weights (Bureau of Labor Statistics, 2019). These de-identified data were exempt from Institutional Review by the Johns Hopkins Bloomberg School of Public Health .

Measures

Claiming the EITC on tax return. Indicators of latent class membership are whether participants claimed the EITC in the past year, from 2003 to 2010. Although, the NLSY began data collection in 1997, the study period began in 2003 when all participants were 18 and legally eligible to claim independence on their tax return. All individuals who answer "yes" to having a source of income in the survey are asked whether they claimed an EITC on their tax return last year. For example, in 2007, participants who reported an income source were asked, "Did [*you/you or your spouse/you or your partner*] claim, or are [*you/you or your spouse/you or your partner*] planning to claim, an Earned Income Tax Credit on your [*or your spouse's/or your partner's*] 2006 Federal Income Tax Return?" Individuals who were originally excluded from the question (individuals without a source of income), were coded as not claiming an EITC.

Demographic Characteristics. All demographic characteristics are self-reported and include sex, race, age, marital status, educational attainment, parent status, and health insurance coverage. The NLSY97 survey staff created a single combined race variable. All respondents are classified as Hispanic /Latino, Black, Non-black/Non-Hispanic, or Mixed race. Hispanic of Latino ethnicity was given prioritized in creation of this variable. Similar to other studies, educational attainment was measured as a binary variable comprised of high school (HS) diploma or less and some college or more (Gomis-Porqueras et al., 2011). Some demographic characteristics are time-varying outcomes, such as age, health insurance, and marital status. To understand whether these variables change over time, I provided estimates from 2003, the baseline year for the study period (2003) and compare them to the year that distal outcomes are measured (2008).

Economic Wellbeing Outcomes. Several income measures and self-reported material hardship indicators were included to measure poverty or economic wellbeing. Specifically, income measures of economic wellbeing included household income-to-poverty ratio, the amount of financial debt the participant owed (excluding housing value), financial assets (including nonfinancial assets), and the net worth of the participants' household. Details on the value of a respondent's financial asset holdings (e.g., real estate, businesses, vehicles) and amount of debt (excluding housing), were generated retrospectively for all participants regardless of survey interview round at age 25. Values for financial assets and debt were top coded at \$300,000 and \$370,000, respectively. Income to poverty ratio is the ratio of household income to poverty level in the previous year, accounting for household size. The range of values in 2008 when study outcomes are measured was 0-19.4, and a higher ratio indicates a lower level of poverty relative to household income. Participants general health was measured by asking individuals *"In general, how is your health?"* Responses ranged from 1 to 5, ranging from Excellent, Very Good, Good, Fair, and Poor. Participants were also asked about unemployment in the household: "*In the last five years, did any adult member of your household (other than yourself) experience one or more periods of unemployment lasting at least six months?*" to which participants answered (yes/no). This question was asked this question from 2007-2009 while participants were 24-26 years on average, until every participant was asked the question. To assess life satisfaction, participants were asked “All things considered, how satisfied are you with your life as a whole these days? Please give me an answer from 1 to 10, where 1 means extremely dissatisfied and 10 means extremely satisfied.” This question was asked once in 2008, when participants were aged 25.

Statistical Analysis

The goal of a latent class analysis (LCA) is to classify individuals into distinct groups of categories based on their individual response patterns. The LCA is a person-centered approach that focuses on relationships among individuals, so that individuals within a group are more similar than individual across different groups (Jung and Wickrama, 2008a). While regression modeling takes a variable-based approach to understand causality, we recognize that variable based approaches are insufficient in situation where there is information bias. On the other hand, a person-centered approach has the opposite goal. Instead of observing the relationships between variables (e.g., sex, number of children, EITC exposure), the LCA approach analyzes the latent structure of people, and sorts them into groups (Jung and Wickrama, 2008b). This approach is required to further understand who EITC participants are through descriptively quantitative methods. As a result, we explore the impact of sex, race, age, marital status, parent status, parental educational attainment, and health insurance coverage on class membership. Measures of economic wellbeing were accessed in 2008, when participants were 25 years old on average, and included as distal outcomes using a three-step approach (Nylund-Gibson et al., 2019). To assess the overall difference between latent classes, a Wald Test was performed. To compare differences between individuals' classes, added additional “model constraints” were added to include pairwise comparisons between individuals' latent classes. All analyses were performed in Mplus, version 8 (Muthen and Muthen, 2017).

LCA Model Fit. LCA models with 1 to 6 classes were fit. Multiple random starting values were used to ensure estimates did not reflect local maxima, and the best log likelihood value was replicated. Models were compared based on standard fit statistics, the Akaike Information Criteria (AIC), Bayesian Information Criteria (BIC), Lo-Mendel-Rubin (LMR), the Log likelihood (LL), the Bootstrapped Likelihood Ratio Tests (BLRT), and the model entropy (Masyn, 2013; Nylund-Gibson, 2007; Nylund-Gibson and Choi, 2018).

3.4. Results

The prevalence of the latent class indicators, demographic characteristics, and distal outcomes for the full analytic sample are provided (Table 1). The NLSY97 sample is 51% male, 51% white, and in 2008 the average educational attainment was at least a high school diploma.

Latent Class Enumeration

Based on fit statistics (Table 2) and substantive interpretation, a four-class model was chosen (Figure 1). Although a 5-class model was initially preferred by some fit statistics (i.e., LMR), the additional class identified was not theoretically meaningful and therefore we chose the more parsimonious model. The first and largest class was composed of individuals who had a probability of less than 9% of claiming the EITC consistently from 2003 to 2010, labeled *Non-claimers* (54% of sample). A second class of those who did not claim the EITC until 2004, labeled *Initiators* (8%). A third class of individuals who claimed the EITC in early years but discontinued after 2007 (13%) and was labeled *Decliner*. Finally, a fourth class was characterized by individuals who had a probability of 80% or higher of claiming the EITC every year, labeled *Consistent claimers* (10%).

Demographic Correlates of Class Membership

For each latent class, the probability of demographic characteristics is presented, and significant associations are bolded (Table 3). Sociodemographic differences are briefly mentioned below, and coefficients and odds ratios are included in the appendix for a referent class of *Non-claimers* (A-Table 3.1) and *Consistent claimers* (A-Table 3.2). Compared to *Non-claimers* (i.e. those who did not claim the EITC), significant correlates among EITC trajectories were sex, education, parent status, marital status, and health coverage (Table 3). There were no significant differences in race/ethnicity by class. Compared to *Consistent claimers*, *Initiators* were less likely to be female (OR: 0.44, $p<0.001$), less likely to be parents (0.21, $p<.001$), and less likely to be married (0.66, $p<0.001$) (A-Table 3.2). Compared to *Initiators*, *Decliners* are significantly less likely to be parents (OR: 0.30, p=<0.001), but more likely to be married (OR: 2.10, $p=0.003$).

Indicators of Material Hardship by Class

General Health. General Health differed marginally by class ($\chi = 7.53$, $p = 0.06$), with the best health reported by *Non-claimers*, with the lowest rating of 2.14, and the worst health rating of 2.47 reported by *Consistent claimers*. *Consistent claimers* were significantly more likely than *Non-claimers* to report a lower general health rating ($\beta =0.14$, $p=0.007$).

Life Satisfaction. Life satisfaction did not differ significantly overall by class ($\chi = 5.415$, $p = 0.14$), however *Consistent claimers* had significantly lower life satisfaction than *Decliners* ($\beta =-0.256$, $p=0.02$).

Pressure from Bill Collectors. The proportion of individuals reporting pressure from bill collectors differed significantly by class ($\chi = 33.6$, $p<0.0001$). EITC *Decliners* were less likely to report pressure from bill collectors than *Consistent claimers* ($\beta =-0.075.$, $p=0.01$), but significantly more likely than *Non-claimers* (β =0.042, p=0.05). Although *Consistent claimers* report more pressure from bill collectors than *Non-claimers* (β =0.117, p<0.001) and *Initiators* (β =0.059, p=0.02), *Initiators* are more likely to report pressure than *Non-claimers* (β =0.017, p=0.001).

Unemployed Household Member. The proportion of individuals reporting an unemployed household member in the last 5 years did not differ overall by class, but there were two significant pairwise comparisons. *Decliners* had a lower proportion of unemployed members than *Consistent claimers* (β =-0.049, p=0.04) and *Consistent claimers* had a higher proportion than *Non-claimers* (β =0.039, p=0.04).

3.4.4. Income Measures by Class

Household Poverty Ratio. The ratio of household income to poverty in the previous year differed significantly by class (χ = 17.02, p = 0.0007). The lowest poverty was among *Non-claimers* with a corresponding ratio of 4.15, while *Consistent claimers* had the highest amount of poverty and lowest ratio of 2.26. *Consistent claimers* had more poverty than *Non-claimers* (β= -0.61, p=<0.001), and *Non-claimers* had less poverty than *Initiators* (β =0.397, p=0.02). However, *Decliners* had significantly less poverty (4.07) than *Consistent claimer*'s (β =0.761, p=0.001) and *Initiators* (β =0.553, p=0.02).

Household Net Worth at 25. Household net worth did not differ significantly overall by class (χ = 3.43, p = 0.33), however *Consistent claimers* had a marginally lower net worth than *Non-claimers* (β =-0.154, p=0.09).

Assets at age 25. The value of financial and nonfinancial assets varied significantly by class (χ = 41.03, p<0.0001). *Non-claimers* had the $3,630 in assets, while *Consistent claimers* had $888.91 in assets. *Decliners* ($3,050) had more assets than *Consistent claimers* (β =0.923, p=0.001) and *Initiators* (β =0.573, p=0.004). *Consistent claimers* had significantly less assets than *Non-claimers* (β =-0.965., p<0.001) and *Initiators* (β =-0.349., p=0.07). *Non-claimers* had significantly more assets (β =0.616, p<0.001.) than *Initiators* ($1,365).

Debts at age 25. The value of debts did not differ significantly overall by class (χ = 4.82, p=0.19), though there were significant pairwise differences. *Non-claimers* had the highest amount of debt $9,996, while *Initiators* had the lowest at $5,978. *Non-claimers* had significantly more debt than *Initiators* (β =0.18, p=0.04). *Consistent claimers* had marginally more debt ($6,714) than *Initiators* (β =0.174, p=0.10).

3.5. Discussion

The goal of this study was to identify whether longitudinal trajectories of claiming the EITC are associated with differential measures of economic wellbeing measured by income-based poverty and material hardship. There were four EITC trajectories: *Non-claimers* (54%), *Initiators* (23%), *Decliners* (12%), and *Consistent claimers* (11%). For income measures, the income to poverty ratio and value of assets varied by class, but there was no difference in household net worth or value of debts. Our findings suggest that compared to assets, evaluating debt-based measures may not be a robust was indicator of income-based poverty, because *Decliners* and *Non-claimers* had more debt than their lower-income counterparts. Typically, attending education would be correlated with higher debt, however we did adjust for education level in these analyses. In terms of indicators of material hardship, general health and pressure from bill collectors varied by class, but overall life satisfaction and unemployment among a member of the household did not. The fact that general health varied marginally by class, while life satisfaction did not is interesting, though future research is required. While only one comparison between *Consistent claimers* and *Non-claimers* was driving the significant association for general health, these two trajectories most accurately represent EITC recipients and non-recipients in the current literature. Previous research on EITC and subjective wellbeing established that EITC recipients have lower health ratings that individuals who do not claim the EITC (Boyd-Swan et al., 2016). Taken together, these findings could provide minor evidence to support the assertion that perceived health measures are less susceptible to self-report bias than more abstract questions about life satisfaction (Boyd-Swan et al., 2016). Furthermore, questions about life satisfaction would more accurately measure subjective poverty (feeling deprived) rather than relative (material deprivation) and absolute (income deprivation) poverty.

Findings from the current study were consistent with results from Chapter 2. EITC *Consistent claimers* and *Initiators* appear similar to one another on income-based poverty measures, while the same is true for *Non-claimers* and *Decliners*. On average, people who stop claiming the EITC (i.e., *Decliners*) stop claiming due to exceeding maximum income levels, rather than failing to meet work requirements or filing an income tax return. Compared to EITC *Initiators*, *Decliners* had significantly more assets (~ $1.4k vs $3k) and significantly less poverty, evidenced by a higher income to poverty ratio. Between *Initiators* and *Decliners* there are no differences by sex, race, or education. Compared to *Initiators*, *Decliners* are significantly less likely to be parents (OR: 0.30, p=<0.001), but more likely to be married (OR: 2.10, p=0.003). Pressure from Bill Collectors is also good measure to illustrate the difference between the *Initiator* and *Decliner* trajectories. *Decliners* had significantly less pressure from Bill Collectors than *Consistent claimers*, but still reported more than *Non-claimers*. It appears that EITC *Decliners* experience increased income after no longer claiming the EITC, but their income is not as high as *Non-claimers*. While this may be unsurprising, it is meaningful to know that on average, individuals in the *Decliner* trajectory did not stop claiming the EITC due to increases in income-based poverty (i.e., job loss). Between *Initiators* and *Decliners* there are no differences by sex, race, or education.

Initiators reported more pressure from bill collectors than *Non-claimer*s, but less pressure than *Consistent claimer*s. Our results suggest that EITC *Initiators* have higher economic wellbeing than *Consistent claimers*, as evidenced by significantly higher assets (~ $1.4k vs $890), marginally less debt (~ $5.9k vs $6.7k). Notably, *Consistent claimers* and *Initiators* did not differ significantly by race, education, or health coverage. Compared to *Consistent claimers*, *Initiators* were more likely to be single males without children. Given that current research focuses on single mothers because they receive the EITC most consistently (although men and childless also claim the credit), it makes sense that the group with the second highest probability of receiving the EITC (i.e., *Initiators*) are comprised of men and childless adults who also claim the credit, but do not receive it as often as single mothers (i.e., *Consistent claimers*).

Our findings suggest that while men are less likely to claim the EITC as often as consistently as women, they are more likely to stop or start claiming the credit. Whether this is due to better economic outcomes than their female counterparts or rarity of receiving the EITC credit is unknown. However, economists and proponents of EITC reform or elimination often point out that the credit does not help low-income families, so much as it helps low-income women (Mead, 2020; Rachidi, 2015b). Researchers from the Cato Institute have suggested that the EITC ends up hurting childless workers who receive no EITC or a small EITC, because it can push down market wages (Edwards and de Rugy, 2015). In another critical review of the EITC, Mead (2014) argues that expanding the EITC credit for men would be ineffective and "recent claims made on behalf of the EITC have stoked false hopes that work incentives alone might bring low-income men into the work force in large numbers." This is based on the assertion that poor men respond similarly to poor women to work incentives. That said, many proponents of the EITC are in favor of expanding the credit so that childless men and adults can benefit from the policy (Aviva Aron-Dine and Sherman, 2007; Kapahi and Fellow, 2019; Maag et al., 2019; Marr et al., 2016). In many cases, childless adults carry a heavier tax burden and have their income pushed below the poverty line due to tax liability (Marr et al., 2014)

Strengths and Limitations. This was the first study to examine the relationship between the EITC and material hardship by using individual trajectories of claiming the EITC through a Longitudinal Latent Class Analysis (LLCA). In addition, the NLSY97 is the only national survey with health information that includes a survey item on claiming the EITC receipt, allowing us to decrease potential misclassification bias of prior studies (Pega et al., 2013). Furthermore, the NLSY97 prevents the probable measurement error of prior studies that used cross-sectional data, by allowing us to control for individual time-invariant heterogeneity and providing more detailed demographic information (i.e., marriage and parental status). State EITCs were not included in this analysis because the purpose was to examine the longitudinal impact of the federal policy. Future research should explore whether there is a unique impact of state EITCs. In addition, we do not know whether individuals who claimed the EITC receive it, limiting us to an intent-to-treat interpretation of the results. There are no nationally representative U.S. health surveys that collect information on individuals' EITC receipt (Simon et al., 2018). However, because the majority of EITC-eligible individuals with children (80–86%) receive the credit, this assumption is standard across studies for modelling EITC-health effects (Falk and Crandall-Hollick, 2018; Pega et al., 2013; Simon et al., 2018). There were several indicators of material hardship (i.e., food security, neighborhood conditions) we were unable to include because they are not accessed in the NLSY97. However, some measures of material hardship are better suited to detect short-term poverty, such as bill collectors. While other factors, such as neighborhood conditions may reflect longer term poverty (Iceland and Bauman, 2007). Our analysis provide further support that including measures of income-based poverty and material hardship may be necessary to capture the multidimensional effects of poverty (Nelson, 2011).

Conclusion

The current study revealed that measures of income-based poverty and indicators of material hardship vary significantly across different EITC receipt trajectories. In terms of income, people who stop claiming the EITC (i.e., *Decliners*) stop claiming due to exceeding maximum income levels, rather than failing to meet work requirements or filing an income tax return. In addition, men appear to claim the EITC for a shorter time than women. This provides further support for the Chapter 1 conclusion that excluding individuals who do not have a fixed EITC exposure, prevents researchers from studying two important groups –people who change EITC status during life (decliners and initiators) and people who claim for shorter periods of time (men). Future research on the EITC should consider using latent class analysis to identify distinct trajectories of receipt to identify these two groups and create an exposure variable that can be used as a covariate in multivariate regression techniques.

Table 3.1. Prevalence of Latent Class Indicators, Demographic Characteristics, and Economic Wellbeing among full NLSY sample (N=8,984)

	Full Sample Proportion or Mean (SD)
Claimed the EITC	
2003	0.19
2004	0.23
2005	0.28
2006	0.30
2007	0.32
2008	0.37
2009	0.36
2010	0.30
Demographic Characteristics	
Male	0.51
Female	0.49
Black	0.27
White	0.51
Hispanic	0.21
Mixed	0.01
HS diploma or less (2003)	0.92
Some college or more	0.08
HS diploma or less (2008)	0.71
Some college or more	0.29
Health Insurance (2003)	0.67
Health Insurance (2008)	0.67
Parent (2003)	0.19
Parent (2008)	0.38
Married (2003)	0.11
Married (2008)	0.29
Material Hardship Indicators (2008)	
General Health	2.24 (0.95)
Life Satisfaction	7.63 (1.85)
Bill Collectors	0.15
Unemployed Member	0.10
Income Poverty Measures (2008)	
Poverty Ratio	3.57 (3.59) [b]
Household Worth at 25 ($)	12,800.33 (4.38)
Assets at 25 ($)	2407.91 (9.22)
Debts at 25 ($)	7,984.68 (4.56)

Notes: [a] Time-varying factors are provided during 2003, the baseline year of the latent class analysis, and 2008, the year distal substance use outcomes are measured. [b] The range of possible income-to-poverty ratio values were 0.00-19.37. P = proportion; M = mean; SD = standard deviation; LCA = latent class analysis; EITC = earned income tax credit; SU = substance use.

Table 3.2. Model Fit Statistics for Trajectories of Claiming the EITC (N=8,514) [a]

	# OF EITC LATENT CLASSES				
FIT MEASURE	**2**	**3**	**4**	**5**	**6**
# of Free Parameters	17	26	**35**	44	53
LL	-30232.90	-29869.24	**-29643.04**	-29584.40	-29557.26
AIC	60499.80	59790.48	**59356.07**	59256.80	59220.52
BIC	60619.64	59973.76	**59602.80**	59566.97	59594.14
LMR	7274.24 <0.001	718.50 <0.0001	**446.92** **<0.001**	115.85 0.0001	53.14 0.20
Entropy	0.723	0.659	**0.614**	0.614	0.588
Smallest Class	31%	12%	**11%**	8%	6%

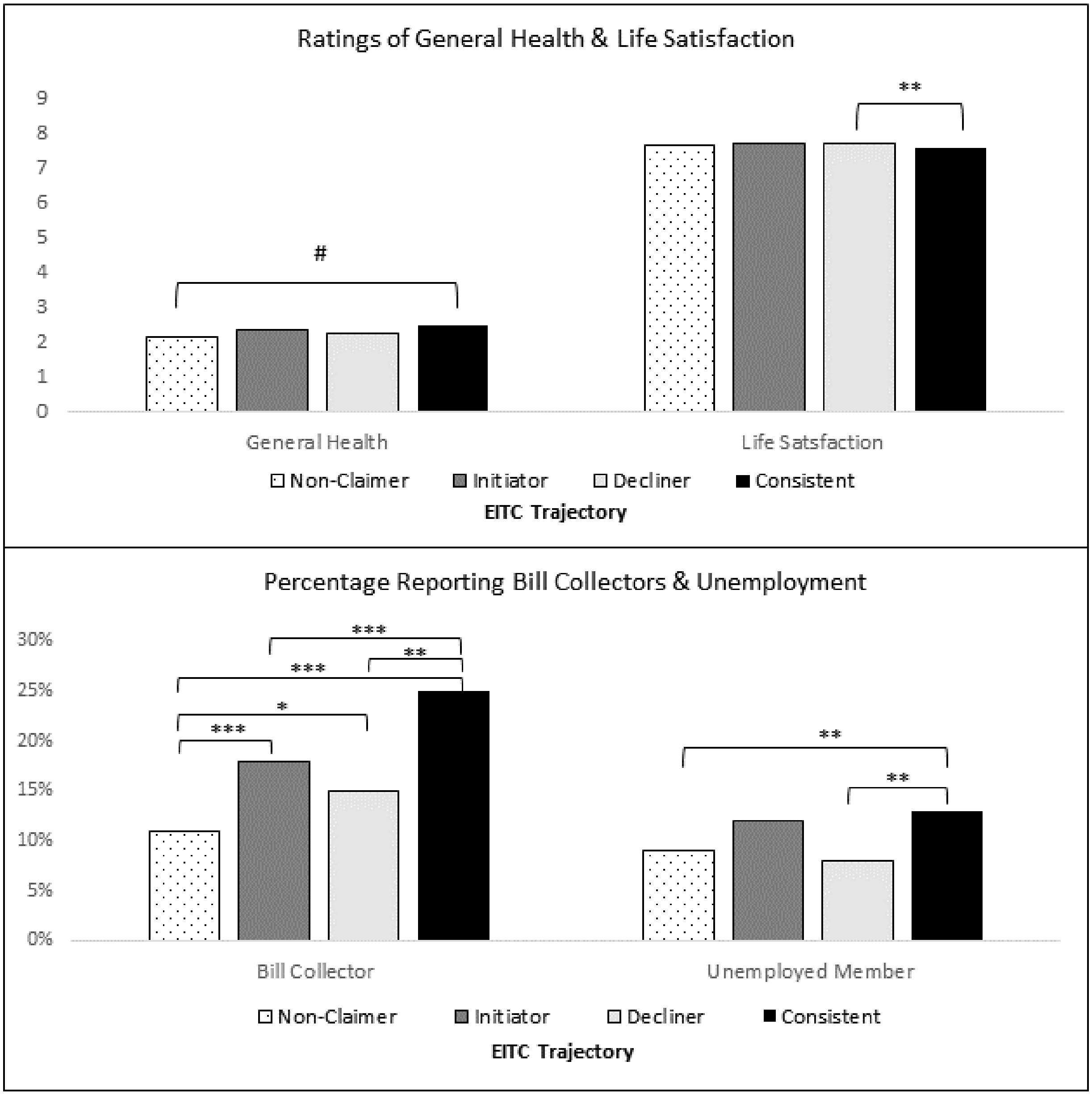
Notes: [a] 470 individuals were excluded from the LCA due to missing data on all indicator variables. LL= log likelihood; AIC= Akaike information criteria; BIC= Bayesian information criteria; LMR= adjusted Lo-Mendell Rubin and p-value.

Table 3.3. Estimated Means for Demographic Covariates by EITC Latent Class

	Non-claimer **Class 1**	***Initiator*** **Class 2**	***Decliner*** **Class 3**	***Consistent claimer*** **Class 4**
Sex				
Female	0.45	0.51	0.44	0.76
Race				
Black	0.22	0.34	0.22	0.39
White	0.60	0.39	0.52	0.37
Hispanic	0.17	0.26	0.26	0.23
Education				
HS diploma or less	0.61	0.82	0.74	0.86
Some college or more	0.39	0.18	0.26	0.14
Parent (2008)	0.17	0.57	0.34	0.90
Married (2008)	0.25	0.27	0.36	0.42
Insured (2008)	0.69	0.60	0.68	0.67

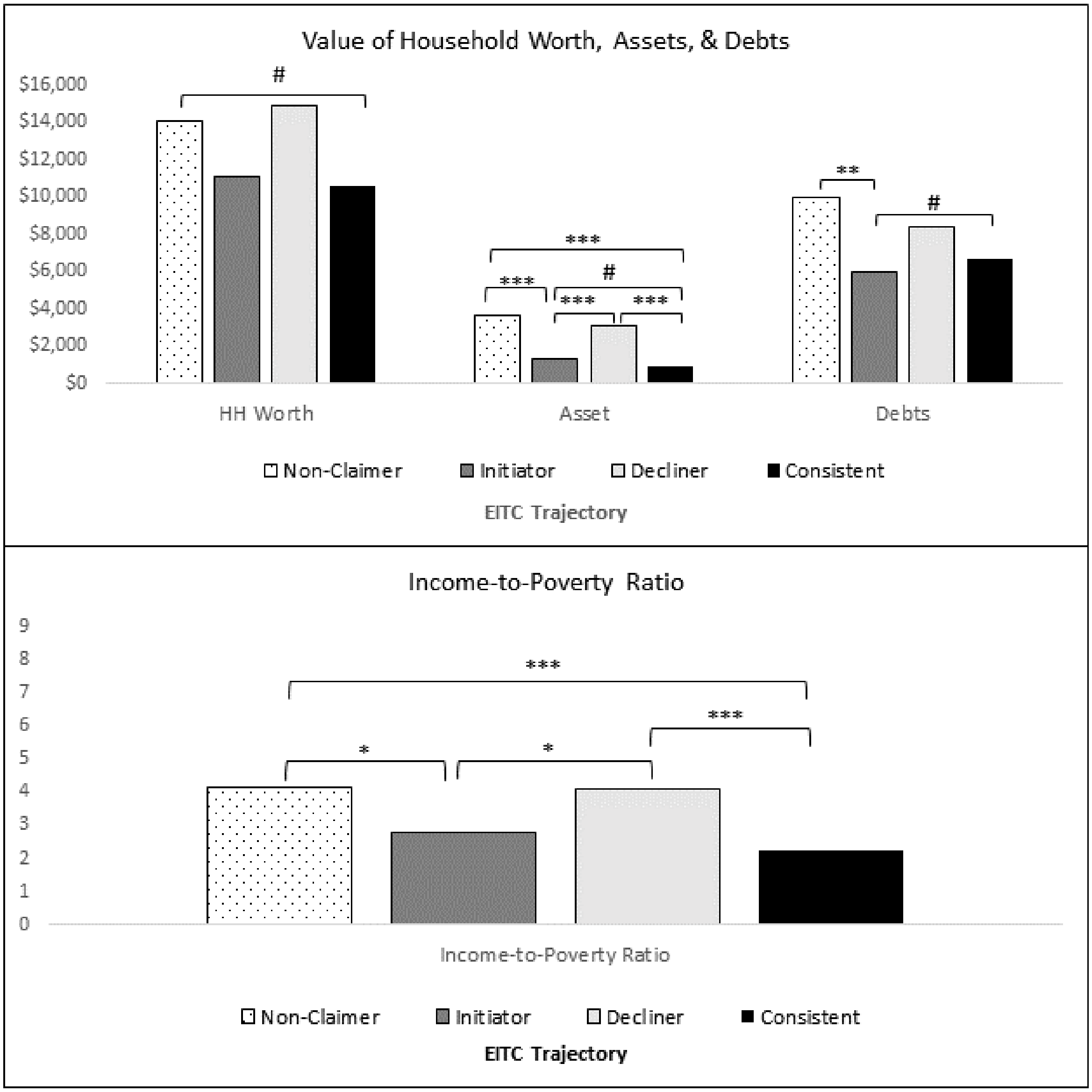
Notes: For relevant statistics refer to Appendix (A-Table 3.1)

Figure 3.1. Material Hardship Indicators by EITC Trajectory (Health, Life Satisfaction, Bill Collectors, Unemployment)



Notes: Significant pairwise comparisons are displayed by class. #=0.10, *= 0.05, **= 0.01, ***=0.001. EITC=earned income tax credit; Unemployed Member= unemployed member in household.

Figure 3.2. Income-based Poverty Indicators by EITC Trajectory (Household worth, Asset, Debts, Income poverty ratio)



Notes*:* Significant pairwise comparisons are displayed by class. #=0.10, *= 0.05, **= 0.01, ***=0.001**.** EITC=earned income tax credit.

CHAPTER 4. Co-occurring Trajectories of Earned Income Tax Credit Receipt and Substance Use: A Latent Transition Analysis

4.1. Abstract

Objective: In Chapter 2, I identified distinct trajectories of EITC receipt and confirmed that people with different EITC trajectories had differential substance use behavior in 2011. In Chapter 3, I further revealed that EITC trajectories also differ on indicators income and poverty. The current study aims to further examine the co-occurrence between these EITC trajectories and patterns of substance use to determine if claiming the EITC may be contributing to differential substance use behaviors. Method: Using data from 8,984 responses to the 1997 National Longitudinal Survey of Youth (NLSY97), which and oversampled Black and Latino respondents, I performed a latent transition analysis (LTA) of EITC trajectories and three substance use trajectories (tobacco, alcohol, marijuana), separately. I also explored whether sex significantly impacts transition probabilities. Results: For tobacco, *Consistent claimers* had the highest probability of being a non-smoker (50%), while *Initiators* had the highest probability of smokers (36%). For alcohol, compared to other EITC groups, *Initiators* had the lowest probability (54%) of being a *drinker* and *Non-claimers* had the highest (64%). For marijuana, *Consistent claimers* had the highest probability (85%) of being a non-user. Conclusion: Although further research is required, these findings suggest people with different patterns of claiming the EITC over time (trajectories) have different substance use behaviors over time as well. While these findings cannot prove that these differential behaviors are caused by EITC trajectory, they are evidence of distinct differences between individuals who have a particular history of receiving the EITC.

4.2. Introduction

While research on the health benefits of the Earned Income Tax Credit (EITC) is growing, research on potential substance use effects remain limited (Pega et al., 2013). There is a need for research evaluating the longitudinal impact of EITC receipt on substance use that addresses the limitations of current EITC studies. That is, studies are needed that consider how claiming the EITC may change over an individual's life course, which has been absent from existing literature. This is concerning because evidence suggests that the EITC is a short-term safety net. Based on analysis of federal tax returns, 61% of EITC recipients claimed the EITC for 1 or 2 years (Dowd and Horowitz, 2011).

Substance use is a point of concern for opponents of economic assistance programs, yet comparatively little research has focused on the EITC. The evidence on smoking after EITC implementation is mixed, one study found no effect five years after EITC implementation (Cowan and Tefft, 2012). Another study found a very moderate reduction in smoking during pregnancy (Strully et al., 2010). Another examination of current smoking behavior found no effect for African Americans, but a decrease for white mothers, two years after implementation (Averett and Wang, 2013). Tobacco studies typically restricted the outcome to women, and used individuals receiving a smaller EITC credit as the comparison group (Averett and Wang, 2013; Cowan and Tefft, 2012; Evans and Garthwaite, 2014). There is only one study examining the impact of the EITC on other drugs including alcohol and marijuana, pooling together cross-sectional data to observe the EITC. The authors concluded that during the months of EITC disbursement, there was no significant impact on alcohol use and an inconclusive decrease in marijuana use (Rehkopf et al., 2014a). However, this study had a few limitations that support the need for future research. The authors were evaluating the 1993 EITC legislative expansion and were therefore limited to adults with two or more children. The Rehkopf (2014) study was unique because they included both men and women in their sample. Women are more likely to claim and receive the EITC credit, but generally less likely to engage in substance use than males(Falk and Crandall-Hollick, 2018; McHugh et al., 2018). For this reason, the few studies that investigate the EITC and tobacco use typically restrict their analysis to women Rehkopf (2014) study was unique because they performed a stratified analysis for men and women. It is important to consider the role of sex in the relationship between the EITC and substance use since women are most likely to claim and receive the EITC credit, but generally less likely to engage in substance use than males (McHugh et al., 2018; Perkins, 2009).

The Current Study. The goal of the current study is to use latent transition analysis to investigate the co-occurring trajectories of EITC receipt and tobacco, alcohol, and marijuana use from 2003 to 2010. I will perform a longitudinal latent class analysis (LLCA) for each factor and then model the probability of joint membership between trajectories. I also explore the impact of sex on the transition probabilities between EITC trajectories and substance use trajectories. By studying the trajectory of the EITC, I am not only studying the developmental trajectory of the EITC target population – low-income adults in the US, but also trying to gauge whether there are co-occurring, long term effects of the policy.

4.3. Methods

1997 National Longitudinal Survey of Youth (NLSY97)

The NLSY97 is a prospective cohort study currently conducted by the Bureau of Labor Statistics which gathers information on the labor force experiences of youth born between 1980 and 1984 as they transition through adulthood (Bureau of Labor Statistics, 2019). This de-identified data were deemed exempt by the Johns Hopkins Bloomberg School of Public Health

Institutional Review Board. Because detailed information on income and number of children is unavailable for prior EITC studies, the 1997 National Longitudinal Survey of Youth (NLSY97) is the ideal dataset to examine the relationship between EITC and substance use. Interviews have been conducted annually from 1997 to 2011, and biannually from 2013 to the present. The initial NLSY97 survey consists of 8,194 participants, comprised of a representative cross-sectional sample of 6,748 respondents and a supplemental oversample of 2,236 Hispanic/Latino and Black respondents. Youth respondents' ages ranged from 12-18 in 1997, and 30-36 in 2015. NLSY97 data are designed to be representative at the national level and cumulative sampling and panel data weights are provided. Because the goal of the current study is to avoid limitations of prior causal inference EITC studies, we used a model-based approach and did not use study weights (Bureau of Labor Statistics, 2019).

Measures

Claiming the EITC. Indicators of latent class membership are whether or not participants claimed the EITC on their tax return in the past year, from 2003 to 2010. Although, the NLSY began data collection in 1997, we began our study period in 2003 when all participants were 18 and legally eligible to claim independence on their tax return. All individuals who answer "yes" to having a source of income in the survey are asked whether they claimed an EITC on their tax return last year. For example, in 2007, participants who reported an income source were asked, "Did [*you/you or your spouse/you or your partner*] claim, or are [*you/you or your spouse/you or your partner*] planning to claim, an Earned Income Tax Credit on your [*or your spouse's/or your partner's*] 2006 Federal Income Tax Return?" Individuals who were originally excluded from the question (individuals without a source of income), were coded as not claiming an EITC.

Past Year Substance Use. Indicators of latent class membership are binary indicators of tobacco, alcohol, and marijuana use since the last NLSY interview from 2003 to 2010. Participants were asked, "Since the date of last interview, have you [smoked a cigarette; drank an alcoholic beverage; used marijuana, even if only once, for example: grass or pot; used any drugs like cocaine or crack or heroin, or any other substance not prescribed by a doctor]?" The NLSY also include definitions the interviewer read to participants. An alcoholic drink is defined as "a can or bottle of beer, a glass of wine, a mixed drink, or a shot of liquor."

Controlling for Sex. Sex was self-reported in the NLSY97. We controlled for sex, because previous evidence confirms that it may impact both substance use and the likelihood of receiving the earned income tax credit. To test whether sex also had an impact on the co-occurrence between EITC trajectory and substance use trajectory, we also tested separately for an interaction.

Statistical Analysis

The goal of LCA is to classify individuals into distinct groups of categories based on their individual response patterns. The LCA is a person-centered approach that focuses on relationships among individuals, so that individuals within a group are more similar than individual across different groups (Jung and Wickrama, 2008a).The Latent Transition Analysis is an extension of this method, typically used to examine transitions from one cross-sectional LCA class to another. In our context, transitions will be interpreted as co-occurrence between long-term trajectories. While there is no distinction the literature, this analysis may be thought of as a "joint trajectory analysis" composed of two conjoined LCA models. The LTA was performed using a three-step approach to prevent shifting of measurement parameters in the LCA model (Nylund-Gibson et al., 2019). The three-step technique was used to specify each LTA model.

This included performing separate LCAs, merging them into one dataset with auxiliary (predictor, outcome) variables, and specifying an LTA model (Nylund-Gibson et al., 2014). To test for the interaction between sex and co-occurring EITC and SU trajectories vary by sex, we included an interaction by including an additional statement regressing sex on substance use in each of the four latent class regressions of EITC and specific substance use trajectory (Nylund-Gibson et al., 2014, 2019). All analyses were performed in Mplus, version 8 (Muthen and Muthen, 2017).

LCA Model Fit. LCA models with 1 to 6 classes were fit for multiple random starting values were used to ensure estimates did not reflect local maxima, and the best log likelihood value was replicated. Models were compared based on standard fit statistics, the Akaike Information Criteria (AIC), Bayesian Information Criteria (BIC), Lo-Mendel-Rubin (LMR), the Log likelihood (LL), the Bootstrapped Likelihood Ratio Tests (BLRT), and the model entropy (Masyn, 2013; Nylund-Gibson, 2007; Nylund-Gibson and Choi, 2018).

4.4. Results

The prevalence of the indicators used in each latent class analysis and demographic characteristics used in the LTA are presented for the full sample in Table 1. The NLSY97 sample is 49 % female.

Latent Class Enumeration

Based on substantive interpretation, a four-class model was chosen for all four latent class analyses (Table 2). Although a 5-class model was initially preferred for the EITC by some fit statistics (i.e., LMR), the additional EITC class identified was not theoretically meaningful and therefore we chose the more parsimonious EITC model. Generally, after class enumeration surpassed four, the substance use classes began to be defined by the rate of change across time, rather than type of change.

EITC LCA. The first and largest class (Figure 1) was composed of individuals who had a probability of less than 9% of claiming the EITC consistently from 2003 to 2010, labeled *Non-claimers* (54% of sample). A second class of those who did not claim the EITC until 2004, labeled *Initiators* (8%). A third class of individuals who claimed the EITC in early years but discontinued after 2007 (13%) and was labeled *Decliners*. Finally, a fourth class was characterized by individuals who had a probability of 80% or higher of claiming the EITC every year, labeled *Consistent claimers* (10%).

Tobacco LCA. The largest class (Figure 1) was characterized by individuals who had a probability of less than 3%, labeled *Non-smokers* (47% of sample). A second class of those who had a probability of 90% or higher of smoking every year, labeled *Smokers* (32%). A third class of individuals who had a probability of 70%, which began to decrease rapidly after 2006 to 16%, labeled *Quitter* (12%). Finally, a fourth class of people who had a probability of 20%, which began to increase rapidly after 2006, labeled *Riser* (8%).

Alcohol LCA. The largest class (Figure 2) was characterized by individuals who had a probability of 90% or higher of drinking from 2003 to 2010, labeled *Drinkers* (62% of sample). A second class of those who had a probability of less than 10% of drinking alcohol from 2003 to 2010, labeled *Non-drinkers* (15%). A third class of individuals who had a probability increasing their use from 30% to 75% and was labeled *Riser* (13%). Finally, a fourth class of people who had a probability of decreasing their use from 80% to 30%, labeled *Quitter*s (10%).

Marijuana LCA. The largest class (Figure 3) was composed of individuals who had a probability of less than 3% and labeled *Non-user* (72% of sample). A second class of those who had a probability of 83% of higher of using marijuana every year, labeled *Users* (12%). A third class of individuals who had a probability of 60%, which began decreasing steadily in 2005 to 15%, labeled *Quitter*s (10%). Finally, a fourth class of people who had a probability of 20%, which began increasing in 2006 to 50%, labeled *Riser* (6%).

EITC Class Trajectory by Substance Use LCA

*Patterns of Tobacco Use by EITC Class***.** Table 3 presents the unconditional transition probabilities which describe co-occurrence between each substance use trajectory and EITC recipient trajectory. *Consistent claimers* had the highest likelihood of being (.50) in the Non-smoker group, while *Initiators* had the lowest prevalence (.40). Slightly more *Initiators* were in the smoker class (.36), compared to .33 or 33% of *Consistent claimers*. Comparing *Decliners* to *Non-claimers*, both trajectories had a similar likelihood of being a *smoker* (.31 vs .32), a *non-smoker* (.45 v .46) and or a *quitter* (.13 v .15). However, 0.12 of *Decliners* were in the *Riser* trajectory, compared to 0.07 of *Non-claimers*. However, individuals in the *Non-claimer* trajectory had a higher likelihood (.15) of being a *Quitter* as opposed to a *Riser* (.07), which was distinct from other EITC trajectories.

*Patterns of Alcohol Use by EITC Class***.** Table 3 presents the unconditional transition probabilities describing co-occurrence between each substance use trajectory and EITC recipient. *Consistent claimer* and *Initiators* had similar likelihood of being in each alcohol trajectory, except for *Drinkers* (.60 v .54). *Initiators* had the lowest likelihood of being a *Drinker* among EITC groups (.54). *Decliners* were less likely to engage in alcohol use than *Non-claimers*, in regard to being a *Drinker* (.60 v .64), *Quitter* (.14 v .10), and *Non-drinker* (.10 v .14), but slightly more likely to increase their use over time (.16 v .12). Of all EITC trajectories, *Non-claimers* had the highest likelihood of being a *Drinker* (.64). *Consistent claimers* had a larger difference between the likelihood of being a *Riser* (.18) as opposed to a *Quitter* (.12), which was distinct from other EITC trajectories.

Patterns of Marijuana Use by EITC Class. Table 3 presents the unconditional transition probabilities describing co-occurrence between each substance use trajectory and EITC recipient trajectory. *Consistent claimers* and *Initiators* were similar in terms of likelihood of being a marijuana user (.10 v .11), but *Initiators* were more likely to be a *Riser* (.01 v .04), *Quitter* (.04 v .09), or *Non-user* (.85 v .77). *Consistent claimers* had the highest probability of being non-users of all EITC trajectories (.85). *Decliners* and *Non-claimers* were similar in terms of being a *User* (.14 v .16) and *Riser* (.03 v .02). However, *Decliners* were less likely to be a *Quitter* (.03 v .10) and more likely to be a *Non-user* (.79 v .72), suggesting lower marijuana use than *Non-claimers*.

Covariate Results for Final LTA Model

Table 4 presents results are presented for the regression of the latent class variable on the covariates (Table 4). This model included an interaction term that allowed the co-occurrence between EITC classes and substance use trajectories to be different by sex(Table 5). In other words, we tested to sex changed the probability of transitioning among the EITC and substance use trajectories.

*Tobacco Use and EITC Trajectories***.** Regarding sex differences, tobacco smokers and *riser*s were less likely to be female than non-smokers. There was one significant interaction for the effect of sex. Compared to *Non-claimers* who do not smoke, females in the EITC *Decliner* class were less likely (OR:0.33, p=0.001) to be *quitters*. In other words, females who no longer claim the EITC over time are more likely to be smokers or *riser*s.

Alcohol Use and EITC Trajectories. Regarding sex differences, *non-drinkers* were less likely to be female than *drinkers*. There was one significant interaction of sex across EITC trajectories. Compared to *Non-claimers* who drink alcohol, female EITC *Initiators* were more likely to be *non-drinkers* (OR: 2.50, p=0.03).

Marijuana Use and EITC Trajectories. Regarding sex differences, marijuana users are less likely to be female than non-users. There was one significant interaction of sex across EITC trajectories. Compared to *Non-claimers* who were non-users, EITC *Initiators* who were female were more likely to be marijuana users (OR: 4.39, p=0.05).

4.5. Discussion

The shape of the EITC trajectories and all three substance use trajectories were similar in pattern. All four LCA's identified four stable trajectories: a high class, a low class, increasing class, and a decreasing class. This common phenomenon, called the cat's cradle, occurs commonly in LCAs of substance use, most commonly alcohol (Sher et al., 2011). Scientists investigated whether this may be evidence of artificial results or underpowered results, through simulation and concluded that most applications identified a four-class model, regardless of sample size. With increased sample, occasionally one or two additional classes are identified by fit statistics, but they often do not have a meaningful theoretical or clinical interpretation (Sher et al., 2011).

For each substance use category, at least one EITC trajectory was characteristically different from the rest of the groups. *Consistent claimers* had the highest probability of being a tobacco non-smoker (50%), while *Initiators* had the highest probability of tobacco smokers (36%). For alcohol, compared to other EITC groups, *Initiators* had the lowest probability (54%) of being an alcohol *drinker*, while *Non-claimers* had the highest (64%). *Consistent claimers* had the highest probability (85%) of not smoking marijuana. There were significant sex differences for each substance and a significant effect of being a female for three groups, female *Decliners* were less likely to quit tobacco, female *Initiators* were more likely to be *non-drinker*, and female *Initiators* were more likely to be a marijuana smoker. Regarding sex differences, Tobacco smokers and *riser*s were more likely to be male than non-smokers. This makes sense considering sex differences in tobacco use prevalence, but also explains why *Consistent claimers* had a 50% chance of being placed in the Non-Smoker trajectory(Perkins, 2009). The EITC population is typically female, therefore the *Consistent claimer* trajectory would reflect the most likely recipients of the credit (Dowd and Horowitz, 2011; Evans and Garthwaite, 2014). In terms of alcohol, *non-drinkers* were more likely to be male than *drinkers*. There were significant sex differences for each substance and a significant effect of sex for three groups, *Decliners* who quit tobacco, *Initiators* who do not drink alcohol, and *Initiators* who smoke marijuana.

Compared to other groups, *Non-claimers* had a larger difference between the probability of being a *Quitter* or *Riser* (.15 v .07). This suggests that *Non-claimers* were more likely than other EITC trajectories to quit smoking tobacco between 2003 and 2010. These findings are consistent with the evidence of that tobacco use declines more slowly in lower-income groups than more affluent populations potentially due to disparities in tobacco use, marketing, and treatment efficacy (Cal Ham et al., 2011; Leas et al., 2019; Yu et al., 2010).

Although *Consistent claimers* and *Initiators* had similar likelihood of being a smoker (10 v 11), *Initiators* were more likely to smoke marijuana because they were more likely to be in the *Riser* or *Quitter* trajectory. *Consistent claimers* were distinctly different from other classes in their marijuana use, with 85% in the non-smoker class. In Chapter 2, results revealed there were no significant differences in marijuana use in 2011 by EITC trajectory. This illustrates the importance of considering trajectories of substance use to understand nuances in behavior.

Surprisingly, *Initiators*, shared similarities common with *Decliners* and *Non-claimers* in *Riser*, *Quitter* and *Non-user* marijuana use trajectories.

Strengths and Limitations. This was the first study to examine trajectories of claiming the EITC and substance use patterns among young adults (20-30) through a Latent Transition Analysis. In addition, the NLSY97 is the only national survey with health information that asks participants to report whether they have claimed the EITC and includes information on health, allowing us to decrease potential misclassification bias of prior studies (Pega et al., 2013). However, there were also a few limitations. State EITCs were not included in this analysis because the purpose was to examine the longitudinal impact of the federal policy, and state EITCS were being introduced and expanded in multiple states. In addition, we do not know whether individuals who claimed the EITC received it, limiting us to an intent-to-treat interpretation of the results. There are no U.S. health surveys that collect information on individuals' EITC receipt (Simon et al., 2018). However, because the majority of EITC-eligible individuals with children (80–86%) receive the credit, this assumption is standard for modelling EITC-health effects (Falk and Crandall-Hollick, 2018; Simon et al., 2018). We also use a crude measure of substance use, observing binary measure as opposed to frequency of use. Finally, this analysis cannot speak to causality or specific mechanisms that may link the EITC to substance use outcomes.

Conclusion

The current study found that certain EITC trajectories were more likely to engage in substance use throughout their life. EITC trajectories appear to have some contribution to differential substance use behavior. This study provides support for previous research that concluded that the EITC is a short-term safety net (Ackerman, 2009; Dowd and Horowitz, 2011).

Current studies present an incomplete picture of the EITC population, since many remove men and childless adults from the sample. Our findings reveal that observing the long-term EITC impact without excluding people based on sex or changing EITC status, is necessary.

Table 4.1. Prevalence of Latent Class Indicators and Sex among full sample (N=8,514)

	Full Sample Proportion or Mean (SD)
Claimed the EITC	
2003	0.19
2004	0.23
2005	0.28
2006	0.30
2007	0.32
2008	0.37
2009	0.36
2010	0.30
Tobacco Use	
2003	0.43
2004	0.43
2005	0.43
2006	0.44
2007	0.43
2008	0.41
2009	0.40
2010	0.38
Alcohol Use	
2003	0.70
2004	0.72
2005	0.76
2006	0.76
2007	0.76
2008	0.77
2009	0.74
2010	0.73
Marijuana Use	
2003	0.23
2004	0.21
2005	0.21
2006	0.19
2007	0.18
2008	0.18
2009	0.16
2010	0.17
Male	0.51
Female	0.49

Notes: P = proportion; M = mean; SD = standard deviation; LCA = latent class analysis; EITC = earned income tax credit; SU = substance use.

Table 4.2. Model Fit Statistics for Four Latent Class Analyses: EITC Receipt, Tobacco, Alcohol, and Marijuana Use

No. of Classes	LL	BIC	LMR (p-value)	Entropy	Smallest Class
EITC (N=8514)[a]					
2	-30232.90	606019.64	7274.24 (<.001)	.723	.31
3	-29869.24	59973.76	718.50 (<.0001)	.659	.12
4	**-29643.04**	**59602.80**	**446.92 (<.001)**	**.614**	**.11**
5	-29584.40	59566.97	115.85 (.0001)	.614	.08
6	-29557.26	59594.14	53.12 (.20)	.588	.06
Tobacco (N=8518)					
2	-24512.03	49177.90	31624.90 (<.0001)	.928	.45
3	-23096.03	46427.35	2797.65 (<.0001)	.850	.21
4	**-22607.37**	**45531.48**	**965.47 (<.0001)**	**.857**	**.08**
5	-22513.70	45425.59	185.07 (<.0001)	.819	.06
6	-22466.39	45412.43	93.46 (.03)	.796	.04
7	-22421.52	45404.13	91.51 (.0001)	.802	.03
8	-22396.72	45435.98	48.99 (.08)	.798	.021
Alcohol (N=8508)					
2	-24785.75	49725.34	17343.61 (<.0001)	.875	.30
3	-23864.47	47964.20	1820.22 (<.0001)	.797	.14
4	**-23553.17**	**47423.05**	**615.05 (<.0001)**	**.787**	**.10**
5	-23492.98	47384.10	118.927 (.0006)	.732	.08
6	-23465.98	47411.55	53.34 (.04)	.686	.05
7	-23429.91	47420.85	71.26 (.005)	.730	.02
8	-23403.57	47449.61	52.04 (.06)	.714	.03
Marijuana (N=8507)					
2	-19996.13	40146.08	16879.37 (<.0001)	.907	.22
3	-19284.97	38804.99	1405.27 (<.0001)	.823	.11

4	**-19084.50**	**38485.70**	**395.87(<.0001)**	**.824**	**.06**
5	-19008.89	38415.90	149.40 (.0001)	.776	.07
6	-18973.68	38426.94	69.55 (.002)	.760	.04
7	-18943.74	38448.50	59.15 (.16)	.761	.02

Note. [a] The initial NLSY 1997 sample was 8,914, respondents that lacked information on all eight indicators were excluded from the LCA. LL= log likelihood; BIC= Bayesian information criteria; LMR= adjusted Lo-Mendell Rubin and p-value.

Table 4.3. Latent Transition Analysis Transition Probabilities Based on the Unconditioned Latent Transition Analysis Model Probabilities (Tobacco, Alcohol, & Marijuana Use Trajectories)

	EITC CLASS TRAJECTORY			
TOBACCO CLASS	***Consistent claimer***	***Initiator***	***Decliner***	***Non-claimers***
Smoker	0.33	0.36	0.31	0.32
Riser	0.09	0.11	0.12	0.07
Quitter	0.08	0.10	0.13	0.15
Non-smoker	0.50	0.43	0.45	0.46
ALCOHOL CLASS				
Non-drinker	0.17	0.15	0.10	0.14
Riser	0.18	0.17	0.16	0.12
Quitter	0.12	0.15	0.14	0.10
Drinker	0.60	0.54	0.60	0.64
MARIJUANA CLASS				
User	0.10	0.11	0.14	0.16
Riser	0.01	0.04	0.03	0.02
Quitter	0.04	0.09	0.03	0.10
Non-user	0.85	0.77	0.79	0.72

***Notes**:* Bold indicates statistically significant logit value for LTA of alcohol on the transition to EITC class. SU = substance use; EITC = earned income tax credit; LCA = latent class analysis

Table 4.4. Covariate Table for LTA Model that Included Interaction Effects

LCA Model		Logit	SE	P Value	OR
EITC LCA					
Claimers	Sex (Female)	1.344	1.107	**<0.001**	**3.83**
Initiators		0.278	0.082	**0.001**	**1.32**
Decliners		0.048	0.116	0.680	1.05
Tobacco LCA					
Smokers	Sex (Female)	-0.472	0.094	**<0.001**	0.62
Increase		-0.465	0.249	**0.062**	0.63
Decrease		-0.180	0.151	0.233	0.84
Alcohol LCA					
Non-drinkers	Sex (Female)	-0.264	0.124	**0.033**	**0.77**
Increase		-0.102	0.175	0.559	0.90
Decrease		-0.003	0.188	0.989	0.997
Marijuana	Sex (Female)				
Smoker		-1.655	0.167	**<0.001**	0.19
Start		0.710	0.438	0.105	2.03
Quit		-0.198	0.202	0.326	0.82

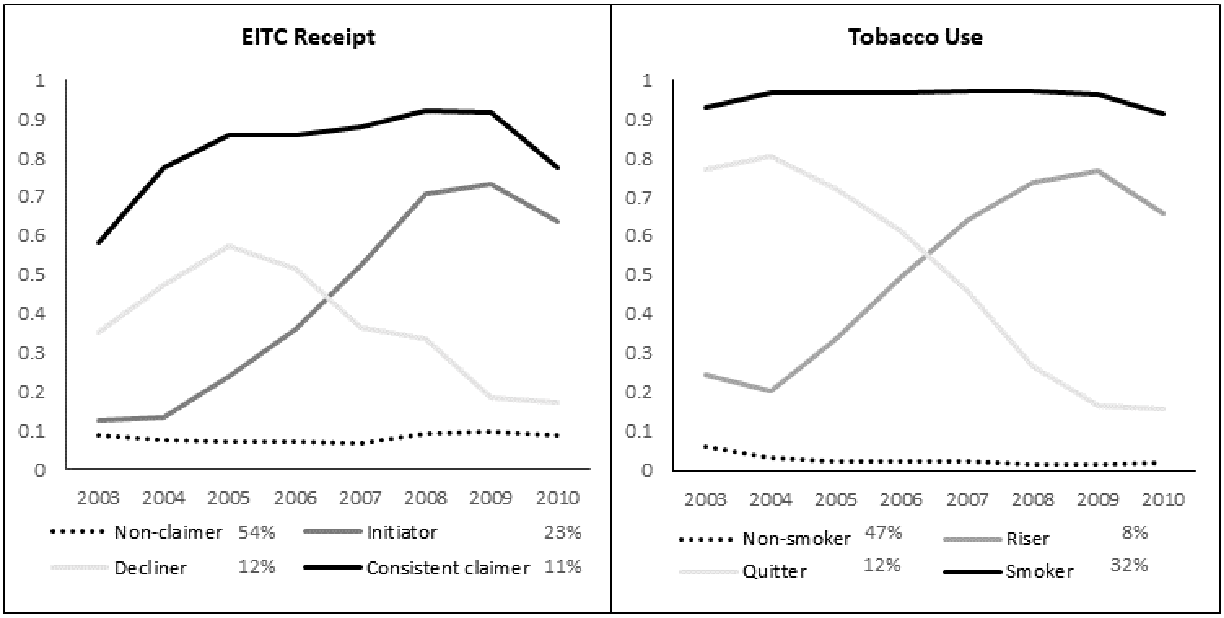
Notes: Referent Group is EITC *Non-claimers*, and *Non-users* for each substance. Alcohol is the only exception, where the referent group is D*rinkers*.

Table 4.5. Interaction Effect of Sex in LTA Model

EITC Trajectory	Substance Use LCA	Logit	SE	P Value	OR	p-value
	TOBACCO					
Claimers	Smokers	0.202	0.251	0.421	1.224	.466
	Riser	0.731	0.704	0.299	2.078	.461
	Quitter	-0.322	0.551	0.560	0.725	.491
Initiators	Smokers	-0.018	0.198	0.928	0.982	.927
	Riser	-0.233	0.446	0.602	0.792	.557
	Quitter	-0.211	0.410	0.606	0.809	.565
Decliners	Smokers	-0.223	0.296	0.451	0.800	.398
	Riser	-0.144	0.570	0.801	0.866	.787
	Quitter	-1.109	0.622	0.074	0.330	.001
	ALCOHOL					
Claimers	Non-drinker	0.806	0.336	0.017	2.24	.100
	Riser	1.906	0.883	0.031	6.73	.335
	Quitter	-0.011	0.455	0.980	0.99	.980
Initiators	**Non-drinker**	0.916	0.271	**0.001**	2.50	**.027**
	Riser	0.322	0.322	0.331	1.38	.406
	Quit	0.144	0.352	0.682	1.16	.703
Decliners	Non-drinker	0.777	0.454	0.087	2.18	.234
	Riser	0.858	0.477	0.072	2.36	.227
	Quit	-0.834	0.611	0.173	0.43	.033
	MARIJUANA					
Claimers	User	0.796	0.449	0.076	2.22	.221
	Riser	7.458	0.851	<.0001	1733.3	.240
	Quitter	0.075	1.082	0.945	1.09	.947
Initiators	**User**	1.478	0.386	**<0.001**	4.39	**.045**
	Riser	-0.753	0.685	0.271	0.47	.101
	Quitter	-0.628	0.517	0.224	0.53	.091
Decliners	User	0.576	0.565	0.308	1.78	.439
	Riser	-0.724	1.018	0.477	0.49	.296
	Quitter	0.128	1.300	0.921	1.14	.926

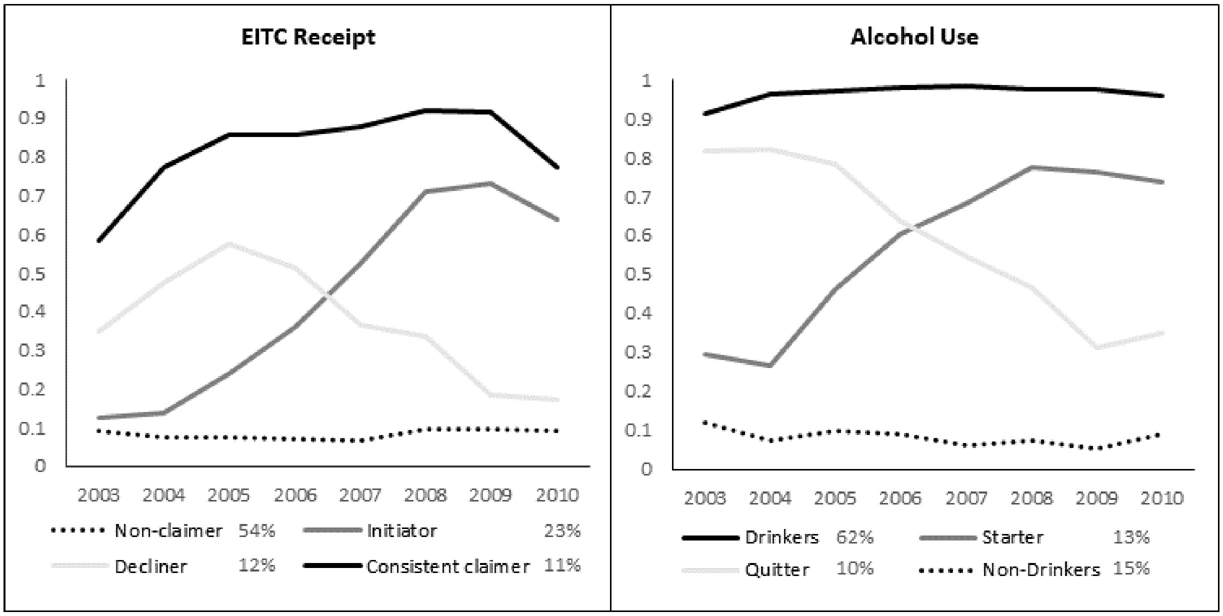
Notes: The effect of SU trajectory on the co-occurrence with EITC Class, SU is the independent variable in regression

Figure 4.1. LCA of EITC Receipt and LCA of Tobacco Use (2003-2010)



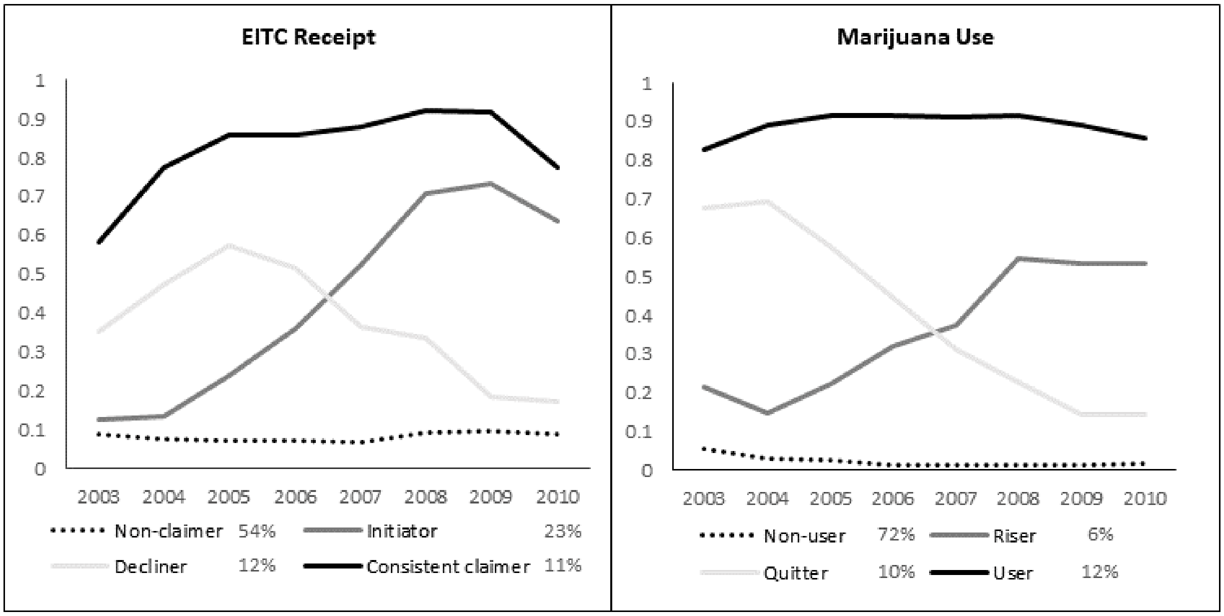
Notes: X-axis is the survey year. Y-axis is the conditional item probability, or likelihood that individuals in each class would answer "yes" to claiming the EITC or using tobacco since the last NLSY survey.

Figure 4.2. LCA of EITC Receipt and LCA of Alcohol Use (2003-2010)



***Notes**:* X-axis is the survey year. Y-axis is the conditional item probability, or likelihood that individuals in each class would answer "yes" to claiming the EITC or using alcohol since the last NLSY survey.

Figure 4.3. LCA of EITC Receipt and LCA of Marijuana (2003-2010)



Notes: X-axis is the survey year. Y-axis is the conditional item probability, or likelihood that individuals in each class would answer "yes" to claiming the EITC or using marijuana since the last NLSY survey.

CHAPTER 5. Discussion

The overall goal of this study was to identify longitudinal patterns of EITC receipt and examine their association with differential health and economic outcomes, to confirm whether the EITC is a short-term safety net and expand upon current literature through further investigation of individuals that comprise the EITC population. We used latent variable modeling to group individuals based on their unobserved heterogeneity and distinct pattern of claiming the EITC from 2003 to 2010. We were interested in capitalizing on the underlying heterogeneity in EITC receipt over time to group individuals into meaningful classes and explore correlates of substance use and economic health outcomes. This investigation replicated previous evidence suggesting the EITC is not claimed consecutively, but sporadically, and provide evidence on whether future studies should consider using alternative study designs that allows consideration of longitudinal EITC trajectory (Ackerman, 2009; Dowd and Horowitz, 2011; Pega et al., 2013).

This study applied a novel technique to examine the EITC since latent variable modeling has not been applied to understand this policy and its recipients. Our findings corroborate previous evidence that the EITC is a short-term benefit, claimed sporadically throughout life (Ackerman, 2009; Dowd and Horowitz, 2011; Masken, 2006). This study revealed four individual trajectories of EITC receipt from 2003 to 2010, consistently claiming the EITC, initiating or declining, and not claiming the credit. This study revealed that two groups of individuals are excluded from the “EITC” population in current studies – those who begin claiming the EITC and those who discontinue the EITC. In conclusion, defining long-term EITC claimers as individuals who claim the credit consecutive years, prevents researchers from observing the full sample of eligible tax filers with differential histories of receiving the EITC.

5.1. Summary of Main Findings

In Chapter 2, we conducted a latent class analysis to identify longitudinal patterns of EITC receipt. We also examined sociodemographic correlates of class membership and tested for differences in four substance use outcomes by each latent class. Indicators of latent class membership are whether participants claimed the EITC in the past year, from 2003 to 2010. All demographic characteristics are self-reported and include sex, race/ethnicity, age, educational attainment, marital status, parent status, and health insurance coverage. Substance use outcomes were accessed in 2011, when participants were 28 years old on average. Tobacco, alcohol, marijuana, and "other illicit drug" use since the last NLSY interview was assessed at each follow-up visit. There were four EITC trajectories: *Non-claimers* (54%), *Initiators* (23%), *Decliners* (12%), and *Consistent claimers* (11%). There were significant differences between EITC trajectories in tobacco and alcohol use, but not marijuana or other illicit drug use. Alcohol use was highest among *Non-claimers* and *Decliners* (76%), followed by *Consistent claimers* (73%), and *Initiators* (71%). Tobacco use was highest for *Initiators* (43%), *Consistent claimer* (39%), *Decliner* (37%), and *Non-claimers* (35%). Among the four groups, *Consistent claimers*/*Initiators* had high tobacco, but low alcohol use, while *Decliners*/*Non-claimers* demonstrated the opposite – low tobacco and high alcohol use. These findings suggest that *Consistent claimers*/*Initiators* and *Decliners*/*Non-claimers* are like one another and may be similar in other factors that determine the EITC, such as employment or annual income.

Chapter 3 expanded upon findings from Chapter 2 by aiming to investigate whether measures of economic wellbeing would also differ by EITC trajectory. We also examined sociodemographic correlates of class membership and tested for differences in eight measures of economic wellbeing outcomes, four income-based poverty measures (household worth, assets, debts, poverty ratio) and four indicators of material hardship (health, life satisfaction, bill collectors, unemployed member). Poverty ratio and assets varied by class, but there was no difference in household net worth or value of debts. EITC *Initiators* had lower income-based poverty than *Consistent claimers*, as evidenced by significantly higher assets (~ $1.4k vs $890), marginally less debt (~ $5.9k vs $6.7k). Consistent with Chapter 2, we revealed that there are distinct patterns of claiming the EITC, and individuals within these trajectories have differential economic health outcomes, in addition to substance use behavior. These results suggest that on average, people who stop claiming the EITC (i.e., *Decliners*) stop claiming due to exceeding maximum income levels, rather than failing to meet work requirements or filing an income tax return.

In Chapter 4, we access whether there is co-occurrence between patterns of substance use EITC trajectories from 2003 to 2010, to examine if EITC receipt trajectories may be contributing to differential substance use behaviors. Using data from 8,984 responses to the 1997 National Longitudinal Survey of Youth (NLSY97), which oversampled Black and Latino respondents, we performed a latent transition analysis (LTA) of EITC trajectories and three substance use trajectories (tobacco, alcohol, marijuana), separately. We also tested for an interaction of sex for each transition. For tobacco, *Consistent claimers* had the highest probability of being a non-smoker (50%), while *Initiators* had the highest probability of smokers (36%). For alcohol, compared to other EITC groups, *Initiators* had the lowest probability (54%) of being a *drinker* and *Non-claimers* had the highest (64%). For marijuana, *Consistent claimers* had the highest probability (85%) of being a non-smoker. These findings showed that certain EITC trajectories were more likely to engage in substance use throughout their life. EITC trajectories appear to have some contribution to differential substance use behavior. This study provides support for previous research that concluded that the EITC is a short-term safety net.

5.2. Synthesis of Findings

This study had two major findings: (1) there are distinct trajectories of EITC receipt and (2) the individuals in these trajectories differ in demographic characteristics, and substance use behavior, and economic health outcomes. This study supports the assertion that the EITC is a short-term safety net and replicates the results of previous IRS studies using data from a health dataset. Studies using special access IRS data found that very few people claim the EITC for consecutive years (Ackerman, 2009; Dowd and Horowitz, 2011; Masken, 2006) This study found that 11% were *Consistent claimers*, 35% were *Initiators* or *Decliners*, and 54% were *Non-claimers.* In other words, of the 3,879 people who were placed in a trajectory that included receiving the EITC, 76% of those EITC claimers (2,956) were people who changed their EITC status at some point during the study period. This study revealed that two groups of individuals are excluded from the "EITC" population in current studies – those who begin claiming the EITC and those who discontinue the EITC. Therefore, excluding individuals who do not have a fixed EITC exposure from the sample, prevents researchers from observing the complete EITC population. Current literature describes EITC participants as low-income, typically unmarried women with have children, because this is the group that receive the credit most often (Falk and Crandall-Hollick, 2018). Current studies present an incomplete picture of the "EITC population" since many remove men and childless adults from the sample. Our findings reveal that observing the long-term EITC impact without excluding people based on sex or changing EITC status, is necessary. Although EITC *Consistent claimers* were 77% female, EITC *Initiators* were 59% female and *Decliners* were 45% female. It appears that while men are less likely to claim the EITC as often as women consistently, they are more likely to stop or start claiming the credit. This finding is consistent with current evidence that suggests men claim the EITC for shorter time periods than women (Masken, 2006) This study also had important implications for beginning to understand substance use behavior in EITC recipients. In Chapter 2, results revealed there were no significant differences in marijuana use in 2011 by EITC trajectory. However, results from Chapter 4, which included trajectories of marijuana use over 8 years, found differences for individuals with different EITC trajectories. This demonstrates that considering trajectories of substance use is necessary to reveal potential nuance in health behavior.

It is important to point out that these EITC trajectories do not cause the differences in substance use that we observed. We may only conclude that substance use appears different across different EITC trajectories (Nylund-Gibson and Choi, 2018). The LCA grouped together similar individuals based on their EITC receipt, and then compared the mean substance use between each group. In theory, *Consistent claimers* could have high SU for another unobserved reason or unobserved similarity between these people in a subgroup, that is not related to the EITC indicators used to form LCA subgroups. Therefore, we examined correlates, or predictors of class membership. *Consistent claimers* are mostly female and have children, the population that mostly get the EITC. Otherwise, the general population of women with children would not typically have higher levels of substance use than men (McHugh et al., 2018). These correlates of class membership are crucial to allow us to interpret the characteristics of each subgroup or latent trajectory. These analyses do not mean the EITC policy alone can explain why a given EITC trajectory has higher substance use or value of assets. This analysis investigated whether a person's individual history (pattern) of claiming the EITC over many years, can have any effect on their substance use, either cross sectionally (Chapter 2) or longitudinally (Chapter 4). While it is reasonable given the income-health gradient to assume that people with different patterns of employment or income would have different levels of health behaviors, this is a challenge all EITC studies face. The EITC directly impacts employment and increases post-tax income, so disentangling the effects of the credit from these factors and the decision whether or not to include them in the model, is a persistent limitation for researchers investigating the EITC (Pega et al., 2013). Future studies should seek to investigate and understand what people in these trajectories look like on a variety of factors, so that we may begin to understand why the substance use outcomes differ among different trajectories. To begin this endeavor, we examined the co-occurrence between EITC trajectories and patterns of substance use (Aim 3).

5.3. Strengths and Limitations

This was the first study to examine trajectories of claiming the EITC and substance use patterns among young adults (20-30) through latent variable modeling. A Longitudinal LCA (also called repeated measures LCA) was conducted. In an LLCA the latent class variable can be used to describe change over time without having to make any assumptions about the structure or functional form of the change process, unlike other longitudinal models such as growth models. That said, an LLCA can be specified before a growth model or a growth mixture model as a baseline model to explore heterogeneity in change. There were also several limitations that present opportunities to improve rigor.

In addition, the NLSY97 is the only national survey with health information that asks participants to report whether they have claimed the EITC and includes information on health, allowing us to decrease potential misclassification bias of prior studies (Pega et al., 2013).. However, there were also a few limitations. State EITCs were not included in this analysis because the purpose was to examine the longitudinal impact of the federal EITC policy, and state EITCS were being introduced and expanded in multiple states. In addition, we do not know whether individuals who claimed the EITC received it, limiting us to an intent-to-treat interpretation of the results. Aside from IRS data, there are no nationally representative U.S. health surveys that collect information on individuals' EITC receipt (Simon et al., 2018). However, because the majority of EITC-eligible individuals with children (80–86%) receive the credit, this assumption is standard for modelling EITC-health effects (Falk and Crandall-Hollick, 2018; Simon et al., 2018). In addition, this analysis cannot speak to causality or specific mechanisms that may link the EITC to substance use outcomes. Finally, the measure of substance use is a limitation. Because we observe annual substance use, as opposed to frequency or other indicators of severity, we are limited in the conclusions we can make in this initial study. However, the 1997 NLSY includes frequency and severity measures of substance use, making this a potential future endeavor.

5.4. Future Directions

Implications for Research. This study provides support for the assertion that the EITC is a short-term safety net. Future studies should consider EITC trajectory and pay consideration to how analysts are restricting their sample to likely EITC recipients. This study provided evidence that excluding individuals who do not have a fixed EITC exposure from the sample, prevents researchers from observing the complete EITC population. Future research on the EITC and health should consider using latent class analysis to identifying distinct trajectories of claiming the EITC, to create an exposure variable that does not require fixed EITC status. These trajectories can then be used in mixture modeling techniques, such as this study, or used as a latent variable in multivariate regression for causal inference studies. Understanding the long-term impact of this short-term income support program will ultimately help researchers identify how tax credits can be utilized as programs to help alleviate poverty and improve health outcomes among low-income, vulnerable populations.

Implications for Policy and Practice. This study confirms that men are more likely to claim the earned income credit for one year. Indeed, men were more likely to belong to a group of individuals who begin claiming the EITC over their lifetime (EITC Initiators). These findings contradict criticism from political opponents of the EITC who assert that the refundable credit is minimally useful only for *low-income mothers* and assert that benefits should not be available to men or childless adults. This research also revealed that indicators of economic wellbeing, like as the income-to-poverty ratio or value of financial assets, differ significantly between individuals who claim the credit consistently and those who begin claiming it over the years. Understanding these differences not only has implication for understanding the relationship between income and health for men and women but understanding how the policy is being implemented and evaluating the impact among the true population of people who receive it.

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APPENDICES

A-Table 2.1. Odds Ratios for Latent regression of EITC Trajectory and Demographic Characteristics for SU Outcomes (Reference, *Non-claimers*)

	Initiator **Class 2**	***Decliner*** **Class 3**	**Consistent Class 4**
		Odds Ratio (p-value)	
Female	1.02 (0.82)	0.94 (0.62)	2.75 (<.001)
Race			
Black	1.52 (0.46)	1.77 (0.63)	1.63 (0.44)
White	0.86 (0.72)	1.74 (0.64)	0.70 (0.39)
Hispanic	1.55 (0.45)	3.02 (0.46)	1.13 (0.82)
Age (2011)	0.86 (<.001)	1.02 (0.66)	1.23 (<.001)
Some college education (2011)	0.53 (<.001)	0.56 (<.001)	0.44 (<.001)
Health Insured (2011)	1.05 (0.63)	1.08 (0.61)	0.91 (0.45)
Parent (2011)	3.43 (<.001)	1.63 (0.008)	12.94 (<.001)
Married (2011)	0.74 (0.002)	1.09 (0.58)	1.05 (0.70)

Notes: Class 1 (*Non-claimers*) is the referent group. EITC = earned income tax credit; SU= substance use.

A-Table 3.1. Odds Ratios for Latent regression of EITC Trajectory and Demographic Characteristics for Economic Wellbeing (Reference, *Non-claimers*)

	Initiator **Class 2**	***Decliner*** **Class 3**	**Consistent Class 4**
	Odds Ratio (p-value)		
Female	0.91 (.350)	0.85 (.169)	2.08 (<.001)
Race			
Black	1.67 (.390)	1.23 (.780)	1.71 (.429)
White	0.90 (.814)	1.10 (.897)	0.74 (.497)
Hispanic	1.66 (.395)	1.85 (.497)	1.13 (.824)
Some college education (2008)	0.62 (<.001)	0.66 (<.001)	0.54 (<.001)
Insured (2008)	0.70 (<.001)	0.95 (.700)	0.68 (<.001)
Parent (2008)	7.46 (<.001)	2.25 (.001)	35.52 (<.001)
Married (2008)	0.62 (<.001)	1.31 (.110)	0.94 (.644)

***Note*s**: Class 1 (*Non-claimers*) is the reference group. EITC = earned income tax credit.

A- Table 3.2. Odds Ratios for Latent regression of EITC Trajectory and Demographic Characteristics for Economic Wellbeing (Reference Group, *Consistent claimers*)

	Non-claimers **Class 1**	***Initiator*** **Class 2**	***Decliner*** **Class 3**
		Odds Ratio (p-value)	
Female	0.48(<.001)	0.44 (<.001)	0.409 (<.001)
Race	0.57 (.177)	0.98 (.972)	0.72 (.637)
Black	1.35 (.616)	1.22 (.787)	1.48 (.687)
White Hispanic	0.88 (.801)	1.47 (.636)	1.63 (.634)
College Education (2008)	1.84 (.005)	1.14 (0.52)	1.21 (0.42)
Insured (2008)	1.48 (.015)	1.04 (.808)	1.40 (.110)
Parent (2008)	0.03 (<.001)	0.21 (<.001)	0.06 (<.001)
Married (2008)	1.06 (.663)	0.66 (.001)	1.39 (.122)

***Note*s**: Class 4 (*Consistent claimers*) is the reference group. EITC = earned income tax credit.

CURRICULUM VITAE

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EDUCATION AND TRAINING

2020 PhD Mental Health
Johns Hopkins Bloomberg School of Public Health
NIDA Drug Dependence Epidemiology Training Program
Dissertation Title: Characterizing Recipients of the Earned Income Tax Credit Across Time – An examination of substance use and financial health outcomes
Advisor: Rashelle Musci, PhD

2016 BA Psychology
Columbia University

2015 The University of Melbourne
Semester in Victoria, Australia

Certifications

2016 HIV Counseling Skills (Level 1), Maryland Department of Health and Mental Hygiene

PROFESSIONAL EXPERIENCE

Start 9/2020 **Postdoctoral Fellowship**
Johns Hopkins Bloomberg School of Public Health
Drug Dependence Epidemiology Training Program
National Institute on Drug Abuse, T-32

2016-2020 **Pre-doctoral Fellowship**
Johns Hopkins Bloomberg School of Public Health
Drug Dependence Epidemiology Training Program
National Institute on Drug Abuse, T-32

2017-2019 **Research Assistant**
Johns Hopkins Bloomberg School of Public Health
Dept. of Health, Policy & Management; Dept. of Health, Behavior & Society.

2018 **Data Manager/Field Interviewer**
Johns Hopkins Bayview Medical Center
Center for Community and Child Health.

2015 **Communications Intern**
The Pennington Institute, Melbourne, AUS

2014 **Policy Intern**
The Drug Policy Alliance, New York, NY
Movement Building Team

2013-2014 **Summer Research Intern**
National Institute on Drug Abuse
Extramural and Intramural Research Programs

TEACHING EXPERIENCE

Classroom Instruction

2019 Practicum Coordinator/Teaching Assistant. "Community Based Learning - Practicum in Community Health"
Johns Hopkins University, Krieger School of Arts and Sciences

2019 Teaching Assistant, "The Epidemiology of Substance Use and Related Problems" (Online)
Johns Hopkins Bloomberg School of Public Health
Department of Mental Health

2018 Teaching Assistant, The Epidemiology of Substance Use and Related Problems
Johns Hopkins Bloomberg School of Public Health
Department of Mental Health

Other Significant Teaching

2012 -2016 Senior Health Educator
Peer Health Exchange, New York, NY.

PUBLICATIONS

Journal Articles (peer review)

Schneider KE, **Brighthaupt SC**, Winiker AK, Johnson RM, Musci RJ, Linton SL (2020). Characterizing Profiles of Polysubstance Use among High School Students in Baltimore, Maryland: A Latent Class Analysis. Drug and Alcohol Dependence. https://doi.org/10.1016/j.drugalcdep.2020.108019

Jones AA, Schneider K, **Brighthaupt S**, Johnson JK, Linton S, Johnson R (2019). Heroin and nonmedical prescription opioid use among high school students in urban school districts. Drug and Alcohol Dependence. https://doi.org/10.1016/j.drugalcdep.2019.107664

Brighthaupt SC, Stone E, Rutkow L, McGinty EE (2019). Effect of Pill Mill Laws in Ohio and Tennessee: A Mixed Methods Case Study. Preventive Medicine, 129. https://doi.org/10.1016/j.ypmed.2019.05.024

Brighthaupt SC, Schneider KE, Johnson JK, Jones AA, Johnson RM (2019). Trends in Adolescent Heroin and Injection Drug Use in Nine Urban Centers in the United States, 1999-2017. Journal of Adolescent Health, 65 (2): 210-215. https://doi.org/10.1016/j.jadohealth.2019.03.026

Johnson RM, Fleming CB, Cambron C, Dean L, Brighthaupt S, Guttmannova K (2018). Race/ethnicity differences in trends of marijuana, cigarette, and alcohol use among 8th, 10th, and 12th graders in Washington State, 2004-2016. Prevention Science. https://doi.org/10.1007/s11121-018-0899-0

Sokolowski K, Esumi S, Hirata T, Kamal Y, Tran T, Lam A, Oboti L, Brighthaupt S, Zaghlula M, Shah NM, Jones KS, and Corbin JG. (2015). Specification of hypothalamic stress-feeding circuits and behaviors by the embryonic patterning gene Dbx1. Neuron, 86 (2): 403-16.

Manuscripts in Preparation

Brighthaupt SC, Schneider KE, Mojtabai R, Musci RJ. Developmental Trajectories of the Earned Income Credit Recipients and Substance Use Behavior. Journal of Studies on Alcohol and Drugs.

Brighthaupt SC, Schneider KE, Johnson RM. Adolescent Heroin and Injection Drug Use vary by Race and Sex across NYC Boroughs, 2003-2017. Addictive Behaviors.

Johnson RM, Boon D, Wang X, Ruprecht M, Beach LB, Brighthaupt SC, Schneider KE, Phillips G. Trends in heroin use and injection drug use among high school students in five urban school districts in the US (2005-2017). Journal of Adolescent Health.

PRESENTATIONS

Oral Presentations in Scientific Meetings

Brighthaupt SC, Schneider KE, Johnson RM. “Trends in Adolescent Heroin and Injection Drug Use vary Across New York City Boroughs – Differences by Sex and Race, 2003-2017”. Oral Presentation in Knee High to a Grasshopper: Adolescent Epidemiology. College on Problems of Drug Dependence, 81st Annual Meeting. June 18th, 2019.

Brighthaupt S, Stone E, Rutkow L, McGinty EE. "Effect of Pill Mill Laws in Ohio and Tennessee: A Mixed Methods Case Study". Oral Presentation. American Public Health Association, Annual Scientific Meeting. San Diego, CA; November 13, 2018.

Jones AA, Schneider KE, **Brighthaupt S**, Johnson JK, Linton S, Johnson RM. "Race/Ethnicity and Sex Differences in Heroin Use Among Adolescents in 3 US Cities: Baltimore, MD, Washington, DC, & Jacksonville, FL (2015)". Serving the Underserved: Health Disparities. College on Problems of Drug Dependence Conference, 80th Annual Scientific Meeting. San Diego, CA; June 12, 2018.

Brighthaupt S, Johnson JK, Jones AA, Schneider K, Johnson RM. "Trends in Adolescent Heroin and Injection Drug Use (IDU) in 13 US Cities, 1999 to 2015". College on Problems of Drug Dependence Conference, 80th Annual Scientific Meeting. San Diego, CA; June 11, 2018.

Brighthaupt S, Fleming CB, Cambron C, Johnson RM, Deal LT, Guttamanova K. "Grade level differences in trends in adolescent marijuana use in Washington State, 2004-2016". Organized Symposium on Adolescent Marijuana Use Amidst Reformed State-Level Marijuana Laws. Society for Prevention Research, 26th Annual Meeting, Washington, DC; June 1, 2018.

Posters in Scientific Meetings

Brighthaupt S, Johnson RM, Johnson J. "Alcohol control policies and youth past 30-day marijuana and heavy marijuana use in45 states, 1991- 2011". College on Problems of Drug Dependence Conference, 79th Annual Scientific Meeting. Montreal, Quebec; June 2017.

Belay H, Bland L, and **Brighthaupt S**. "Picture a Responsible Community @ Columbia" Bacchus Initiatives of NASPA General Assembly Conference. Orlando, FL; November 2014.

Brighthaupt S, Lupica C. "Role of the lateral habenula in cocaine self-administration behavior." Presented at the National Institute on Drug Abuse, Baltimore, MD on August 5, 2014 and National Institutes of Health, Bethesda, MD on August 7, 2014.

Belay H, Bland L, **Brighthaupt S**, and Canales C. "Responsible Communities at Columbia and Beyond." Bacchus Initiatives of NASPA General Assembly Conference. Reston, VA; November 2013.

Brighthaupt S. "Characterizing Hypothalamic circuitry in the dbx-1 cKO mouse." Children's National Medical Center, Washington, DC on August 3, 2013.

Brighthaupt S. "Now And Later: A Study On Delay Discounting." Charles Herbert Flowers High School Research Symposium, Springdale, MD on May 30, 2012.

Invited Seminars

Speaker. "DSIP Lunch Series." Diversity Summer Internship Program. Johns Hopkins Bloomberg School of Public Health. Baltimore, MD; May 29, 2019.

Panelist. "Doctoral Student Wellbeing: Welcome to the First Year". Office of Student Life. Johns Hopkins Bloomberg School of Public Health. Baltimore, MD; January 31, 2019.

Speaker. “Research Spotlight: Insights from an NIH Trainee”. Substance Use Lecture Series. Hi-Step Summer Program. National Institutes of Health. Bethesda, MD; August 2, 2018.

Speaker. “DSIP Lunch Series.” Diversity Summer Internship Program. Johns Hopkins Bloomberg School of Public Health. Baltimore, MD; June 8, 2018.

Panelist. “Science Honors Program: Science Undergraduate Panel.” Panel Presentation. Columbia University Office of Undergraduate Admissions. New York, NY; October 24, 2015.

Panelist. “Creating Community: An Introduction to Student Life.” Multicultural Recruitment Committee Open House. Columbia University Office of Undergraduate Admissions. New York, NY; September 13, 2014.

PROFESSIONAL ACTIVITIES

Participation on Advisory Panels

Global Alliance on Behavioral Health and Social Justice, Early Career Sub-Committee, 2016-2017

Johns Hopkins Bloomberg School of Public Health, Graduate Student Assembly (Departmental Representative), 2016-17

Columbia University, Student Health Advisory Committee (Council Member), Columbia University, 2014-16

EDITORIAL ACTIVITIES

Ad-hoc Reviewer

Journal of Adolescent Health

AWARDS & HONORS

2016 - 20	Drug Dependence Epidemiology Training Grant (T32), Awarded by National Institute on Drug Abuse
2020	Michael J. Klag and Lucy Meoni Centennial Scholarship, Awarded by JHSPH Mental Health Dept.
2018	Symposium Abstract of Distinction, Awarded by Society for Prevention Research
2015	Work Exemption Program Grant ($2,063), Awarded by Columbia University
2015	Alumni and Parent Internship Fund ($1,632), Awarded by Columbia University
2014	Outstanding Presentation Award, Awarded by the National Institute on Drug Abuse

2013 - 15	Dean's List, Columbia University
2012	Horace E. Davenport Named Scholarship, Awarded by Columbia University
2012 - 15	America Needs You Fellowship ($2,500)