7-2013

Longitudinal Analysis of Resource Competitiveness and Homelessness Among Young Adults

Matt F. Prante
Utah State University

LONGITUDINAL ANALYSIS OF RESOURCE COMPETITIVENESS AND HOMELESSNESS AMONG YOUNG ADULTS

by

Mathew F. Prante

A thesis submitted in partial fulfillment
of the requirements for the degree

of

MASTER OF SCIENCE

in

Psychology

Approved:

Jamison D. Fargo, Ph.D. Major Professor	Maria C. Norton, Ph.D. Committee Member
Scott C. Bates, Ph.D. Committee Member	Mark R. McLellan, Ph.D. Vice President for Research and Dean of the School of Graduate Studies

UTAH STATE UNIVERSITY
Logan, Utah

2013

ABSTRACT

Longitudinal Analysis of Resource Competitiveness and

Homelessness among Young Adults

by

Mathew F. Prante, Master of Science

Utah State University, 2013

Major Professor: Jamison D. Fargo, Ph.D.
Department: Psychology

Homelessness occurs when individual resources are not enough for the demands of a given environment. Exploring homelessness as a process of resource loss on a continuum of poverty leads to research and explanations concerning how people transition from being housed to being homeless. This study assessed the influence of age, gender, and race along with a set of eleven resource competitiveness variables on the risk of youth becoming homeless. Resource competitiveness variables were: parental income, personal income, possession of a driver's license (DL), live-in partner, parenthood, education and training, annual weeks-employed, substance abuse, and incarceration history. The data came from the Bureau of Labor Statistics' National Longitudinal Survey of Youth 1997 (NLSY97). This sample was restricted to those that were homeless or unstably housed and were between the ages of 18 and 24 (n = 141). Each case was then matched by age, gender, and race to two individuals randomly selected from the remaining NLSY97 sample (*n* = 282). This resulted in an overall *N* of 423. A growth model was used to analyze the data longitudinally. Partnership, education and training, DL, annual weeks-employed, and personal income were significantly associated with experiences of homelessness and unstable housing. All were negatively related, except for age, which was positively related to incidents of homelessness and unstable housing. Comparisons across the homeless, unstably housed, and control samples showed incremental changes in nearly all the covariates in this study, in relation to changes in housing status, supporting the importance of studying homelessness as a point on a continuum of resource loss versus a discrete state of being.

(77 pages)

PUBLIC ABSTRACT

Longitudinal Analysis of Resource Competitiveness and

Homelessness among Young Adults

by

Mathew F. Prante, Master of Science

Utah State University, 2013

Major Professor: Jamison D. Fargo, Ph.D.
Department: Psychology

Homelessness occurs when individual resources are not enough for the demands of a given environment. It is not an arbitrary state of being, or a class of individual, it is a marker that signals a person has fallen to the extreme low end of a continuum of poverty. Perceiving homelessness as a point on a spectrum versus a discrete state, leads to research and explanations concerning how someone goes from being housed to being homeless, which can lead to more meaningful results than conceptualizing the homeless population as a class of people. It allows for the exploration of identification markers of at-risk individuals, and more effective designs for preventive measures versus just intervention efforts. This study looks at some potential factors involved in an individual's ability to attain resources and deal with environmental stresses. By identifying variables that co-occur across time, in a specific direction with the outcome of homelessness, we can identify indicators of extreme resource depletion and imminent homelessness, which can then be used to flag high-risk individuals in the population. The results of this study suggest that external resource pressures meet with poor ability to earn and maintain individual resources during the early adult years of an individual's life, but then stabilize around the early to mid-twenties. During this time, education and training, along with having a live-in partner are the most important protective factors against experiencing homelessness. The number of weeks worked annually, personal income, and having a driver's license are also significant protective factors against the onset of homelessness. Incremental changes in each of these factors in relation to housing status was identified, supporting the study of homelessness as a transitional state on a continuum of poverty versus a discrete state of being. Pro-social affiliation is discussed as a possible underlying reason for resource stability and low risk of homelessness.

ACKNOWLEDGMENTS

I would like to thank Jamison Fargo for having faith in me during the early part of my graduate career, for guiding me throughout the process with great kindness and wisdom, and for making this all possible. I would like to offer special thanks to Maria Norton for having faith in me at the beginning of my graduate career and taking me on as a student. I’d also like to thank Scott Bates for being on my committee and offering his time and advice to me on this project as well as other endeavors.

Mathew F. Prante

CONTENTS

LIST OF TABLES

LIST OF FIGURES

INTRODUCTION

Homelessness is a serious social problem in the United States. The homeless population at any given time is nearly 650,000, based on recent censuses of homeless individuals, such as the point in time counts (PIT) done during the winters of 2010 and 2012, which looked at who was on the streets or in a shelter during one night of the winter of each respective year (Kravitz, 2012). Also, based on an annualized estimate done between October 2009 and September 30, 2010 nearly 1.6 million people experience homelessness every year (United States Interagency Council on Homelessness [USICH], 2010). In addition to the above estimates, there is a large number of homeless youth: children and young adults, unaccompanied by a parent or legal guardian, between the ages of 12 and 24 (National Alliance to End Homelessness [NAH], 2012; USICH, 2010). Accurate estimates of the homeless youth population are difficult to obtain due to multiple factors, such as distrust of authorities, couch surfing with friends, or low use of common adult homeless services (Flick, 2007; Haber & Toro, 2004; Kidd & Scrimente, 2004; Ringwalt, Greene, Robertson, & McPheeters, 1998). However, recent estimates put the number near 600,000 with approximately 380,000 under the age of 18 (Hammer, Finkelhor, & Sedlack, 2002).

The current study examines factors related to an individual's ability to obtain or maintain resources and how these individual-level factors protect against or increase the risk of homelessness among young adults. By identifying risk and protective factors related to long-term homelessness for young adults better preventive measures can be designed and by extent decreases in the incidence of long-term adult homelessness.

LITERATURE REVIEW

There are three primary homeless subpopulations recognized in the literature: unaccompanied youth, single adults, and families (Haber & Toro, 2004). From there, further subdivisions by age, time homeless, and family composition are usually made. In addition, there are different definitions of what constitutes homelessness. Common definitions for homelessness range from only including those that are on the streets or in shelters to a more liberal definition of homelessness encompassing all individuals that are unstably housed, such as transitional and supportive housing, couch surfing, or living in motels.

Regardless, it seems appropriate to regard homelessness as a point on a continuum of resource stability with unstable housing demarcating the tipping point toward homelessness and literal homelessness demarking the far edge. Haber and Toro (2004) argued for this same notion using basic concepts from the Conservation of Resources (COR) model proposed by Hobfoll to clarify their point (as cited in Haber & Toro, 2004). The COR model implies that poverty is not a state of being, but a process of continual resource loss, where poverty is the cause and the outcome of this process. From this vantage, homelessness represents one extreme form of poverty.

This perspective provides a better model to approach homelessness research, because it implies that homelessness is part of a continuum of poverty reflected by housing instability, versus a discrete state of being. This implies that there is a chain of events and transitions that are differentiated along a continuum of housing instability, which if followed far enough leads to literal homelessness. If homelessness is considered to be a discrete variable, then there must be a qualitative difference between those that are marginally housed and those that are homeless. The goal in this situation would be to clarify the differences between the two states in order to better identify the deficits observed in the homeless population. In this way interventions can be designed in order to better help homeless people exit street life. If homelessness is considered as a point on a continuum of poverty, then the focus becomes identifying markers along the path to homelessness. The goal, therefore, becomes early identification and preventive program development (USICH, 2010). According to recent research, there is little difference between those who have recently lost their housing and those who are a “paycheck away” from homelessness (Burt, Aron, Lee, & Valente, 2001; Haber & Toro, 2004; Tompsett & Toro, 2010), thus considering homelessness as a point on a continuum of poverty most closely approximates the evidence.

Unaccompanied Homeless Youth

Homeless youth are not a homogenous population, thus characterizations are often dependent on the methods used for their identification (Karabanow, 2008; Kidd & Scrimente, 2004). The age of the sample will influence the observed characteristics, with older samples showing more problem behaviors such as crime, substance abuse, and mental illness (Haber & Toro, 2004). The majority of homeless youth come from dysfunctional families with histories of abuse, neglect, and family tension. Many homeless youth are either runaways or throwaways (been thrown out of their home by a legal guardian). They experience loneliness, feelings of being trapped, neglected, victimized, and depressed (Karabanow, 2008; USICH, 2010; Wolfe & Toro, 1999). A large portion of homeless youth has experienced placement or custody, such as foster care, the juvenile justice system, or family protective services (Miller, Donahue, Este, & Hofer, 2004; USICH, 2010). Approximately 30,000 youth exit the foster care system every year due to “aging out” of their minor status or getting a legal emancipation. Over a quarter of them will experience homelessness within four years (USICH, 2010). There are many reasons for leaving home, or being pushed out of home, but it usually reflects some form of family conflict. Almost every study on homeless youth references a history of abuse, including sexual, physical, and emotional (Burt et al., 2001; Cauce et al., 1994; Haber & Toro, 2004; Karabanow, 2008; Miller et al., 2004; Tompsett, Fowler, & Toro, 2009; USICH, 2010; Whitbeck, Hoyt, & Yoder, 1999; Wolfe & Toro, 1999). Karabanow (2008) indicated that many homeless youth in his longitudinal case study (N = 128) felt as though street life gave them more freedom and security than they experienced at home. Haber and Toro (2004) estimated between 17-60% of homeless youth have been sexually abused and 16-60% physically abused. Thompson, Bender, Windsor, Cook, and Williams (2010) reported that over 50% of youth enter foster care due to domestic abuse. Cauce et al. (1994) found the following prevalence in a random sample of homeless youth (N = 229): 29% had been physically abused; 23% reported family violence; and 12% said they left home because of sexual abuse. Another 25% reported family conflict and 15% cited neglect, while only 11% reported leaving home due to a problem of their own making. In addition, many homeless youth will experience further victimization on the streets (Kidd & Scrimente, 2004; Tompsett & Toro, 2010; USICH, 2010). Homeless youth experience a disproportionately high amount of poor mental health issues, such as loneliness, feeling trapped, anxiety, depression, suicidal ideation, or a combination of these (Karabanow, 2008; Kidd & Shahar, 2008; USICH, 2010; Wolfe & Toro, 1999).

Many homeless youth drop out of school, do not graduate, and do not obtain a GED (Miller et al., 2004; USICH, 2010). Some statistics cite a high prevalence of learning difficulties among homeless youth including developmental delays due to life disruption (e.g., USICH, 2010), but this has not been consistently reported across studies. Personality and mental disorders, as well as drug and alcohol abuse are consistently reported as being more prevalent among homeless youth compared to their stably housed peers (Karabanow, 2008; USICH, 2010). However, a recent study completed by Tompsett and Toro (N = 374; 2010) found that when “parental monitoring” and “parental deviance” were accounted for, association with deviant peers increased and the difference in the prevalence of antisocial and deviant types of behaviors, such as substance abuse, theft, and conduct disorders, disappeared between homeless and housed adolescents. This suggests that a lack of parental monitoring coupled with deviant peer influence are the dominating variables in determining many of the homeless youth deviant behaviors, versus something unique in the youth that leads them to the street, or the street experience itself. Tompsett and Toro (2010) did, however, note that deviant behaviors linked to survival activities, such as theft and trespassing, had a higher prevalence among homeless youth, and were more likely to persist into young adulthood if the youth remained on the street, whereas most housed youth decrease criminal activity as they age.

Tompsett and colleagues (2009) reported that younger adolescents showed significantly less chronic physical health problems, mental disorders, and substance abuse issues than either young adults or older adults. This supports the model that Whitbeck et al. (1999) developed concerning maladaptive behavior patterns, called the Risk Amplification Model (RAM). The concept is similar to the COR model, but focuses on maladaptive behavior instead of poverty. The basic concept behind RAM is that maladaptive behaviors have a negative cumulative effect over time, leading to increasingly worse experiences and responsive behaviors. Whitbeck and colleagues (1999) performed a study based on the RAM model with the cooperation of 255 homeless youth from four Midwestern states. The results showed that, for both male and female youth, street experiences such as increased substance abuse and deviant peer-association, amplified the negative effects of prior home abuse through increased victimization above that normally experienced on the streets. For women, street experiences amplified depressive symptoms as well (Whitbeck et al., 1999).

The proportion of males and females in the youth homelessness population is approximately equal (Kidd & Scrimente, 2004; Miller et al., 2004), whereas the adult population is predominantly male (Burt et al., 2001; Roll, Toro & Ortolo, 1999; USICH, 2010), with figures as high as 80% in the chronically homeless population (Tompsett & Toro 2010; USICH, 2010). Fewer females exist in the youth homeless population as age increases. One hypothesis for this finding is that unprotected sex, which is common among homeless youth (USICH, 2010), leads to pregnancy and later female identification as mothers as part of a family, instead of being classified as a single adult experiencing homelessness. Recently the conceptualization of homeless youth has been changed to include single mothers thus the extreme gender difference identified in the past may be re-conceptualized (NAH, 2012).

Unaccompanied Homeless Adults

The single adult homeless population shares many of the characteristics and needs of the youth population, with the strongest similarities existing between those closest in age. There is not a qualitative difference between a one year age difference, thus the standard practice of still considering 24 as part of the youth population versus demarcating 18 as the cut-off point. Due to the overlap in shared needs, behaviors, and potential outcomes across all homeless age groups, it is an important component of comprehensive research, to at least explore and be aware of common traits in the adult population.

Homeless adults show less heterogeneity when divided into subgroups relating to length of time homeless. This is an important point, because it demonstrates the deleterious effects of an extended street life, (e.g., Tompsett et al., 2009), such as increased substance abuse, poor mental and physical health, liver disease, and early mortality (Flick, 2007). The prevalence of mental and physical health problems is higher for homeless adults than for the general population, and the discrepancies increase with age (Burt et al., 2001; Roll et al., 1999; Tompsett et al., 2009; USICH, 2010). The fact that the disparities in health outcomes between the homeless population and the general population increase with age, supports the RAM model, and the increasingly negative influence that street life has on an individual over time, and stresses the importance of minimizing the time a person spends on the streets. The USICH hopes that some of this will be managed by changes in the Medicaid policy coming into effect in 2014. Some of the health problems suffered by the older adult and chronically homeless populations may be due to natural aging effects, though limited health care, stress, substance abuse, lack of shelter and poor hygiene most likely enhance this effect.

Homeless single adults show a higher prevalence of schizophrenia, personality disorder, and substance abuse (USICH, 2010), although the rates of various mental illnesses may not be as disproportional from the general population as commonly reported. Bellavia and Toro (1999) utilized multiple measures including structured interviewing (*N* = 143) to assess the reliability of commonly used measurement instruments. They found the prevalence rates of mental disorders ranging from 3-73% depending on the instrument used, cut off points for symptom severity, and whether the data identified substance abuse as a separate issue from mental health. Substance abuse and mental health disorders often overlap because admittance to a mental hospital for substance abuse may look like a mental health disorder in extant data bases, and substance abuse is identified as mental disorder in its own right (Bellavia & Toro, 1999). This does not mean that mental disorders and substance abuse are not overrepresented in the homeless population, it merely serves as a reminder that the exact prevalence is confounded by measurement error.

The majority of the homeless single adult population has weak social support networks, chronic disabilities both mental and physical, do not have regular work, and have substance or alcohol abuse problems (Burt et al., 2001; Roll et al., 1999; Toro et al., 1999). A large portion of the homeless population is 31-50 years old and 13% are veterans (USICH, 2010). Over time, the substance abuse and mental health problems are likely to increase in severity due to the stresses of street life (Flick, 2007; USICH, 2010), making escape from the streets even more difficult. Though substance abuse and a history of arrests are strongly related with male homelessness, females tend to differ in this regard. Roll and colleagues (1999) contrasted a number of single homeless men and women from various parts of Buffalo (*N* = 228). They found that females tended to have a more recent experience of assault, were more likely to have contact with family and friends, have greater psychological distress, and were less likely to have a history of arrests and substance abuse than men.

Minorities are enormously overrepresented in all of the homeless populations, particularly poor African Americans (Burt et al., 2001; Roll et al., 1999; Tompsett et al., 2009; USICH, 2010; Wolfe & Toro, 1999). Burt and colleagues (2001) reported that 43% of the homeless population is African American, whereas they only represent about 12% of the U.S. population. Toro and colleagues (1999) reported that homeless African Americans were overrepresented 4 to 6 times that of their proportional representation. Tompsett and colleagues (2009), using a pooled sample of multiple age groups (*N* = 823), noted 44% of the adolescents (13-17), 77% of the young adults (18-34), and 86% of older adults (35-78) were African American.

Risk Factors for Homelessness

Caton and colleagues (2005) studied risk factors for long-term homelessness by following a population of newly homeless adults (N = 377) for 18 months. They found that older age and a history of arrests were the most significant predictors of still being homeless after 18 months, and similar to later findings in a comprehensive literature review by Caton, Wilkins, and Anderson (2007), unstable employment history, poor emotional coping and mental functioning, victimization, and low levels of family support were also significant predictors of long term homelessness.

There are some interesting connections between risk factors for long-term homelessness and youth homelessness. Van Den Bree and colleagues (2009) performed a large scale longitudinal assessment (N = 10,433) of risk factors for adolescent homelessness and isolated three independent predictors: victimization, school adjustment problems, and family relation problems. Victimization and family conflict were two of the factors in the Caton et al. (2005) study that delineated the differences between short- and long-term adult homelessness. Thompson and colleagues (2010) noted that one of the prime reasons youth leave home is to escape abuse, either physical, emotional, sexual, or a combination, and that those that had been abused were more likely to experience further victimization later in life, thus many youth already carry at least one of the predictors for long term adult homelessness. Tompsett and colleagues (2009) found that the majority of chronically homeless older adults had experienced abusive home environments in their past. Karabanow (2008) observed the same phenomenon with a youth sample, noting that nearly every participant had some type of history of physical or sexual abuse either against their person or directed toward another in the home, as well as family conflict and low parental support. Victimization and low family support or conflict, are consistent predictors for both youth homelessness and long-term adult homelessness (Burt et al., 2001; Tompsett & Toro, 2010; USICH, 2010; Wolfe & Toro, 1999).

A number of risk factors for homelessness are exacerbated by an increasing number of homeless episodes and the duration of homelessness that reinforce the cycle of homelessness, such as mental illness, drug and alcohol use for coping, sexual and physical abuse on the streets, and societal marginalization (Burt et al., 2001; Flick, 2007; Haber & Toro, 2004; Tompsett & Toro, 2010; Van Den Bree et al., 2009). The homeless youth population starts life on the streets at an earlier age and, therefore, has a greater potential for rapidly accumulating a series of negative life experiences. The longer a person is homeless, the more likely they are to remain homeless. Therefore, becoming homeless at a young age might itself be a risk factor for long-term adult homelessness.

Homeless adolescents show more resilience to past and current trauma than older homeless individuals, including young adults (Tompsett et al., 2009), and are more sensitive to interventions than their older counterparts (Flick, 2007). Tompsett and colleagues (2009) noted that despite common perceptions of youth homelessness being primarily related to psychological trauma and adult homelessness being related to low income and physical health, homeless youth showed significantly fewer mental health disorders, were physically healthier, reported more friends, and despite the use of alcohol and drugs, substance dependence was rare. Homeless youth have had less time to crystalize daily patterns and behaviors perpetuating the homeless lifestyle than long-term homeless adults. Despite an increased adaptability to change, an episode of homelessness may be more detrimental to youth in some ways, such as the inevitable disruption in critical skills development needed to successfully compete for resources and potentially rise up the "social ladder" (Haber & Toro, 2004). By identifying risk factors for homelessness, as well as the age that those risk factors become the most prevalent and influential, it may be possible to prevent the experience of homelessness at an earlier age, thus alleviating many of the compounding negative effects experienced during episodes of homelessness as well as prevention of adult homelessness.

The majority of current research supports the idea that homelessness is the result of an interaction between system and person level influences intersecting with poverty (Burt et al., 2001; Gould & Williams, 2010; Shinn, Knickman, & Weitzman, 1991; Toro et al., 1999; USICH, 2010). When system-level influences exert pressure, such as decreased affordable housing due to high rates of gentrification, the forces of selection become much more demanding and the most vulnerable in the population will be at the highest risk for the loss of survival resources. Homelessness is basically an extreme form of poverty (Haber & Toro, 2004), and by identifying those variables responsible for poverty, early identification of risk factors for homelessness may be possible. Employment and personal income are the most obvious avenues for resource attainment. The better someone is at finding and retaining employment that pays a wage above the poverty line, the less likely the experience of poverty or homelessness. Social support can also buffer against temporary resource loss, offering another means of resource attainment, such as financial and emotional support from parents or a "life partner." Many of the variables related to these resources are easily identifiable and fairly common in surveys and data sets, such as income, marital status, parental occupation, etc. Thus they offer the most proficient and universal means, which are already in use, to identify high-risk individuals within a population.

The intent of the current study is to identify risk or protective factors for the onset of youth homelessness, as well as the age that each factor is most influential, in order to help inform preventive research. The next several sections describe factors that are hypothesized to impinge on access to resources, thus increasing risk of homelessness.

Incarceration History

Upon reentry into the community, most ex-prisoners do not have money saved, jobs, or places to stay waiting for them. They are often estranged with existing social support systems, have outstanding legal fees, and must work to readjust to life outside of prison (Metraux, Roman, & Cho, 2007; Murphy, Fuleihan, Richards, & Jones, 2011). People with criminal records are one of the most stigmatized groups in the United States, and being a minority with a criminal record exacerbates these issues (Pager, 2003). Burt, Aron, Valente, Lee, and Iwen (1999) reported that 54% of the homeless population has a history of incarceration in either jail or prison. A study conducted in New York City (N = 7,200) of the homeless population found that 23% had experienced some form of incarceration within the last 12 months (Metraux & Culhane, 2006).

Criminal background checks are becoming increasingly commonplace. Most states allow employers to perform criminal background checks and employ them as tools in the selection process for employees (Rodriguez & Emsellem, 2011). The National Employment Law Project reported that employers were 50% less likely to hire individuals with a criminal record than matched peers with similar skill sets (Rodriguez

& Emsellem, 2011). Some job sectors completely bar people with criminal records from employment due to legislation, and many federal benefits including food stamps, student loans, the right to vote, and driving privileges are limited by criminal conviction and history (Legal Action Center, 2004; Pager, 2003).

Piquero, Farrington, Nagin, and Moffitt (2010) conducted a 40-year longitudinal study on 411 boys in London, starting at ages 8 and 9 and ending at 48. Their interest was to determine whether criminal activity had an influence on later job outcomes. Criminal activity was tracked through government law enforcement, thus in the study it only reflected actual convictions. They found that those that were never convicted, or as juveniles were only convicted a few times, were much more likely to work in white-collar occupations than those that had a more consistent record of convictions and incarcerations. Harrison and Schehr (2004) noted that 60% of ex-prisoners will still be unemployed a year after release. This becomes a problem, not only due to the loss of resources over time, but also because of the lack of consistency of employment. Consistency of employment refers to the ratio of time employed over a given number of years. Lindstrom, Doren, and Miesch (2011) found the second most influential factor in determining an individual's level of success in obtaining employment and wages was consistency of past employment. Kemp and Davidson (2010) in a study involving 798 people on incapacity benefits in Great Britain, found that men with consistent work experiences prior to the initiation of incapacity benefits were significantly more likely to return to work within a year than those without a consistent work history ($OR = 3.13$, $p < .05$).

A complex interplay exists between prejudices held by employers towards those who have been previously arrested and incarcerated for criminal offenses, the time spent unemployed while in prison, the loss of access to many state and federal assistance programs, and being excluded from many jobs due to a criminal record, which puts ex-prisoners at a great disadvantage when competing for employment. Such difficulties increase the risk of becoming homeless, and are further exacerbated by the experience of homelessness.

Partnership Status

An absence of relationships or the existence of poor relationships may be related to the inability to access resources, which may in turn result in homelessness. For example, recent studies have found that being married or having a live-in partner is a significant predictor of employment for men, though no significant trends were noted for women (Kemp & Davidson, 2010; Percheski & Wildeman, 2008). Percheski and Wildeman (2008) did an analysis of employment patterns for fathers using data from the longitudinal study, *Fragile Families and Family Well Being* (N = 4,900). In their analysis they controlled for marriage before and after children. They found a significant difference between the hours worked by married men with no children and single men with no children ($p < .01$).

Kemp and Davidson (2010) in their study regarding variables that influence the speed that a person on incapacity benefits returns to the work force, found that married or cohabitating men returned to work significantly faster than their single peers (OR = 5.02, $p < .001$), while women did not show a significant difference in either condition.

Percheski and Wildeman (2011) speculated that this relationship with men and work had to do with multiple societal influences including selection, social pressure, and institutionalization. Selection is based upon the idea that those men with better work history and prospects also have an advantage in the dating pool and marriage. Once married, men may experience social pressure from their spouses to give up some of their bachelor style behaviors and focus on activities that promote the security and safety of their wife and family. The institution of marriage has certain gender expectations and stereotypes, including the expectation for the man to be the bread winner, which is further reinforced through friends and family.

Marriage and partnership have consistently shown a prosocial effect on males. Sampson, Laub, and Wimer (2006) performed a longitudinal study (*N* = 552) on a group of high risk boys (*n* = 500), and followed them from adolescents to 32, while simultaneously following a stratified sample of men (*n* = 52) until the age of 70. They noted that on average, criminal activity decreased 35% after marriage for the same man.

Parenthood

A new child, as seen from the perspective of economic resource abundance, is an added financial burden, however studies have found that men usually increase the time they spend in employment endeavors after the birth of a child, suggesting this may actually serve as a protective factor against resource loss and homelessness. Percheski and Wildeman (2008) included childbirth as a variable in their study regarding marriage and work. They were able to identify 1,084 men that had a new child within the duration of their study. The single men in this group worked significantly less than the married men before the birth of a child, but after the birth of a new child this changed. Within five years, the single men nearly doubled the hours they worked and made the difference between the two groups indistinguishable.

Kemp and Davidson (2010) also included childbirth in their model, and found that fathers had an increase in the odds ratio for returning to work after the birth of a new child, and previously childless single men were twice as likely to return to work after the birth of a new child as married and cohabitating men. There were not any significant differences associated with women. The odds ratio for single fathers returning to work compared to single men without children was 10.24 ($p < .01$); for married and cohabitating men, the birth of a new child increased the odds ratio to 4.73 ($p < .01$) compared to married men without new children.

For women the picture is much different. Kemp and Davidson (2010) found that women were 75% less likely to return to work after childbirth ($p < .05$) regardless of relationship status. The fact that men increase their attachment to the labor force through both childbirth and relationship status, coupled with the fact that women decrease their attachment to the labor force in both situations, fits well within the ideas put forth by Percheski and Wildeman (2008). The inverse of these traditional notions, especially for new mothers, would be that it is okay for the woman not to work. In fact, she may experience pressure in the opposite direction, with motherhood taking priority over employment.

Education/Training

Employment marketability is essentially a matter of supply and demand, with the supply side representing an individual's skill set, and the demand side reflecting how rare that skill set is versus how much room there is within the current economic climate to employ that particular skill set. Thus it follows that the greater the breadth and proficiency contained within an individual's skill set, the more likely he or she will be able to fill a vacant niche within a given economic climate. The more an individual's skill set is in demand, the less likely they are to have trouble finding employment with wages above the poverty line. Thus education and training in a marketable skill serve as protective factors against poverty and homelessness.

Lindstrom and colleagues (2011) performed a longitudinal case study over a ten-year period, exploring the interactions and pathways that eight disabled youth followed from high school through career development and employment. The top theme listed as critical for obtaining employment with wages above the poverty line was participation in postsecondary education or training. Sahin and Willis (2011) analyzed employment patterns from January, 2010, through November, 2011, in an attempt to identify employment trends as the number of jobs returned from their 2009 lows. They found that similar to the trend of the preceding ten years, people with at least some college education were the most sought after. Furthermore, during the most recent period, they were the only labor sector showing an increase in available jobs, while those with less than two years of college or its equivalent in training continue to find declining employment opportunities.

Driver's License

For people living in large cities, a driver's license is not necessarily a critical item for employment, due to the availability of public transportation. In smaller cities and rural communities, public transportation is not as readily available, thus without a driver's license it is much more difficult to go to job interviews, make it to work shifts on time, or even do basic things like shopping and going to the doctor. Kemp and Davidson (2010) found that having a driver's license increased the predicted odds of working at the one-year follow-up by 2.6. This odds ratio is nearly as high as that for having steady employment for most of adult life (*OR* = 3.1), and having no health condition at follow-up (*OR* = 3.06), which is the whole basis of IB in the first place.

Corn and Sacks (1994) reported on a case study (*N* = 110) involving low vision and blind people that were unable to qualify for a driver's license. The top two frustrations reported by the low vision group were difficulties with dating and employment. This group consistently identified their inability to obtain a driver's license as the mediating reason.

Substance Abuse

Substance abuse has been repeatedly associated with the homeless population, (e.g. Burt et al., 2001; USICH, 2010). Substance abuse can lead to poor work performance (Milby et al., 2010), loss of social and family contacts (Caton et al., 2007), and negative peer associations, all of which decrease an individual's ability to successfully compete for resources and maintain housing. Milby and colleagues (2010) followed 103 adults through a drug treatment program that included housing and vocational training. Half of this group received cognitive behavioral therapy and half did not. They looked at the outcome of housing and employment stability and found that groups did not differ on either of these, but they did find that housing and employment stability were positively associated with length of abstinence.

Though substance abuse is often associated with homelessness, the chronological relationship has rarely been effectively explored. Some research argues that substance abuse is more often the result of homelessness versus the cause (e.g. Flick, 2007; Haber & Toro, 2004). Johnson and Chamberlain (2008) examined the prevalence of drug abuse for 4,291 adults. They identified 43% of the sample as having a problem with substance abuse. Of this group, 34% had an issue before becoming homeless, while 66% developed a substance abuse disorder after homelessness. Those with a substance abuse problem usually stayed on the streets for 12 months or longer. They noted that substance abuse sometimes precedes homelessness but more often it follows it. They explained that homelessness is not the result of a single issue, rather it is the result of multiple complications converging with resource depletion, and that substance abuse sometimes interacts with this situation by leading to the irrational maintenance of expensive habits. The more common path is for individuals to pick up substance use and later abuse through "social adaptation" while on the streets. Substance use is a normative behavior on the streets and is often the only common factor allowing for social connection.

Research Questions

The research questions for this study were based on the hypothesis that homelessness is the result of an inability to successfully compete for resources in a given environment. The variables for analysis were chosen based on prior research involving predictors of resource attainment and homelessness, thus those variables that benefit resource attainment should decrease the risk of homelessness. Below are the specific questions that were addressed in this study:

1. What demographic, employment, and criminal justice factors increase the risk of young adults becoming homeless?
2. Do these risk factors for homelessness vary with increased age?

METHODS

Sample

The National Longitudinal Survey of Youth 1997 (Bureau of Labor Statistics [BLS], 2007) is one of a series of longitudinal surveys under the advisement of the BLS, that explore the educational and labor market experiences of various cohorts within the US. The NLSY97 survey is a nationally representative longitudinal random survey, with approximately 9,000 youths that were between the ages of 12 and 18 at the time of the first interview in 1997. The actual survey is done annually and usually person to person, unless such arrangements become too difficult, in which case phone interviews are completed. It takes approximately one hour to complete. The interview covers many topics involved in the transition from youth to adulthood, with the primary focus on how the individual interacts with the labor market.

In 1996, prior to the start of the survey, parents were also interviewed, in order to create a profile of the youths' home environment. Parents continue to be followed over time for a few questions, but with much less involvement than during the first five years of the study. Minorities were oversampled to ensure appropriate coverage of national proportions, but weights are provided and adjusted annually to compensate for true probability of selection by race and gender. The survey is given once a year and currently has a retention rate of over 85% (see the technical sampling report on the BLS website for further information [Moore, Pedlow, Krishnamurty, & Wolter, 2000])

For the purposes of this study, the sample was restricted to those that responded under the housing domain as being homeless or unstably housed. This group was further restricted to ages 18-28. Each case was then matched by age, gender, and race to two individuals randomly selected from the remaining NLSY97 sample. This resulted in an overall *N* of 423, with *n* = 141 with one or more experiences of homelessness or unstable housing and *n* = 282 for the matched group. This sample was then restricted to only those that experienced literal homelessness, which resulted in an overall *N* of 147, with *n* = 49 with one or more experiences of homelessness, and *n* = 98 for the matched group. The second sample served as a comparison for the larger sample. If mean comparisons and model specifications are the same or very similar, then the addition of the unstably housed did not significantly alter the population in question.

The number of homeless and unstably housed individuals and incidences may be underreported in the NLSY97 data base, due to the inherent difficulty of tracking a person once they are homeless. Supporting this idea is the much smaller proportion of homeless individuals in the overall NLSY97 sample than found in the target population. However, the demographic stratification within the homeless sample is reflective of current demographic estimates (USICH, 2010): female = 53%, male = 47%; African American = 28%, Hispanics = 14%, and Whites = 58%.

Measures

Data from the NLSY97 were used for all the variables in this study. The following variables were included in the analyses: homeless status; parental income;

gender; race; age; partner status; history of incarceration; parenthood; education and training level; work history; personal income; driver’s license; and substance abuse.

Homelessness and Incarceration

These were assessed using the following query and possible responses (Center for Human Resource Research, 2004):

In what type of place are you currently living?

1) House

2) Condo

3) Apartment/Flat

4) Dormitory (inc. fraternity/sorority) or Military Barracks

5) Hotel, Motel, Rooming, or Boarding House

6) Shelter (for homeless or abused) or on street

7) In Jail/Prison/Detention/Work Release

8) Mobile Home

9) Hospital

10) Group Home or Treatment Center

11) Other Type of Housing

12) Farm or Ranch.

There was not a prerequisite length of time required for an individual to be considered as “living” in a specific domicile, though a temporary excursion, such as summer camp, was not considered a change in living conditions. Due to the inherent instability of the homeless population, the length of time an individual spends in a single location does not discriminate group membership, thus the above query is appropriate for the current study.

For the purposes of this study, a response of six to this item denoted “literal homelessness,” seven identified those that had a “history of incarceration,” and five (along with an income that was less than five times the current poverty level) marked the “unstably housed.” Each of these was treated as a binary indicator of group status. The group that was identified as unstably housed was combined with the literally homeless group (LH) to create the combined sample that was used for the majority of the analyses, the unstably housed with literal homeless sample (ULH). Group membership for incarceration history had the properties of a time varying variable and a fixed variable, because group membership status could change during the course of the study. Once membership status for the incarceration group was marked as positive, the youth was considered part of that group for the remaining time points.

Driver’s License

Driver’s license status was queried each year, and recorded as a binary indicator. It was used as a binary time varying indicator in the current study.

Current Age

The age of all individuals was recorded annually in the NLSY97 data base. The interviews were also conducted annually, but due to variation in the space between interview dates, the ages recorded for youth were not always reflective of a one year time interval (i.e., if two interview dates were separated by less than 11 months, then the age of the respondent was the same for 2 consecutive years). In order to account for this, age was adjusted to reflect their birth year instead of month. Age was used as the time variable instead of the survey round, with 18 as the zero point, and 28 as the eleventh time point. Múthen and Múthen (2000) employed a similar method when confronted with the same problem in the NLSY97 data set. The problem is that the age range at each measuring point is 7 years, and many of the experiences and risks are quite different for a youth that is 13 versus 21. Thus age is a better cohort designator than time of measurement and was used for this study.

Relationship Status

This was recorded annually as a dichotomized variable for whether a romantic partner or spouse had lived with the respondent for at least 30 days prior to the date of the most recent interview. This is not a confounder for homelessness because the question asks if a romantic partner is staying with the youth in the place that the youth considers their place of living, as responded to in the question on “homelessness and incarceration.” The question specified living within a marriage-like relationship, defined as a partner of the opposite sex that has lived with the respondent for at least 30 days. After 2004, this definition was altered to no longer require opposite sex as part of the “marriage-like” relationship.

For the intents of this study, distinctions between changes in relationship partners were not made, only whether or not a partner was living with them. Thus relationship status was treated as a binary time-varying indicator of group membership.

Parental Income and Personal Income

In the NLSY database, these two variables were recorded as the ratio of income to poverty. The operational definition is income/poverty x 100. This means that a value of 50 represents 50%, which infers an income equal to half the poverty level. Parental income was measured once in 1996, and was used as a fixed continuous predictor representing socioeconomic status (SES). Personal income was measured annually and treated as a continuous time varying predictor. Both of these variables range from 0-27 times the poverty level (0-2700).

Consistency of Employment

This was taken from the annually recorded number of weeks an individual worked during the respective year. It was used as a continuous time-varying predictor with a range of 0-53 weeks.

Parenthood

This reflects the number of biological children a youth has had, irrespective of whether the child lives with the youth or not. Parenthood was treated as a continuous time-varying predictor that increased in value with each child born. Child mortality was not accounted for in the number of children a youth had at any given point in time. If the value was missing for whether an individual had a child or not, it was dealt with using last observation carried forward (LOCF).

Education and Training

These values were taken directly from a set of questions recorded annually that kept track of the respondents' annual activities toward increasing either their level of education or training. Education was rated as follows: 0 = No GED and no high school diploma (HD); 1 = GED; 2 = HD; 3 = associate's degree; 4 = bachelor's degree; 5 = master's degree; and 6 = PhD and/or Professional. There was also a binary variable within the database that identified whether an individual earned any type of training certificate or vocational license. Those that were positively scored had 1 additional point added to the education total as listed above. These two variables were combined and treated as an ordinal time-varying predictor with a range of 0-7.

Substance Abuse

This was reflected in three variables: marijuana use, alcohol abuse, and hard drug use. Marijuana use reflects how many times the respondents used marijuana in the 30 days prior to the interview. Alcohol abuse reflects how many days the respondents drank 5 or more alcoholic drinks during the 30 days prior to the interview. Alcoholic drinks were defined as 1.5 ounces of liquor, a bottle of beer, a glass of wine, or a mixed drink. "Hard drug use" reflects how many times the respondent used a hard drug "similar to cocaine" during the last "year" (excluding marijuana). The response range for drinking and marijuana use was 0-30 (one possible response per day) and drug use was 0-500 (allowing for multiple uses per day throughout the year). Each of these was treated as a time-varying continuous predictor. Zero values were imputed for missing values that were given a valid skip response. This is because the preceding questions for many of the interviewees screened for whether or not the respondent had used the substance in question; if not, then the question regarding quantity was skipped, and a valid skip response was recorded.

These three variables had a lot of missing values that were not valid skip responses. Multiple imputation (MI) was the first method attempted to solve this missingness, but the degree of missingness, lack of other correlates, and the frequency of zero cell values, made convergence impossible when all other variables for the study were included in the imputation model. In an attempt to account for this, LOCF was used.

LOCF is not an ideal method for imputation, due to the fact that people are not static across time, and thus values reflecting human response should not be carried forward across time. This is an acknowledged weakness of the study, but LOCF seemed to be the best method available considering the existing constraints. However, this was not a completely unreasonable method for these variables, since the essence of a habit is repetition. Thus it may be a fair prediction to assume habits such as drug use do not fluctuate wildly from year to year. It also seemed reasonable to assume that missingness related to a refusal to answer a question about current drug use is suggestive of actual drug use; couple this with the recorded information on the prior year's drug use and reasonable evidence for current drug use and the use of LOCF emerges.

Data Analysis

Data cleaning, creation of new variables, data screening, computation of descriptive statistics, and matching cases to controls was performed using R (R, Version 2.15, 2013). Mplus was used for the analysis and missing data imputation (Mplus, Version 6.12, 2012). Mplus is a multivariate structural equation modeling environment for statistical computing. MI was used to deal with the relevant missing data. Growth modeling (GM) was used to assess the effect that age has on the risk of becoming homeless or unstably housed, and how race, gender and the above mentioned time-varying covariates explain the change in risk of homelessness over time. Potential issues from nesting within matched groups were accounted for by using a matching identifier as a stratification variable in the modeling framework.

A GM was computed in Mplus under the pseudonym latent growth curve analysis (LGC). This method was chosen because it is robust to violations of normality, allows for easy modeling of nonlinear development curves, which is often the case with binary outcomes. It is also available in Mplus, which is important because Mplus is able to pool the results from the GM analysis for all the data sets created by multiple imputation, using the appropriate pooling methods for the standard errors developed by Rubin (1987). Maximum likelihood estimation is the default estimator for Mplus and was used for the analysis along with a sandwich estimator to increase robustness against violations of normality and identification of a rare binary outcome (Múthen & Múthen, 2010a).

Initially, an unconditional model was tested for the best parameterization of time (i.e. linear or curvilinear). The determination of which model specifications offered the best fit was made, as suggested by Múthen and Múthen (2010b), with both the log likelihood ratio tests and substantive theory. Múthen and Múthen (2010b) suggest a few ways to deal with non-linear change in growth models, three of which were attempted. The first way is to manually specify the loadings (slopes) for the outcome at each time point. For example, in a study with 6 time points, if positive linear growth was seen in first 3 observation periods, but then plateaued for the latter three, a slope would be specified for the first 3 time points, and then a constant (indicating no change) in the latter three. The next way involved piecewise growth modeling. This is similar to the above method, only it involves breaking the model into segments of time and specifying each segment separately, then bringing them together in a single statistical model. Finally they recommend the use of traditional polynomials (e.g., quadratic, cubic, etc.), or allowing each time point to be freely estimated by the software to best match the sample data. The last method was not used because it led to model saturation and sample specific predictions.

The above methods were applied to both the LH and ULH samples separately in order to see if there was a significant difference between groups. Once the best model for time was identified, the fixed effects with intercepts and random slope interactions were tested. From this point, each time-varying covariate was individually estimated using an alpha of .20 and a log likelihood ratio test for model fit with variable inclusion. The final model was then selected by dropping covariates with high *p* values from the study and using the log likelihood ratio test to assess the conditional model as covariates were dropped and added in different combinations. After a final model was selected for both the LH and ULH samples, the results were contrasted to ensure that the inclusion of the unstably housed to the LH sample did not introduce a significantly different population.

LGC and Multilevel Modeling

LGC and multilevel modeling (MLM) are both forms of GM. Because of this, both are very similar, except that LGC treats time as a loading parameter on the outcome at each time point, whereas MLM treats time as a variable, and the cases are repeated at each time point and treated as additional observations. This makes MLM more robust to many types of missingness at random time points, since a single observation can be dropped if a predictor is missing at that time point versus all observations connected to a case for a single missing observation point, as with LGC. On the flip side, LGC is more robust to a lack of linearity between the outcome and time and it can easily be used with MI data sets in the Mplus environment.

LGC estimates the change in an outcome over time using a structural equation modeling (SEM) framework. A representation of the covariance structure for the correlational dependency created by the same subjects being repeatedly measured on the same variable over time is expressed in the latent slope factor. The nesting of individuals in time is accounted for by treating the outcome at each time point as a separate dependent variable. The model is then tied together through the latent slope factor, which is created by assigning a loading to the outcome at each time point reflective of the changing rate of growth between the mean of the dependent variable over time compared to the mean at the starting point (intercept). Mixed effects with the intercept and slope can be estimated with an LGC just as they can with MLM. However, unlike MLM, LGC provides a separate coefficient for the covariates at each time point versus an omnibus coefficient as found in MLM (Stoel, van Den Wittenboer, & Hox, 2003). This can make interpreting LGC more tedious, but it also has the advantage of offering more information about what is happening at each time point or age in this case.

Missing Data

The NLSY97 dataset has sporadic missingness throughout the survey responses across all years. This is a common problem in complex longitudinal survey design (Enders, 2010; Múthen & Múthen, 2010a; Rubin, 1987). If the missing data are not appropriately addressed, then bias will most likely be introduced, and a large number of cases dropped due to missing cell values and the default use of listwise deletion. Despite listwise deletion being the default method for dealing with missing data for many software programs, it will usually result in bias and decreased power. If the data are not missing completely at random (MCAR) then the deleted cases may represent a unique subset of information, and dropping these cases will not only result in a decrease in power but biased results (Enders, 2010).

The overall proportion of missing data within the NLSY97 data set is between 13-14% for most variables, including housing, driver's license, partner status, employment history, and education and training level, and approximately 26% for income and drug use responses. LOCF and multiple imputation methods were used to deal with the missing data that had stable outcomes. A missing data analysis was run using Mplus to identify the various missing data patterns for individuals within the study sample. The first part of the analysis created binary variables for all the covariates, representative of missing or not missing. A chart was then created listing each of the missing data patterns and the frequency of each. The data patterns were then used to identify the missing data mechanisms as defined in Rubin's missing data theory (1976). Of note, the analysis was employed after LOCF was used to fix missingness on aforementioned variables, thus they were excluded from the missing data table. Of concern at this point, was establishing that the missing data were not representative of a unique subset within the population that could only be identified by values that did not exist within the data.

Mean comparison between the cases with missingness and those without, can be used to confirm whether there is a unique subset within the population. If the means are different between the two groups, then the group identified by the missing data pattern represents a unique subgroup, if not then they are the same, and missingness can be treated as MCAR. If the missing data can be predicted by other values within the data set, then the missing data mechanism is missing at random (MAR) and missingness can be regressed from other values. If the data mechanism is missing not at random (MNAR) the methods for imputation or estimation of missing values becomes much more difficult. MI and maximum likelihood estimation (ML) are appropriate for dealing with missing data that are MAR or MCAR (Enders, 2010; Graham, Hofer, & MacKinnon, 1996). This is because if the data are MCAR, then they do not represent unique information, and if they are MAR, then by definition the missingness is related to information within the data set.

In the current study, there were 180 cases with missing data and 240 without. The top two patterns with the highest frequency of subjects missing data constituted the large majority of the total missing data in the sample with 130 cases. These two patterns showed missingness at the last time points of the study. They represent attrition and aging out due to changing the cohort from time of measurement to age. They both represent patterns where all the data are missing from either the very last time point, or the last 2 time points. The pattern representing missingness at the last time point (age 26) has a frequency of 79, for all variables. The other pattern has a frequency of 51, and shows missingness on the last 2 time points (25-26) for all variables, reflecting 13% and 35% missingness at time points seven and eight respectively. There were three more patterns that each had four cases of missingness. Interestingly, each of these represented missingness on income at only 1 time point. It was noted in the NLSY97 technical sampling report (Moore et al., 2000) that there was not a significant difference in the response rate due to income level, which means that the missing values of income are not the determiners of missingness, thus the data is not MNAR and can be estimated using available information. The remaining missing data patterns all had a frequency of one, and a single individual does not make up a unique subpopulation.

The two missing data patterns that were reflective of missing by design and attrition were also treated as MCAR. The reason for assuming MCAR with the data missing by design (changing cohort from time of measure to age of measure leading to aging out of some participants at ages over 24) is fairly intuitive, but the data missing due to attrition requires a little more explanation. Two studies were completed (Graham, Hofer, Donaldson, MacKinnon, & Schafer, 1997; Enders, Dietz, Montague, & Dixon, 2006) that focused on previously completed longitudinal studies where special attention was spent on identifying the reason for missingness. These studies included follow-up analyses as one of the ways to test for MNAR. The results from both studies provided evidence that attrition-based missing data in longitudinal studies are most likely not due to specific subgroups within a population, but are actually MCAR and attributable to chance situations, such as moving, starting a new job, or some other random normal life event. Enders (2010) said that assumptions of MNAR for attrition based missingness are usually wrong.

Whether the missing data mechanism for the three patterns that each had four cases were MCAR or MAR, both of these mechanisms are appropriate for MI methods for missing data analysis. On top of this, auxiliary variables were included during the imputation process, increasing the number of potential correlates for missing variables, thus increasing the chance of MAR and making the assumption of MNAR very unlikely (Asparouhov & Múthen, 2010; Baraldi & Enders 2010; Múthen & Múthen, 2010b).

Multiple Imputation (MI)

MI is a regression-based procedure supported by a sequential regression algorithm, such as the expectation-maximization algorithm (EM) used in ML, to generate and save multiple copies of a data set with slightly different estimates for the missing values. The MI algorithm in the Mplus software program was used to generate 20 imputed data sets. Graham, Olchowski, and Gilreath (in Enders, 2010) recommended at least 20 for most situations, and Enders (2010) said that 20 data sets match the power of ML estimation and increases beyond this do not serve any practical utility.

Another consideration is how often to save each data set during the imputations. Following the common theory that the closer in time a repeated measure is to the last measurement, the more correlated they will be, so are the outcomes of each iterations of the MI algorithm. The closer each saved imputation is to the one prior, the stronger the correlation between data sets. Fifty iterations are recommended between each saved data set, and higher numbers of iterations are usually better if not just the same (Enders, 2010; UCLA, 2012). Increasing the number of iterations between each data set also increases the predictive power of the MI algorithm without dramatically increasing the memory demands of the computer (Múthen & Múthen, 2010a). Due to computational restrictions based on the available hardware and the added complexity of imputing categorical and continuous variables at the same time, the number of iterations between data sets was set to 300.

The actual imputation included time points 0 to 8 (representing ages 18-26). Time points 9 and 10 had too much missingness to include in the model. Time points 8 and 9 had 13-35% missingness as noted above, and were not used in later analyses. Having the extra time points included in the imputation process did not exert a negative impact, rather the addition of possible correlates with the missing values increased the efficacy of the procedure. The more variables that are included as correlates in the imputation process, the more accurate the estimations will be. The covariates that were imputed include homelessness, income, parent income, and employment history. The variables used as correlates for missingness include race, gender, education and training, having a driver's license, having children, incarceration history, relationship status, and drug use.

Due to the use of age as the time indicator instead of time of measurement, only those that were 17 or older for the first round of the study filled all age brackets from 18-28. This led to four less time points being used in the analysis than initially planned. Those that were younger than 17 at the start of the study were one year short of the last age point for each year they were younger, meaning they had missing data for later age points. The age range at the start of the survey in 1997 was 12-18, the vast majority were 14-16, thus the majority of age related dropout due to the study design is represented after age 26, but there was still enough missingness at age 25 to warrant dropping all ages over 24. Incidentally this also made the study sample a better representation of what is normally considered the youth population in homeless research.

A final issue regarding multiple imputation is the choice of model to use for identifying the relationships between variables. There are two classes of imputation model, H_1 and H_0 models. The H_1 model is developed from sequential regression of all the variables and correlates included in the imputation. The H_0 model is specified according to theory and knowledge of variable interactions. Asparouhov and Múthen (2010) ran multiple simulations to assess the bias introduced by the choice of modeling type. They found that the differences between an H_1 model and a properly specified H_0 model were not practically significant, but differences between an improperly specified H_0 model and an H_1 model were significant. They concluded the study by recommending that unless the sample data and theoretical relationships between variables are well known, and the researchers know exactly what they are doing, an H_1 model should always be used. They also showed through their simulations that data sets with both categorical and continuous data showed very negligible gains from properly specified H_0 modeling over H_1 modeling, and thus for data sets with mixed variable types, H_1 modeling should always be used. H_1 modeling for the imputation was used in the current study.

After creating the data sets, the analysis was performed, and the results were pooled together using Rubin's (1987) formula. This formula averages all parameters except for the standard error (SE). It includes an additional variance parameter reflective of the variance across all of the imputed data sets in order to account for the noise that is inherently introduced by the imputation process then pools the SE's. Methodologists currently regard MI as a "state of the art" method for dealing with missing data relative to other missing data handling methods (Enders, 2010). It increases the accuracy and power, with little to no bias, and adjusts appropriately for the residual error within a single imputed data set as well as adding the additional variance parameter to account for noise introduced through imputation.

RESULTS

A summary of the demographic and study variables is included in Tables 1 and 2, as well as comparisons between each sample and their matched control groups. Table 1 shows the LH sample information and Table 2 shows the ULH sample information. Significance tests for difference between samples were applied to all of the study variables using Welch's *t* tests for continuous variables and two sample proportional difference tests using the chi-square distribution for categorical variables.

The LH and ULH categorical and ordinal variables were recorded as dichotomous grouping variables, reflecting whether youth fit the criteria for group inclusion or not. For example, the value recorded for the variable marijuana use represents a count of each individual that used marijuana at least one time in the month preceding an annual interview, rather than a count of all positive incidences of "marijuana use" during the seven years of the study. The only categorical or ordinal variable not recorded in this way was "Partner." Partner reflects the total number of times a youth in the sample reported that they had a romantic partner that lived with them in order to appropriately account for the proportion of time a youth spent with a partner, versus the very different question of whether the youth had ever had a partner live with them for 30 days or more. The LH sample had significantly higher proportions of risk variables, and lower levels on the protective factors than the control group. Education, driver's license, incarceration history, having a partner, number of weeks worked annually, parental income, and personal income were all significantly different from matched controls ($p < .05$). Using a hard drug at least once during the year before an interview, having more than 5 drinks in

Table 1

Descriptive Statistics and Tests for Differences between the Literally Homeless (LH) and Control Samples

Variables	LH Homeless		LH Control		Difference Tests
	N	%	*N*	%	χ^2 and *t* test
Group Totals	49	100%	98	100%	-
Male	21	43%	42	43%	-
Female	28	57%	56	57%	-
White	14	29%	28	29%	-
Black	25	51%	50	51%	-
Hispanic	10	20%	20	20%	-
Grouping Variables					χ^2
Driver's License (yes)	28	57%	87	87%	17.38***
Incarcerated (yes)	10	20%	1	1%	15.05***
Children ≥ 1 (yes)	29	59%	46	47%	1.51
Partner (yes) [a]	56	16%	166	24%	7.92**
High School Diploma	21	43%	77	79%	17.18***
Hard Drugs (time/year)	16	33%	17	17%	3.56
Drink ≥ 5 (day/month) [b]	34	69%	68	69%	0.00
Marijuana (day/month)	28	57%	39	40%	3.29
Continuous Variables	*M*	*SD*	*M*	*SD*	*t* test
Annual Weeks Worked	21.55	20.63	35.58	13.97	-8.22***
	123.10		282.28	249.60	
Parent SES (% poverty)[c]	140.93		11.72***		
	154.05		280.83	230.34	
Youth SES (% poverty)[c]	232.86		4.25***		

Note. Day/month, day/year and time/year represent the question format at time of interview. The values in this table reflect the number of individuals that participated in the behavior at least one time.
[a]Partner reflects the sum of positive indications from all youth within a given sample across all interview points from ages 18-24. The percentage value reflects the average proportion of time the youth in a given sample had a partner.
[b]Drink +5 = Youth had ≥ 5 drinks per day during the month before an interview.
[c]Parent SES and Youth SES = income/poverty x 100 (i.e. a value of 100 = poverty level). Both were first calculated within individuals before aggregated by group.
**p* < .05. ***p* < .01. ****p* < .001.

Table 2

Descriptive Statistics and Tests for Differences between the Unstably Housed with Literally Homeless Sample (ULH) and Control Sample

Variables	ULH Homeless		ULH Control Tests		Difference
	N	%	*N*	%	χ^2 and *t* test
Group Totals	141	100%	282	100%	-
Male	66	47%	132	47%	-
Female	75	53%	150	53%	-
White	52	37%	104	37%	-
Black	59	42%	118	42%	-
Hispanic	30	21%	60	21%	-
Grouping Variables					χ^2
Driver's License (yes)	106	75%	254	90%	15.30***
Incarcerated (yes)	17	12%	6	2%	16.14***
Children ≥ 1 (yes)	65	46%	111	39%	38.79***
Partner (yes) [a]	234	24%	521	26%	2.36
High School Diploma	70	50%	236	83%	52.76***
Hard Drugs (time/year)	40	28%	45	16%	8.26**
Drink ≥ 5 (day/month) [b]	99	70%	185	66%	0.71
Marijuana (day/month)	78	55%	101	36%	13.86***
Continuous Variables	*M*	*SD*	*M*	*SD*	*t* test
Annual Weeks Worked	25.32	20.33	36.12	13.28	-10.49***
Parent SES (% poverty)[c]	235.85	300.39	254.76	235.82	-1.48
Youth SES (% poverty)[c]	216.68	281.35	321.41	251.30	-5.68***

Note. Day/month, day/year and time/year represent the question format at time of interview. The values in this table reflect the number of individuals that participated in the behavior at least one time.
[a]Partner reflects the sum of positive indications from all youth within a given sample across all interview points from ages 18-24. The percentage value reflects the average proportion of time the youth in a given sample had a partner.
[b]Drink +5 = Youth had ≥ 5 drinks per day during the month before an interview.
[c]Parent SES and Youth SES = income/poverty x 100 (i.e. a value of 100 = poverty level). Both were first calculated within individuals before aggregated by group.
$^{*}p < .05$. $^{**}p < .01$. $^{***}p < .001$.

one night or having marijuana the month before an interview were all insignificant at the .05 level.

The ULH had nearly identical results compared to the control group, except the use of hard drugs and marijuana, and the number of youth with at least one child were all significantly higher for the ULH group (χ^2 = 8.26, 13.86, and 38.79 respectively, $p < .01$). Also the proportion of time youth from the ULH sample spent with a partner was not significantly different than the control group (24% versus 26%, χ^2 = 2.36, $p > .05$).

Unconditional Growth Model for the ULH Sample

An unconditional model was run first to assess the parameterization of the growth factor. A quadratic growth term best accounted for the growth trajectory in the final unconditional model and was the most parsimonious way to handle the curvilinear trend. The following formula specifies the unconditional model that was selected before adding the covariates:

$$\hat{Y}_{it} = \eta_{1i} + \lambda_t \eta_{2i} + \lambda_t^2 \eta_{3i} + \varepsilon_{it}$$

where the subscript i denotes (1, 2,…, 423) individuals, and the subscript t denotes (1, 2,…, 6) time points of measurement, η_{1i} represents the intercept or starting point, which in this study is centered at age 18 (i.e. 18 = time 0), η_{2i} represents the linear term and η_{3i} is the quadratic term, λ_t denotes time steps or factor loadings for the growth factor, and ε_{it} denotes individual residual variation that is not correlated with the linear or quadratic terms (Múthen & Múthen, 2000).

Final Growth Model for ULH Sample

Table 3 presents the results of the final growth model for this sample. Significant predictors were education/training, employment history, income, possession of a driver's license, and a partnership. Inclusion of these predictors significantly improved the fit of the final model over the unconditional model (χ^2 = 252.75, df = 43, p <.001, n = 400). Interactions amongst the predictors, as well as between the predictors and time (age) were also tested in the growth model, but these did not improve fit. History of incarceration and the interaction between incarceration and parental income increased model fit, but they also led to non-convergence of the statistical model due to an unstable level of correlation across time points, and thus had to be dropped from the final model.

After controlling for the covariates, a growth curve emerged with a starting value of 0 and an exponentiated log mean growth rate of 2.86 (see Table 4). The estimated odds of homelessness were 0 at baseline with a growth rate of 2.86% per year when the other covariates were held constant. Although statistically non-significant between the intercept and the first time point, as noted in Table 2, the quadratic effect significantly improved model fit, and the data show a quadratic tendency over time (see Figure 1). Also, the standardized results showed a significant linear slope by quadratic interaction (*AOR* = .37, p < .001) along with significant quadratic estimates for all time points after age 19, supporting the inclusion of a quadratic growth factor. The adjusted odds ratio of the quadratic effect was 0.86, indicating that although linear growth was positive it was increasing at a decreasing rate of approximately 14% per year.

Table 4 shows how much of the variation in the outcome is accounted for by the

Table 3

Results of Growth Model for Unstable Housing and Literal Homelessness as a Function of Age and Time-Varying Covariates

Predictor		Log Odds	*S.E.*	*OR*	95% *CI*	*P*-Value
Homeless Age 19	ON					
Driver License (yes/no)		0.105	0.737			0.887
Education/Training (level)		-0.982	0.378	0.375 **	[0.179, 0.786]	0.009
Partner > 1month (yes/no)		-2.748	1.125	0.064*	[0.007, 0.581]	0.015
Weeks Employed (annual)		0.006	0.014			0.649
Income (% of poverty)		-0.003	0.002			0.180
Homeless Age 20	ON					
Driver License (yes/no)		-0.271	0.571			0.635
Education/Training (level)		-0.589	0.255	0.555*	[0.337, 0.915]	0.021
Partner > 1month (yes/no)		-2.636	0.875	0.072**	[0.013, 0.398]	0.003
Weeks Employed (annual)		-0.015	0.013			0.222
Income (% of poverty)		-0.002	0.001			0.239
Homeless Age 21	ON					
Driver License (yes/no)		-0.654	0.632			0.301
Education/Training (level)		-0.314	0.270			0.244
Partner > 1month (yes/no)		-1.325	0.791	0.266†	[0.056, 0.125]	0.094
Weeks Employed (annual)		-0.037	0.013	0.964**	[0.939, 0.989]	0.005
Income (% of poverty)		-0.003	0.002	0.997†	[0.993, 1.001]	0.052
Homeless Age 22	ON					
Driver License (yes/no)		0.753	0.668			0.259
Education/Training (level)		-0.839	0.260	0.432***	[0.260, 0.719]	0.001
Partner > 1month (yes/no)		-1.270	0.615	0.281*	[0.063, 0.701]	0.039
Weeks Employed (annual)		-0.028	0.014	0.972*	[0.946, 0.999]	0.024
Income (% of poverty)		-0.003	0.002	0.997†	[0.993, 0.001]	0.086
Homeless Age 23	ON					
Driver License (yes/no)		-1.560	0.773	0.210*	[0.046, 0.956]	0.044
Education/Training (level)		-0.598	0.321	0.550†	[0.293, 1.032]	0.062
Partner > 1month (yes/no)		-1.060	0.596	0.346†	[0.108, 1.114]	0.075
Weeks Employed (annual)		-0.028	0.017			0.110
Income (% of poverty)		-0.002	0.002			0.349
Homeless Age 24	ON					
Driver License (yes/no)		-0.587	0.674			0.384
Education/Training (level)		0.307	0.305			0.313
Partner > 1month (yes/no)		-1.797	0.681	0.166**	[0.044, 0.630]	0.008
Weeks Employed (annual)		-0.072	0.021	0.931***	[0.893, 0.970]	0.001
Income (% of poverty)		-0.002	0.002			0.268

Note: Bold font designates the outcome and age at each time point.
ON = Regressed on.
AOR = exponentiated odds ratio adjusted by the inclusion of the other *covariates*.
CI = exponentiated confidence interval.
**p* < .05, two-tailed. ***p* < .01, two-tailed. ****p* < .001. †*p* < .05, one-tailed.

Table 4

Variance in the Outcome at Each Time Point Explained by Time-varying Covariates, and Growth Rate Estimates

Age Homeless	R^2 Estimate	*S.E.*	*P*-Value
18	0.54	0.20	0.01
19	0.54	0.14	0.00
20	0.51	0.10	0.00
21	0.61	0.10	0.00
22	0.60	0.09	0.00
23	0.56	0.09	0.00
24	0.56	0.16	0.00
Slope Estimates	Exponentiated Mean	*S.E.*	*P*-Value
Slope	2.86	0.53	0.05
Quadratic	-0.84	0.08	0.14

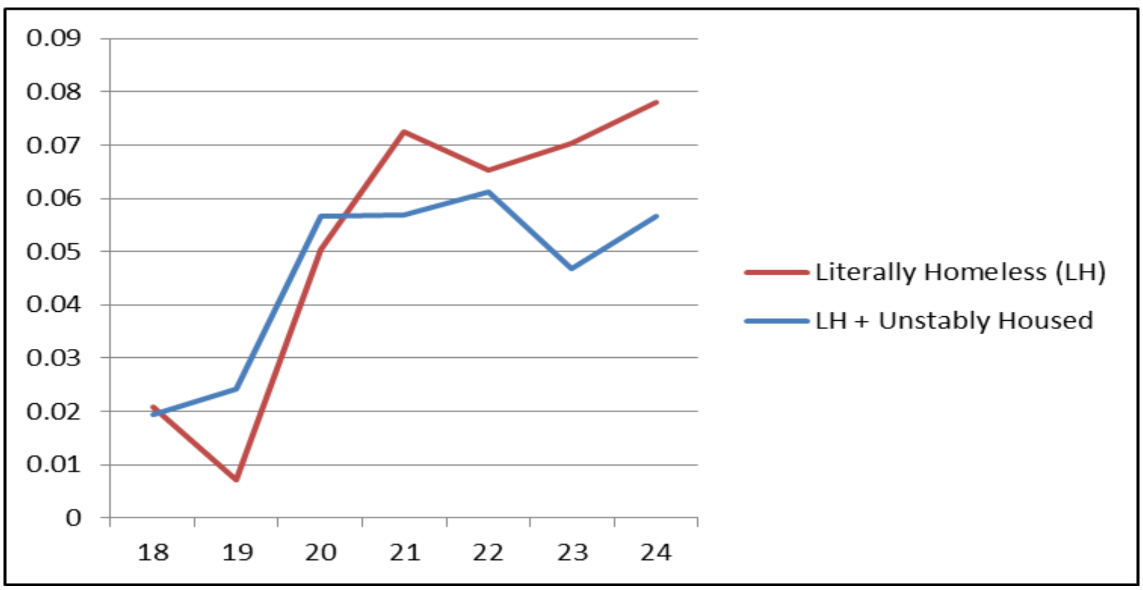

Figure 1. Proportion of sample that experienced literal homelessness (LH) and those that experienced literal homelessness or unstable housing (ULH) from 18-24.

growth factor (age) and the set of predictors at each time point. The model accounted for a significant portion of the variability in the odds of homelessness at each time point ($R^2_{t0\text{-}t6}$ = 0.54 - 0.61, $p < .01$). Although the variables included in the final growth model significantly improved model fit, they were not always significantly associated with the outcome at every time point (see Table 3). For example, at age 18 nothing was significant, and at age 20, only education/training (*AOR* = .555, $p < .05$) and having a partner (*AOR* = .072, $p < .01$) were significant.

Partnership is significant across all time points after age 18 at $p < .10$, and at ages 19, 20, 22, and 24 at $p < .05$. Education/training is significant across ages 19, 20, and 22 at $p < .05$, and at 23 with $p < .06$. Employment decreases the odds of being homeless at time points 21, 22, and 24 by more than 3% for every week worked in a year, topping out with an *AOR* of 0.93 at 24 signifying a decrease of 7% in the odds of being homeless for every week worked. Income is significant at ages 21 and 22 (*AOR* = .997, $p < .05$), meaning the odds of homelessness decrease by 0.3% for every 1% increase in the ratio of income to poverty level.

Growth Model for LH Sample

The initial model for the LH sample included the same set of predictors that were found to be significant in the ULH model, but possibly due to the different sample sizes there was one variation: the inclusion of parental income. Although the adjusted odds ratio did not offer much practical significance (*AOR* = .996, $p < .001$), the addition of parental income did significantly increase model fit. When the final ULH model was fitted to the LH sample, the model fit was excellent, the LH and the ULH models were highly similar with both groups sharing similar growth trajectories (see Figure 1).

The potential differences between the LH and ULH samples were further explored by separating all of the literal homeless from the ULH sample and then comparing the literally homeless to the unstably housed sample. Table 5 shows the descriptive statistics for both groups, as well as the test results from comparisons of the two samples. The LH sample differed from the unstably housed sample in the same way that the LH and ULH samples differed from their respective control groups (i.e., the LH sample had less protective factors and more risk factors than the unstably housed sample, and partnership, the use of alcohol, hard drugs and marijuana were not significantly different between samples).

Table 5

Descriptives and Test for Difference Between the Literally Homeless (LH) and the Unstably Housed Only (UH) Samples

Variables	LH Homeless		UH Homeless		Difference Tests
	N	%	*N*	%	χ^2 and *t* test
Sample Totals	49	100%	92	100%	-
Male	21	43%	45	48%	-
Female	28	57%	47	52%	-
White	14	29%	38	41%	-
Black	25	51%	34	37%	-
Hispanic	10	20%	20	22%	-
Response Categories					χ^2
Driver's License (yes)	28	57%	79	86%	12.89***
Incarcerated (yes)	10	20%	7	8%	3.81*
Children ≥ 1 (yes)	29	59%	36	39%	4.40*
Partner (yes) [a]	56	16%	178	28%	15.22***
High School Diploma	21	43%	49	53%	5.78***
Hard Drugs (time/year)	16	33%	24	26%	0.39
Drink ≥ 5 (day/month) [b]	34	69%	66	72%	0.01
Marijuana (day/month)	28	57%	51	55%	0.00
Continuous Variables	*M*	*SD*	*M*	*SD*	*t* test
Annual Weeks Worked	21.55	20.63	27.51	14.01	-3.44***
Parent SES (% poverty)[c]	123.10	140.93	291.27	338.73	-9.78***
Youth SES (% poverty)[c]	154.05	232.86	253.41	252.41	-2.93**

Note. Day/month, day/year and time/year represent the question format at time of interview. The values in this table reflect the number of individuals that participated in the behavior at least one time.
[a]The *N* value for Partner reflects the sum of positive indications from all youth within a given sample across all interview points from ages 18-24. The percentage value reflects the average proportion of time the youth in a given sample had a partner.
[b]Drink +5 = Youth had ≥ 5 drinks per day during the month before an interview.
[c]Parent SES and Youth SES = income/poverty x 100 (i.e. a value of 100 = poverty level). Both were first calculated within individuals before aggregated by group.
**p* < .05, two-tailed. ***p* < .01. ****p* < .001.

DISCUSSION

The hypothesis that guided this research was based on two key concepts: (1) homelessness is a point on a continuum of poverty; and (2) risk markers for homelessness are related to the ability that a person has to successfully compete for resources. The purpose of this study was to assess the validity of some known and potential risk markers for homelessness and how they interact with age. This goal was met, though on a smaller scale than initially anticipated. Many of the hypothesized covariates did not demonstrate significant or increase model fit. The covariates that were identified as significant were partnership, education/training, personal income, number of weeks worked per year, and whether a person had a driver's license or not. Many of these covariates have already been identified as risk markers in previous studies or are directly connected to resource attainment, such as personal income, thus they are not a unique contribution. However, the present study does offer three unique contributions: further supportive evidence that homelessness should be considered an extreme point on a continuum of poverty; the identification of a longitudinal pattern between the covariates and age; and the identification of partnership as a significant protective factor.

As noted earlier, recent research has shown that there are few differences between the literally homeless and their housed peers that are living pay check to pay check, thus there is not a discrete difference between the homeless and their unstably housed peers, leading to a transitional conceptualization of homelessness versus class comparison. This study further supports this hypothesis through the results found after contrasting the differences between the literally homeless sample and the unstably housed sample, as well as the difference identified between each of them and their respective control groups.

The literally homeless youth and the unstably housed youth differed from their stably housed peers on the same variables and in the same direction as each other, supporting the concept that the two samples make up a very similar population. When the literal homeless and unstably housed groups were contrasted with each other, the differences identified between them were in the same direction and with the same variables as those noted with their control group.

The literally homeless showed slightly higher prevalence of risk factors and less protective factors than the unstably housed sample (see Table 5), and the unstably housed sample showed the same relationship with the control groups. The risk and protective factors associated with housing status changed in an incremental fashion with changes in housing status, meaning that it should be possible to identify levels of risk and intervene, versus having to wait for the binary situation of homelessness and the negative effects that come with it. This supports the concept that housing status and the underlying association with risk and protective factors for homelessness reside on a continuum of housing instability and poverty.

Interestingly, the variables reflecting substance and alcohol abuse were not significantly different between the LH sample and control. However, a single point increase in the number of hard drug users in the LH sample, or a 2-point increase in the total number of individuals in the control group made the results significant, which infers that the lack of significance in hard drug use is due to sample size versus a real lack of difference. The use of marijuana and hard drugs was significantly different between the ULH sample and control group, though the proportional difference between samples was similar to that found between the LH sample and control group (see Tables 1 & 2), further supporting the point that lack of significance for the LH comparisons is due to a smaller sample size (LH = 49, ULH = 141). In summary, the results show that the group that experienced one episode of homelessness or suffered from unstable housing, were more likely to also use some type of drug than the more stably housed.

The proportion of people that experienced incarceration was significantly higher for the sample with the least stable housing status, for example, between the literally homeless and unstably housed group the proportions were 20% and 8% respectively, and for the ULH sample and its control group the proportions were 12% and 2%. Having a history of incarceration is a risk factor for homelessness and unstable housing. This may be because finding employment with a criminal record is difficult, thus resource stability is likely to be decreased, and the illegality of a number of common routines practiced by homeless youth, such as loitering, trespassing, or substance use in public spaces. Relaxing current regulations regarding the criminalization of behaviors that are often driven by the necessities of homelessness, and decreasing the length of time past crimes remain on publicly available criminal records would decrease the association between incarceration and homelessness, and possibly decrease the high rate of recidivism.

Overall, the study results for the combined ULH sample show that the risk of homelessness increases with age, but begins to flatten out around 21 to 22. The people in the sample started the study at 18 years old with a nearly zero chance of being homeless.

The risk of homelessness increased in a curvilinear way with a 2.86% annual increase in the odds ratio of becoming homeless and a 16% decline in the rate of annual growth. The rapid rise in the odds of becoming homeless coincides with the time period that youth leave home or are legally separated from various government assistance programs. Thus, the rapid initial rise in homelessness from 18 to the early twenties may represent the difficulty that youth face in trying to adapt to the adult world.

Living with a partner was significantly related to decreased odds of homelessness across all ages ($p < .05$), by more than 70% versus those without a partner except for age 23 (*AOR* = 0.35, $p < .10$). It is possible that this difference is significant due to the use of the phrase "living with" in the question about having a partner; some youth may have inferred that this meant they had to have a place of residence to live with someone. While this is a possible confounding factor, the question was not meant to be interpreted this way and there were 8 incidents out of 73 total incidents in the literal homeless group that reported living with a partner while being homeless, thus the likelihood of this information being confounded by misinterpretation seems less than for that of it representing a real trend in the population.

Partnership is important throughout the years, and is the most consistent buffer against housing loss of all the covariates with an odds ratio ranging from half as likely to twice less likely to be homeless with a partner than for those without a partner ($p < .001$). It is difficult to parcel out temporal precedence, whether those that have the ability to effectively compete for resources are also more likely to attract a partner, thus the partner influence could be selection based as noted by Percheski and Wildeman (2008), or if the supports afforded by a partner act as a buffer against resource loss, such as the benefits gained by an extra wage, emotional support, personal care in times of sickness, and supportive encouragement. It is most likely a blending of the two, possibly taking the following form: partnership selection by potential mates favors those that are most capable in multiple areas of life (Sampson et al., 2006), and those that are most capable are more likely to successfully compete for resources; and partnership helps buffer against later resource loss by offering mental stability, an additional income source, and more social connections to assist in times of need such as job searching, carpooling, or emergency loans.

Education and training decrease the odds of homelessness by an average of 50% for every increase in educational status. Education and training offered the most significant reduction to risk during the late teens to early twenties and stabilized as age increased. As the protective benefits of education and training waned, the importance of employment and income increased. The results hint at the ever increasing influence of income generating activities as young adults leave home. Income is significant at ages 21 and 22 ($AOR = .997$, $p < .05$), though the practical significance of this odds ratio is questionable. This is most likely due to a few outliers identified in both the LH and ULH samples (see Figure 2). The unstably housed portion of the sample had individuals that made 5 times poverty level, which was the cutoff level for income for this portion of the sample, and the literally homeless group showed outliers as high as 20 times poverty level while experiencing homelessness, meaning that the variance overlap could have confounded results.

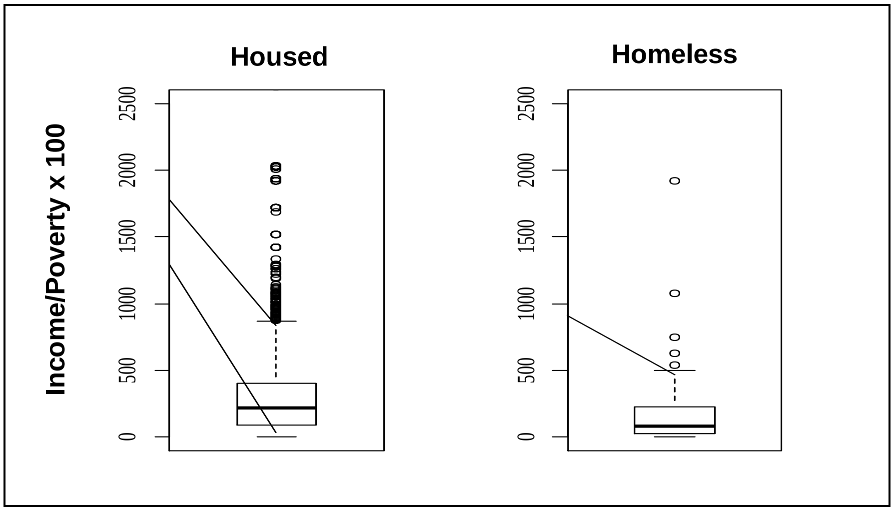

Figure 2. Comparison of the average income distribution for those that were housed versus those that were experiencing homelessness at the time of the survey.

Some of the early significance of education and training may be mediated by the extension of dependence benefits, such as legal guardians allowing them to remain home longer, or federal loans and grants for continuing education. This idea is further supported by the observation that jobs resulting from education and training by the ages of 18 to 21are unlikely, since very few will have an educational level beyond a couple years of college. Vocational training may be short enough to increase employment opportunities by 20 to 21, but the level of significance for education and training at this age seems to suggest a wider population trend than the few youth that may have vocational training and get a better job because of it. An alternative explanation to this could be that youth that are willing to put effort into education are also more willing to put effort into other things, such as saving money or bargain shopping for clothing and groceries. Either way, it seems likely that the protective influence of education and training is mediated by other factors.

A history of incarceration increased the model fit significantly, but it caused other problems with model estimation, specifically with the standardization of results making coefficient and model fit estimates suspect. Problems related to this variable may be due to the low level of positive incidence throughout the study (i.e., some of the early years had zero incidence of incarceration and caused mathematical problems in the estimation), as well as higher correlation across time than any other variables due to the coding style used. It would be good to further explore this variable, but an alternative coding method would have to be incorporated to avoid the extreme correlational issue introduced across repeated measures.

Limitations

The largest limitations in this study were the lack of queries within the NLSY97 data base that directly aligned with the research questions, and the small sample size. Two examples of the former involve a scarcity of information regarding mental and physical health. Mental health is a well-documented prevalent characteristic that many homeless youth endure (USICH, 2010), thus including it would have increased the explained variance in the outcome, and decreased the chance of confounding factors. The problem was that there was only one question in the survey that referred to a mental health condition and it was only asked four times between 1997 and 2009. Additionally, the item on the questionnaire did not refer to a condition that was necessarily chronic in nature and it also did not specify when the condition began making it impossible to arrive at assumptions about an individual's mental health during the intervening years. Questions regarding physical health conditions that were chronic in nature and could limit a person's ability to work were included in the same section as the mental health question, and during the same 4 years. Thus, it was impossible to make accurate assumptions about an individual's physical condition during the intervening years. The types of physical health questions that were asked annually referenced more generic health questions, such as height, weight, and how much a person exercised.

An increased sample size would have increased the generalizability of the findings, increased inferential power, and decreased hetroscedasticity across time. With increased power and decreased variance, income and employment would most likely show a much higher level of significance than has been identified. Potential threats to the assumption of homoscedasticity in the outcome can be noted in Figure 1 and Table 6, where the proportion of youth experiencing homelessness from year to year fluctuated much more wildly than would be found in the general population or a larger sample. A larger sample would likely result in a smoother slope, indicating a more consistent and generalizable trend for time. It is counterintuitive that a one year difference in age could change the probability of homelessness by 50% as found from age 22 to 23 (see Table 6), without some theoretical underpinning such as changing from minor status to adult status.

Future Research

Creating a model to more clearly depict the relationship between partnership and resource competitiveness including temporal precedence would be great for future research. This could possibly be done through the exploration of a mediating variable or construct that partnership shares a strong relationship with, or by using latent class

Table 6

Housing Status by Age

Age	Housing Status	Proportion
18	Housed	0.98
	Homeless	0.02
19	Housed	0.97
	Homeless	0.03
20	Housed	0.93
	Homeless	0.07
21	Housed	0.94
	Homeless	0.06
22	Housed	0.92
	Homeless	0.08
23	Housed	0.96
	Homeless	0.04
24	Housed	0.93
	Homeless	0.07

analysis, and identify whether early partnership, years of partnership, or some other type of social class identifier leads to different resource attainment outcomes.

Future research would do well by using formative latent variable techniques to help compensate for some of the missing data. A couple examples of where this would have been useful are with parent and youth socio-economic status. If multiple indices were used to measure economic worth, such as asset to debt ratios, investments, or owning a functional business, then problems such as the large variance parameters with income, or all the missing parental income values could have been decreased. This would have allowed for identification of how close a person was to being resource deficient, in terms of actual ownership, versus assessing resource stability only on annual monetary intake.

Risk of homelessness by age is at its highest during the years that youth typically leave home. Identifying common reasons that youth fail in their attempts at establishing independence away from their childhood home could lead to great opportunities for preventive measures, such as specific skills development during the last year of high school. Also, identifying youth populations that are at higher risk for such skill gaps would allow for targeted interventions for at risk groups.

Each of the significant covariates relate to activities that show some type of pro-social effort or acceptance (e.g., employment, earning and keeping a valid driver's license, finding a mate). Future studies may be do well identifying a way to measure a pro social construct and assessing its relationship to resource attainment. Exploring the motivational reasons behind identifying with pro-social activities versus social disaffiliation could also lead to the design and creation of programs that would address the growing social problems related to youth and adult disenfranchisement from society.

Finally, a better classification system needs to be developed to identify the needs of youth that spend a period of time under the umbrella term "homeless," versus classifying them all as homeless youth. Various classification systems have been attempted in the past, but thus far researchers have failed at identifying an appropriate means of identifying subpopulations with common needs. By identifying an effective classification system, service providers could meet the needs of individuals more rapidly and with better resource efficiency, and researchers could more effectively explore the issue within the appropriate subpopulations.

Conclusion

Although this study failed to identify a large number of previously unknown markers of homelessness, it did identify a significant covariate that has not been explored thoroughly in the homelessness literature: the protective effects of partnership. Living with a romantic partner acted as a protective factor against homelessness across nearly all ages. It was also shown that homelessness resides along a continuum of poverty, and that the prevalence of risk and protective factors changes incrementally along a continuum from homelessness to stable housing. This means that if enough variables were identified that fluctuate along this continuum, then a risk threshold could be defined that would mark the point for intervention efforts to be initiated before a state of homelessness was experienced. Finally, a common trend across homeless youth from 18 to 24 was identified: the rapid increase in the proportion of homeless individuals from late teens to early twenties. Since this is the age that United States (US) youth transition from dependent status to adult status, and often leave the home of their upbringing, a portion of homelessness is probably related to the difficulty that some of these youth experience in making this transition. Identifying what difficulties are most common to this group may be a good place to start for the research and design of preventive measures that could be taught in the high schools of high-risk populations.

The development of a needs based taxonomical system that could divide the population of homeless youth into smaller homogenous subgroups would increase the efficacy of current research and service intervention, and should be one of the major focuses of research in this field. The current study provides a small example of the importance of using the appropriate population. As shown in the current study, even the simple constraint of age to a minimum of 18, versus all youth under 25 greatly increased the chances that all of the variables that were identified as significant in the study were identified at all. For example, the reason a fourteen year-old boy is homeless has very little to do with having a driver's license, his employment status, income, education level, or whether he lives with a romantic partner. If the younger age group were included, these variables could become obscured by the inclusion of a population that doesn't relate to them. This is an example of what is currently happening in the homeless youth research community, and what can be done to fix it.

REFERENCES

Asparouhov, T., & Múthen, B. (2010). *Multiple imputation with mplus* [PowerPoint slides]. Retrieved from Mplus Technical Report site: www.statmodel.com

Baraldi, A. N., & Enders, C. K. (2010). An introduction to modern missing data analyses. *Journal of School Psychology, 48*(1), 5-37. doi:10.1016/j.jsp.2009.10.001.

Bellavia, C. W., & Toro, P. A. (1999). Mental disorder among homeless and poor people: A comparison of assessment methods. *Community Mental Health Journal, 35*(1), 57. Retrieved from EBSCOhost

Bureau of Labor Statistics. (2007). *National longitudinal survey of youth 1997* [Data file]. Retrieved from www.bls.gov/nls/nlsy97.htm.

Burt, M., Aron, L. Y., Lee, E., & Valente, J. (2001). *Helping America's homeless: Emergency shelter or affordable housing?* Washington, DC: Urban Institute Press.

Burt, M. R., Aron, L., Valente, J., Lee, E., & Iwen, B. (1999). Homelessness: Programs and the people they serve. *Findings of the National Survey of Homeless Assistance Providers and Clients.* Washington, DC: Urban Institute Press. Retrieved from EBSCOhost

Caton, C. M., Dominguez, B., Schanzer, B., Hasin, D. S., Shrout, P. E., Felix, A., & Hsu, E. (2005). Risk factors for long-term homelessness: Findings from a longitudinal study of first-time homeless single adults. *American Journal of Public Health*, *95*(10), 1753-1759. doi:10.2105/AJPH.2005.063321

Caton, C., Wilkins, C., & Anderson, J. (2007). People who experience long-term homelessness: Characteristics and interventions. *The 2007 National Symposium on Homelessness Research.* Retrieved from http://aspe.hhs.gov/hsp/homelessness/symposium07/caton/report.pdf

Cauce, A. M., Morgan, C. J., Lohr, Y., Wagner, V., Moore, E., Sy, J., Wurzbacher, K., Tomlin, S., & Blanchard, T. (1994). Effectiveness of intensive case management for homeless adolescents: Results of a 3-month follow-up. *Journal of Emotional and Behavioral Disorders, 2,* 219‒227. Retrieved from EBSCOhost

Center for Human Resource Research. (2000). *NLSY97 questionnaire and interviewer's reference manual round 2, p. 4*. Retrieved from https:// www.nlsinfo.org/sites/nlsinfo. org/files/attachments/121212/nlsy97r2_quex.pdf

Corn, A. L., & Sacks, S. Z. (1994). The impact of not driving on adults with visual impairments. *Journal of Visual Impairment & Blindness, 88*(1), *53.* Retrieved from EBSCOhost

Enders, C., Dietz, S., Montague, M., & Dixon, J. (2006). Modern alternatives for dealing with missing data in special education research. In T. E. Scruggs & M. A. Mastropieri (Eds.), *Advances in learning and behavioral disorders,* (pp. 101-130). New York, NY: Elsevier.

Enders, C. K. (2010). *Applied missing data analysis*. New York, NY: Guilford Press.

Flick, U. (2007). Homelessness and health: Challenges for health psychology. *Journal of Health Psychology, 12*(5), 691-695. doi:10.1177/1359105307080576

Graham, J. W., Hofer, S. M., Donaldson, S. L., MacKinnon, D. P., & Schafer, J. L. (1997). Analysis with missing data in prevention research. In K. Bryant, M. Windle, & S. West (Eds.), *The science of prevention: Methodological advances from alcohol and substance abuse research*, pp. 325-366. Washington, DC: American Psychological Association.

Graham, J. W., Hofer, S. M., & MacKinnon, D. P. (1996). Maximizing the usefulness of data obtained with planned missing value patterns: An application of maximum likelihood procedures. *Multivariate Behavioral Research, 31(2),* 197-218. doi:10.1207/s15327906mbr3102_3.

Gould, T. E., & Williams, A. R. (2010). Family homelessness: An investigation of structural effects. *Journal of Human Behavior in the Social Environment, 20*(2), 170-192. doi:10.1080/10911350903269765

Haber, M. G., & Toro, P. A. (2004). Homelessness among families, children, and adolescents: An ecological developmental perspective. *Clinical Child & Family Psychology Review, 7*(3), 123-164. Retrieved from EBSCOhost

Hammer, H., Finkelhor, D., & Sedlack, A. (2002, October). Runaway/thrownaway children: National estimates and characteristics. *National Incidence Studies of Missing, Abducted, Runaway or Thrownaway Children.* Retrieved from http://www.missingkids.com/en_US/documents/ nismart2_runaway.pdf

Harrison, B., & Schehr, R. (2004). Offenders and post-release jobs: Variables influencing success and failure. *Journal of Offender Rehabilitation, 39*(3), 35-68. Retrieved from EBSCOhost

Johnson, G., & Chamberlain, C. (2008). Homelessness and substance abuse: Which comes first? *Australian Social Work, 61*(4), 342-356. doi:10.1080/03124070802428191

Karabanow, J. (2008). Getting off the street: Exploring the processes of young people's street exits. *American Behavioral Scientist, 51*(6), 772-788. Retrieved from

EBSCOhost

Kemp, P. A., & Davidson, J. (2010). Employability trajectories among new claimants of incapacity benefit. *Policy Studies*, *31*(2), 203-221. doi:10.1080/01442870903429637

Kidd, S., & Shahar, G. (2008). Resilience in homeless youth: The key role of self-esteem. *American Journal of Orthopsychiatry*, *78*(2), 163-172. doi:10.1037/0002-9432.78.2.163

Kidd, S., & Scrimente, K. (2004, August). Evaluating child and youth homelessness. *Evaluation and Review*, *28*(4), 325-341. doi: 10.1177/0193841X04264820

Kravitz, J. (2012). Hud reports slight decline in homelessness in 2012: Seven percent decline reported among veterans and chronically homeless. *Hud.Gov: U.S. Department of Housing and Urban Development, HUDNo. 12-191*. Retrieved from http://portal.hud.gov/hudportal/HUD?src=/press/press_releases_media_advisories/2012/HUDNo.12-191

Legal Action Center. (2004). After prison: Roadblocks to reentry. Retrieved from http://www.lac.org/roadblocks-to-reentry/upload/lacreport/LAC_PrintReport.pdf

Lindstrom, L., Doren, B., & Miesch, J. (2011). Waging a living: Career development and long-term employment outcomes for young adults with disabilities. *Exceptional Children*, *77*(4), 423-434. Retrieved from EBSCOhost

Metraux, S., & Culhane, D. P. (2006). Recent incarceration history among a sheltered homeless population. *Crime & Delinquency*, *52*(3), 504-517. doi:10.1177/0011128705283565

Metraux, S., Roman, C., & Cho, R. (2007, September). Incarceration and homelessness. *The 2007 National Symposium on Homelessness Research*. Retrieved from http://aspe.hhs.gov/hsp/homelessness/symposium07/index.htm

Milby, J. B., Schumacher, J. E., Wallace, D., Vuchinich, R., Mennemeyer, S. T., & Kertesz, S. G. (2010). Effects of sustained abstinence among treated substance-abusing homeless persons on housing and employment. *American Journal of Public Health*, *100*(5), 913-918. doi:10.2105/AJPH.2008.152975

Miller, P., Donahue, P., Este, D., & Hofer, M. (2004). Experiences of being homeless or at risk of being homeless among Canadian youths. *Adolescence*, *39*(156), 735-755. Retrieved from EBSCOhost

Moore, W., Pedlow, S., Krishnamurty, K., & Wolter, K. (2000). *National longitudinal survey of youth 1997: Technical sampling report*. Chicago, IL: National Opinion Research Center. Retrieved from https://www.nlsinfo.org/sites/nlsinfo.org/files/

attachments/121221/TechnicalSamplingReport.pdf

Mplus (Version 6.12). [Computer Software]. Los Angeles, CA: Muthén & Muthén.

Murphy, D. S., Fuleihan, B., Richards, S. C., & Jones, R. S. (2011). The electronic 'scarlet letter': Criminal back grounding and a perpetual spoiled identity. *Journal of Offender Rehabilitation, 50*(3), 101-118. doi:10.1080/10509674.2011.56054

Múthen, B., & Múthen, L. (2010a). *Mplus user's guide* (6th ed.). Los Angeles, CA: Múthen & Múthen.

Muthén, B. O., & Muthén, L. K. (2000). The development of heavy drinking and alcohol-related problems from ages 18 to 37 in a U. S. national sample. *Journal of Studies on Alcohol, 61*(2), 290-300. Retrieved from EBSCOhost

Múthen, L., & Múthen, B. (2010b). Growth modeling with latent variables using Mplus: Introductory and intermediate growth models [PowerPoint slides]. Retrieved from Mplus Technical Report site: www.statmodel.com

National Alliance to End Homelessness. (2012, March). *An emerging framework for ending unaccompanied youth homelessness.* Retrieved from http://www.endhomelessness.org/library/ entry/an-emerging-framework-for-ending-unaccompanied-youth-homelessness

Pager, D. (2003). The mark of a criminal record. *American Journal of Sociology, 108,* 937-975. Retrieved from EBSCO host

Percheski, C., & Wildeman, C. (2008). Becoming a dad: Employment trajectories of married, cohabiting, and nonresident fathers. *Social Science Quarterly, 89*(2), 482-501. Blackwell Publishing Limited. doi:10.1111/j.1540-6237.2008.00543.x

Piquero, A. R., Farrington, D. P., Nagin, D. S., & Moffitt, T. E. (2010). Trajectories of offending and their relation to life failure in late middle age: Findings from the Cambridge study in delinquent development. *Journal of Research in Crime & Delinquency, 47*(2), 151-173. doi:10.1177/0022427809357713

R (Version 2.15). [Computer Software]. (2013). R Core Development Team. *R Foundation for Statistical Computing*. Vienna, Austria. Retrieved from http://www.R-project.org

Ringwalt, C. L., Greene, J. M., Robertson, M., & McPheeters, M. (1998). The prevalence of homelessness among adolescents in the United States. *American Journal of Public Health 88(9),*1325-29. Retrieved from EBSCOhost

Rodriguez, M. N., & Emsellem, M. (2011, March). The national employment law project. Retrieved from http://www.nelp.org/page/-/SCLP/2011/65_Million_Need_Not_

Apply. pdf? nocdn=1

Roll, C. N., Toro, P. A., & Ortolo, G. L. (1999). Characteristics and experiences of homeless adults: A comparison of single men, single women, and women with children. *Journal of Community Psychology*, *27*(2), 189-198. Retrieved from EBSCOhost

Rubin, D. B. (1976) Inference and missing data. *Biometrika, 63,* 581-592.

Rubin, D. B. (1987) *Multiple imputation for nonresponse in surveys*. New York, NY: Wiley.

Şahin, A., & Willis, J. L. (2011). Employment patterns during the recovery: Who are getting the jobs and why?. *Economic Review, 96*(3), 5-34. Retrieved from EBSCOhost

Sampson, R. J., Laub, J. H., & Wimer, C. (2006). Does marriage reduce crime? A counterfactual approach to within-individual casual effects. *Criminology*, *44*(3), 465-508. doi:10.1111/j.1745-9125.2006.00055.x

Shinn, M., Knickman, J. R., & Weitzman, B. C. (1991). Social relationships and vulnerability to becoming homeless among poor families. *American Psychologist*, *46*(11), 1180. Retrieved from EBSCOhost

Stoel, R., van Den Wittenboer, G., & Hox, J. (2003). Analyzing longitudinal data using multilevel regression and latent growth curve analysis. Retrieved from joophox.net/publist/ StoeletalSpanish.pdf

Thompson, S. J., Bender, K., Windsor, L., Cook, M. S., & Williams, T. (2010). Homeless youth: Characteristics, contributing factors, and service options. *Journal of Human Behavior in the Social Environment*, *20*(2), 193-217. doi: 10.1080/10911350903269831

Tompsett, C. J., Fowler, P. J., & Toro, P. A. (2009). Age differences among homeless individuals: Adolescence through adulthood. *Journal of Prevention & Intervention in the Community*, *37*(2), 86-99. doi:10.1080/10852350902735551

Tompsett, C. J., & Toro, P. A. (2010). Predicting overt and covert antisocial behaviors: Parents, peers, and homelessness. *Journal of Community Psychology*, *38*(4), 469-485. doi:10.1002/jcop.20375

Toro, P. A., Wolfe, S. M., Bellavia, C. W., Thomas, D. M., Rowland, L. L., Daeschler, C. V., & McCaskill, P. A. (1999). Obtaining representative samples of homeless persons: A two-city study. *Journal of Community Psychology*, *27*(2), 157-177. Retrieved from EBSCOhost

UCLA. (2012). *Statistical computing seminars multiple imputation in stata, part 1* [PowerPoint slides]. Retrieved from Academic Technology Services, Statistical Consulting Group site: http://www.ats.ucla.edu /stat/stata/seminars /missing_data/miin_stata_pt1.htm

United States Interagency Council on Homelessness. (2010, June). *Opening doors: Federal strategic plan to prevent and end homelessness*. Retrieved from http://www.ich.gov/PDF/OpeningDoors_ 2010_ FSPPreventEndHomeless.pdf

Van Den Bree, M., Shelton, K., Bonner, A., Moss, S., Thomas, H., & Taylor, P. J. (2009). A longitudinal population-based study of factors in adolescence predicting homelessness in young adulthood. *Journal of Adolescent Health*, *45*(6), 571-578. doi:10.1016/j.jadohealth.2009.03.027

Whitbeck, L. B., Hoyt, D. R., & Yoder, K. (1999). A risk-amplification model of victimization and depressive symptoms among runaway and homeless. *American Journal of Community Psychology*, *27*(2), 273. Retrieved from EBSCOhost

Wolfe, S. M., & Toro, P. A. (1999). A comparison of homeless and matched housed adolescents on family environment variables. *Journal of Research on Adolescence*, *9*(1), 53-66. Retrieved from EBSCOhost