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# Neighborhood Effects on Economic Outcomes of Youths

By

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A Thesis Submitted to

Department of Economics

Skidmore College

In Partial Fulfillment of the Requirement for the B.A Degree

Thesis Advisor: Qi Ge

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## Abstract

This paper analyzes the long-term neighborhood effects on incomes of youths in the United States. The working dataset comes from the National Longitudinal Survey of the Youths and consists of the youths between the age of 12 and 14 in 1997. Their neighborhood characteristics between 1998 and 2001 are analyzed to predict their household incomes in 2015. Using two-stage probit models and OLS regressions, this paper suggests two main findings. First, the youths in safe neighborhoods between 1998 and 2001 are 81.5 percentage- point more likely than the youths from risky neighborhoods to earn above the median household income in 2015. Also, living in safe neighborhoods increases the youths' incomes in 2015 by 221.2 percentage- point. These results show that the neighborhood environment in which the individuals grow up as youths has a significant impact on their adulthood incomes. As a result, this paper supports policy initiatives that actively seek to assist low-income families to move into affluent neighborhoods to break the poverty trap.

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## 1. Introduction

In societies world-wide, income inequality has been an alarming issue recently. Virtually all countries have experienced rising top shares of income and wealth (Alvaredo, Chancel, Piketty, Saez, & Zucman, 2017). Although the magnitudes of the rise vary by the countries, the increasing inequality has gained scholarly attentions.

According to Hufe, Peichl, Roemer, and Ungerer (2017), 43 percent of income inequality in the United States is attributable to the inequalities in individual circumstances. Circumstances are personal and environmental characteristics, such as race, gender, and family backgrounds, that individuals cannot control. The authors argue that inequality is more attributable to the consequences of the circumstances than to individual efforts (Hufe et al., 2017).

Following the rationale and findings of Hufe et al. (2017), this paper attempts to understand possible reasons for persisting inequality by examining the effects of neighborhoods on the economic performance of individuals. Specifically, it analyzes the long-term effects of moving out of disadvantaged neighborhoods on youths' incomes in their adulthood. It is hypothesized that the youths who move out of the disadvantaged neighborhoods have higher chances of earning a household income above the median than the youths who stay in their deprived neighborhoods. Testing for this hypothesis will provide necessary insights into the impacts of neighborhood resources on the economic outcomes of the youths, which in turn will allow deeper understandings on the widening gap between the wealthy and the poor.

To answer the research question, the National Longitudinal Survey of Youth 1997 (NLSY97) by the Bureau of Labor Statistics (BLS) is utilized. The NLSY97 is a longitudinal survey started in 1997 on a sample of youths between 12 and 18 years old in the United States. A number of different aspects of the youths are surveyed, including educational achievements, employment status, criminal records, and forms of interactions with their parents. Among these variables, this study focuses on the youths' neighborhood characteristics, migration history, and household income. The working dataset consists of the youths in deprived neighborhoods in 1997 with valid records of migration history.

With the working dataset, two- stage probit models and OLS regressions are conducted. In the first- stage probit, the probability of the youths living in safe neighborhoods is predicted as a function of their migration history. It is hypothesized that the youths who migrate between 1998 and 2001 have higher probability of living in the safe neighborhoods in 2001 than the youths who do not migrate.

Then, in the second stage, the probability of the youths earning incomes above the median household income in 2015 is predicted as a function of their neighborhood characteristics in. The youths in the safe neighborhoods in 2001 are hypothesized to have higher probabilities of earning above the median household income than the youths in risky neighborhoods.

The two- stage probit models yield the following main findings. First, the youths who have a history of migration between 1998 and 2001 are 8.56 percent point more likely to be in the safe neighborhoods in 2001 than the youths who do not migrate. Second, the gross household income in 1997 has a positive and statistically significant impact on the probability of the youths living in safe neighborhoods. Third, the youths who are in safe neighborhoods in 2001 are 81.5 percent point more likely to earn above the median household income in 2015 than the youths who are in risky neighborhoods.

In addition to two-stage probit models, OLS regressions are performed to show the magnitude of the neighborhood effects on household incomes of the youths in 2015. The results from these analyses show that living in the safe neighborhoods increases the youths' incomes by 221.2 percent point. Living in a safe neighborhood consistently has a positive and statistically significant effects on household incomes of the youths in 2015 across different race, age, sex, and number of household members under 18 in 1997.

Using a unique set of neighborhood characteristics, this study shows that the previous findings on neighborhood effects are robust. The majority of the past studies utilizes statistical data, such as the poverty and unemployment rates, to determine the level of deprivation in the neighborhoods, or census tracts. In this study, however, the interviewers' assessments on the youths' neighborhoods are employed to understand the neighborhood deprivations. Then, the positive features of the neighborhoods, such as high level of safety, are found to increase the household incomes of the youths. As a result, this paper contributes to the existing literature by showing that neighborhood effects on economic outcomes are robust.

The rest of this paper is structured in following order. First, past studies on the relationship between neighborhood characteristics and individuals' economic outcomes will be examined in section 2. Following literature review will be a discussion on data, which will give in- depth explanations about the NLSY97 dataset, sampling strategy, and variables utilized in this study. Then, in the fourth section, the probit and OLS models are explained. In section 5, the results will be given along with tables, and the last two sections will discuss the contributions and limitations of this paper as well as policy implications.

## 2. Literature Review

In an attempt to answer the research question of this paper, this section explores past studies on long-term neighborhood effects on individuals' employment opportunities and incomes. The majority of the studies focuses on the topics of gentrification and Moving to Opportunity (MTO), which is an experiment conducted by the U.S. Housing and Urban Development (HUD). Therefore, the two of the following subsections are devoted to each topic. The last subsection focuses on the studies that use different methodologies to incorporate the selection effects into neighborhood-effects models.

Neighborhood effects, which are the focus of this paper, are defined as the impacts of residential environments on individual outcomes (van Ham, Boschman, & Vogel, 2018). The body of literature on neighborhood effects examines whether and to what extent certain aspects of neighborhood environments, such as the rate of poverty and the number of employment opportunities, influence the level of education, income, and health status of individual residents.

According to Durlauf (2003), studies on neighborhood effects have gained attention for two reasons. First, neighborhood effects provide explanations for why poverty trap may exist (Durlauf, 2003). Role model and peer group effects can be used to understand this idea (Ioannides & Zabel, 2008). For example, when a high school graduate decides whether to attend a college, her decision is likely to be influenced by the adult members and peers in her community who she has frequently interacted with. If the majority of the members in the community has not received college education, then she may also decide to not attend a college. Therefore, if a community is initially composed of poor and less-educated individuals, then it is likely that the community will continue to have poor and less-educated individuals through interpersonal interactions between the members, leaving them in generations of poverty (Durlauf, 2003). As suggested by Galster (2012), the role model and peer group effects maintain and reproduce negative social externalities in disadvantaged neighborhoods.

Another reason that neighborhood effects are important to understand is that they may amplify the effects of private incentives (Durlauf, 2003). As explained in the previous paragraph, the interpersonal interactions between the members of a neighborhood reinforce negative social externalities, such as the lack of education and a high poverty rate. However, the interactions between the members can also spread positive effects of private incentives to the entire community. For example, suppose that scholarships are given to students in a high school to increase graduation rates. If information about the scholarships is spread among the students, a large number of the students can be motivated to complete their degrees, although the scholarships are only given to a limited number of students. In other words, the interactions between the students can generate neighborhood effects that affect not only the students who receive the scholarships but also the students who do not (Durlauf, 2003). This idea, known as "social multiplier," shows that policies that target disadvantaged neighborhoods may have amplified effects on the residents (Cooper & John, 1988; Manski, 1993; Durlauf, 2003).

Upon recognizing the significance of the neighborhood effects, the following subsection studies the long-term effects of gentrification.

### *2.1 Long-term Effects of Gentrification*

Gentrification is a social phenomenon which refers to the migration of relatively affluent middle-class families into neighborhoods that have been primarily concentrated by disadvantaged and low-income population (Meltzer & Ghorbani, 2017). The majority of the past studies on gentrification has been focused on two aspects of gentrification: relationship between gentrification and displacement of indigenous inhabitants and the impact of gentrification on employment outcomes of the residents. Although this paper does not focus on gentrifying neighborhoods for its analysis of neighborhood effects on youths' earnings, these studies provide insights into neighborhood qualities that affect migration and labor market behaviors of the youths.

First, studies on the impact of gentrification on the displacement of incumbent residents present contradicting findings. Some studies show that gentrification is a direct cause of displacement while others deny the causal relationship between the two. For example, Marcuse (1985) argues that gentrification forces the migration of incumbent residents in the neighborhoods by increasing the housing and rental prices. The majority of these incumbent residents are individuals with low income who cannot afford the high prices.

Ley (2003) supports Marcuse's (1985) findings by focusing on the relocation of artists in gentrifying neighborhoods. The artists, who, in general, value aesthetics more than economic gains, tend to concentrate in high-poverty neighborhoods with low costs of living. When gentrification process begins, however, these neighborhoods with high cultural capital gradually transition to neighborhoods with high economic capital, and the artists are driven out (Ley, 2003).

Martin and Beck (2018) and Freeman (2005) present findings that are contrary to the conclusions made by Marcuse (1985) and Ley (2003). In their study, Martin and Beck (2018) hypothesize that gentrification displaces homeowners by raising the property tax rates and that placing a cap on property tax rates will protect the homeowners. By utilizing a hierarchical linear model with the Panel Study of Income Dynamics (PSID) and the state-level property tax data, they show that they do not support the hypotheses (Martin & Beck, 2018). First, they do not find any statistically significant evidence that displacement of homeowners is more common in gentrifying neighborhoods than in non-gentrifying neighborhoods. Also, there is no evidence that the cap on property tax rates prevent the homeowners from relocating themselves (Martin & Beck, 2018). Freeman (2005) largely supports these findings by showing that displacement is not the primary cause of demographic and socioeconomic shifts in gentrifying neighborhoods.

While these studies do not arrive at a consensus on the causal relationship between gentrification and relocation, they provide perspectives that are necessary perspectives to understand the neighborhood circumstances and individual migration decisions. This paper expands on these perspectives by focusing on a sample of youths whose family migrate from disadvantaged to relatively advantaged neighborhoods. Since the previous studies that have been discussed so far do not incorporate in their models the destination of the displaced residents, this study would allow for an additional analysis on neighborhood circumstances and migration quality. According to Mollborn, Lawrence, and Root (2018), migrations differ by the qualities of origin and destination neighborhoods.

In addition to the association between gentrification and displacement, past studies on gentrification have analyzed its impact on labor market outcomes in the neighborhoods. In this paper, two of these studies are explained in detail. First, Meltzer and Ghorbani (2017) discuss the impact of neighborhood gentrification on employment status of incumbent residents in the long- term of ten years. Lester and Hartley (2014) also examine the consequences of gentrification on employment, but they expand the time period to 20 years.

Meltzer and Ghorbani (2017) study whether the incumbent residents of gentrifying neighborhoods benefit from the economic and social changes that accompany gentrification. The proponents of gentrification often argue that the economic changes are beneficial as they bring in new business establishments that create job opportunities for local residents (Meltzer & Ghorbani, 2017). Also, the residential integration of affluent and educated households generates positive social externalities, such as improved networks, on incumbent residents (Meltzer & Ghorbani, 2017). The extent of these economic and social benefits, however, depends on the types of businesses and the types of employers. If the businesses require highly educated and skilled individuals, or if the employers simply discriminate against the local residents, then the employment opportunities are not available for the incumbent residents (Meltzer & Ghorbani, 2017). Therefore, the authors examine whether the benefits from the economic and social changes stay within the gentrifying neighborhoods in the form of employment opportunities for the local residents.

In order to address their research question, Meltzer and Ghorbani (2017) study low-income neighborhoods experiencing gentrification in New York-Newark, NY-NJ-CT-PA Combined Statistical

Area, as defined by the LEHD Origin-Destination Employment Statistics (LODES) in years 2002-2011. The neighborhoods are operationalized as census tracts. Once the low-income gentrifying neighborhoods are identified, four levels of live-work zones are defined around that neighborhood: census tract and 1/3-, 1-, and 2-mile-radius rings around the census tract (Meltzer and Ghorbani, 2017). Then, OLS regression is performed to assess the extent of local job opportunities offered to local residents in gentrifying neighborhoods, controlling for changes in local business activities and in demographic and socioeconomic circumstances of neighborhoods and live-work zones.

Meltzer and Ghorbani (2017) suggest three main findings. First, gentrifying neighborhoods experience larger increase in the total number of jobs than non-gentrifying neighborhoods do. In other words, gentrification does bring economic changes that can potentially benefit the local residents. Second, at smaller live-work zones (within the census tracts and 1/3-mile-radius-ring), the incumbent residents in gentrifying neighborhoods experience more job losses than the local residents in non-gentrifying neighborhoods. The incumbent residents see job gains only in the larger live-work zones, within the 1-mile and 2-mile ring regions. The authors, however, show that OLS overestimates the magnitude of the job losses in the smaller live-work zones due to the newcomers searching for local jobs by performing 2SLS regression. Finally, the job losses within the census tract and 1/3-mile ring are concentrated in goods-producing and service sectors, which are often low- and moderate- wage positions.

Although not mentioned by the authors, there is one significant limitation of this study. The neighborhoods are defined as low-income if they are in the bottom quintile of the neighborhood income distribution in 2000 and as gentrifying if there is a positive change in their incomes (Meltzer and Ghorbani, 2017). By this definition of gentrification, the authors imply that gentrification must bring the positive changes in neighborhood's income, which may not always be the case. As a result, the neighborhoods which saw the migration of affluent households but did not experience an increase in their aggregate incomes at the time of the authors' study due to fluctuations may have been left out from the sample.

Lester and Hartley (2014) improves on the Meltzer and Ghorbani's (2017) definition of gentrifying neighborhoods by using educational attainment, instead of income, as an indicator of gentrification. According to Lester and Hartley (2014), gentrifying neighborhoods are neighborhoods, or census tracts, that have seen greater percentage increases in education attainment than that in the metropolitan areas that they are part of. Also, the neighborhoods should have seen an increase in the real housing value to be identified as gentrifying.

In addition to the improved definition of gentrifying neighborhoods, Lester and Hartley (2014) examine the impact of gentrification on employment and economic restructuring by making two other distinctions from Meltzer and Ghorbani (2017). First, they examine employment changes in gentrifying neighborhoods for a longer period of time, from year 1990 to year 2000. Also, they study a larger number of cities across the U.S., which includes 20 large cities that have various neighborhood characteristics, such as New York City, Chicago, Dallas, and Cleveland.

By utilizing data from the National Establishment Time Series (NETS) database and measuring the effects of gentrification by a difference-in-differences (DD) approach, Lester and Hartley (2014) suggest two main findings. First, gentrification is associated with a mild increase in the number of employment opportunities available in the gentrifying neighborhoods. Also, gentrification directly contributes to the industrial shifts from manufacturing jobs to service sector jobs. In each of the 20 cities, gentrifying neighborhoods saw faster decline in manufacturing sector than non-gentrifying neighborhoods in the same city did. The authors, however, are unable to provide evidence that gentrification is the direct cause of the observed industrial shifts.

The findings by Meltzer and Ghorbani (2017) and Lester and Hartley (2014) underscore the importance of considering gentrification in my study, because they show that gentrification accompanies significant changes in employment opportunities and industrial structures in the neighborhoods. However, the National Longitudinal Survey of Youth 1997, which is the source of the dataset utilized in this paper, does not contain information on the existence of gentrification in the neighborhoods. As a result, the economic changes that are potentially brought in by gentrification in the neighborhoods in the sample would not be identified and controlled, which may lead to estimation bias.

### *2.2 Long-term Neighborhood Effects on Children*

The relationship between childhood neighborhood qualities and health, educational, and economic outcomes in adulthood is the most discussed topic in neighborhood effect literature. Researchers from diverse fields, such as sociology, psychology, and economics, have examined the impacts of various aspects of neighborhoods on children's development. While these researchers focus on different features of neighborhoods and children, they generally agree that childhood neighborhood characteristics have significant impacts on children's life qualities in their adulthood.

First, Wodtke, Harding, and Elwert (2011) and Chetty and Hendren (2018) find that the duration of exposure to neighborhoods determine the magnitude of impacts that those neighborhoods have on children's outcomes in adulthood. Chetty and Hendren (2018) name this finding as "childhood exposure effects." According to these two studies, the childhood exposure effects hold true for children's educational achievements and economic earnings.

Wodtke et al. (2011) studies the causal relationship between the duration of exposure to disadvantaged neighborhoods and high school graduation. By using a sample of 4,154 children retrieved from the Panel Study of Income Dynamics (PSID), the study compares the high school graduation rates of black and nonblack students. As a result, it shows that for black students, a constant exposure to disadvantaged neighborhoods from age 2 to 17 reduces the graduation rates by 65 percent; for non-black students, it reduces the graduation rates by 40 percent. In support of this study, Chetty and Hendren (2018) show that the economic outcomes of children improve linearly by approximately 4 percent per additional year of exposure to advantaged neighborhoods. Incorporating these findings by Wodtke et al. (2011) and Chetty and Hendren (2018), this paper controls for the age of the youths in the sample.

Using the identical dataset as Wodtke et al. (2011) do in their study, Vartanian and Houser (2010) examine the health outcome by comparing the magnitudes of the impacts that childhood and adulthood neighborhoods have on the outcome. They suggest two main findings. First, growing up in affluent neighborhoods have significant positive impacts on self-reported health in adulthood (Vartanian & Houser, 2010). Also, the neighborhood qualities that an individual experience as an adult have significantly less influence on their health than the neighborhood qualities they experience as a child do (Vartanian & Houser, 2010). The second finding implies that childhood is a critical point of intervention to improve the adult health (Vartanian & Houser, 2010).

While these studies examine the neighborhood effects on children's long-term outcomes in general, the following studies analyze the neighborhood effects on a sample of children who were the participants of Moving to Opportunity (MTO) experiment form1994 to 1998. Chetty et al. (2015) and Chyn (2018) show that living in low-poverty neighborhoods has significant positive impacts on children's long-term outcomes by focusing their studies on a sample of children whose families move out from public housing to relatively affluent neighborhoods.

First, Chetty et al. (2015) study the long-term impacts of Moving to Opportunity (MTO) experiment on children's economic outcomes. Since their study specifically focuses on children whose family participated in the MTO experiment, it is worthwhile to briefly introduce the experiment. The Moving to Opportunity (MTO) is an experiment conducted by the U.S. Department of Housing and

Urban Development (HUD) between the years 1994 and 1998. To explore the impact of moving into low-poverty neighborhoods on low-income families, 4,604 families residing in public housing were recruited in five cities: Baltimore, Boston, Chicago, Los Angeles, and New York (Ludwig et al., 2012; Chetty et al., 2015). These families were randomly assigned into three groups: (1) an experimental group, which received housing voucher and was relocated to census tracts with 1990 poverty rates lower than 10 percent; (2) Section 8 group, which received housing voucher but was not relocated to low-poverty census tracts; and (3) a control group, which neither received housing voucher nor moved to lower-poverty neighborhoods (Ludwig et al., 2012; Chetty et al., 2015). Chetty et al. (2015) track and compare the long-term outcomes of children in all three groups by matching MTO Participant Baseline Survey data to federal income tax data.

Based on previous findings, which suggest that the duration of exposure to better neighborhoods is the key determinant of the neighborhood effects on children's long-term outcomes, Chetty et al. (2015) test two hypotheses. First, relocation to neighborhoods with low poverty rates improves the long-term economic outcomes of children who were young at the time of relocation. Second, this positive impact of relocation decreases with the children's age. The sample of 7,340 children are divided into two groups: (1) those who were below age 13 at the time of random assignment; and (2) those who were between ages of 13 and 18 at the time of random assignment (Chetty et al., 2015).

Within the two groups of children, the hypotheses are tested by two estimation methods. First, "intent-to-treat" (ITT) effects, which are the differences in treatment and control group means, are estimated using OLS. Second, "treatment on the treated" (TOT) effects, which are the impacts of MTO relocation, are estimated by instrumenting MTO voucher take-up rates with indicators for random assignment into experimental and Section 8 groups (Chetty et al., 2015). Using these methods, the authors suggest important findings about long-term neighborhood effects on children's economic outcomes.

First, 48 percent of younger children (those below age 13) in experimental group and 66 percent of them in Section 8 group took up the MTO voucher when they were offered (Chetty et al., 2015). The take-up rates for the older children (those between age 13 and 18) were only slightly lower than those of younger children (Chetty et al., 2015). The compliance with MTO voucher, however, had different impacts on younger and older children's incomes as adults. First, younger children whose families took up the MTO voucher had higher individual earnings between years 2008 and 2012. For example, the younger children in experimental group earned annual incomes that were $1,624 higher than those of the younger children in control group (Chetty et al., 2015). Similarly, the younger children in Section 8 group had annual incomes that were 1,109 dollars higher than those of the younger children in control group (Chetty et al., 2015). On the contrary, older children whose families took up the MTO voucher had annual incomes that were lower than those of the older children in control group (Chetty et al., 2015). Those in the experimental group had incomes that were 967 dollars lower, and those in the Section 8 group had incomes that were about 1,132 dollars lower. The authors, however, emphasize that these negative impacts on older children are statistically insignificant (Chetty et al., 2015).

Chyn (2018) disagrees with the findings by Chetty et al. (2015) that moving to low-poverty neighborhoods has a negative impact on the older children's long-term economic outcomes. In order to get to this claim, Chyn (2018) studies the long-term impact of public housing demolition on children in Chicago. In the late 1990s, Chicago Housing Authority (CHA), which is a city department that manages all public housing developments in Chicago, decided to demolish a number of public housing buildings which constantly had maintenance problems (Chyn, 2018). The residents of the affected buildings were given three choices to displace themselves: first, they could receive Section 8 vouchers to rent a housing in any private market; second, they could transfer to different buildings that were not affected by the demolition in their current public housing projects; third, they could transfer to different units in different public housing projects (Chyn, 2018). In his study, Chyn (2018) focuses on the households that received Section 8 voucher and relocated themselves to neighborhoods with lower poverty rates. The sample includes 5,250 children between age 7 and 18 (Chyn, 2018).

To study the impact of public housing demolition and relocation on children's long-term economic performances, the author uses a linear model that regresses the individual child's outcomes on the dummy variable that takes a value of 1 if the child experienced the demolition (Chyn, 2018). Using this model, the long-term outcomes of children who were displaced and those of children who were not displaced were compared; this comparison was restricted to children from the same public housing developments, so the author makes the assumption that any differences in outcomes are attributable to the different relocation decisions (Chyn, 2018). The data are gathered from various administrative sources. For example, building records from the CHA and public assistance records from the Illinois Department of Human Services (IDHS) were combined to create the sample, and unemployment insurance records from the Illinois Department of Employment Security (IDES) were merged to track the long-term employment outcomes of the children in the sample (Chyn, 2018).

Overall, the findings by Chyn (2018) correspond to those by Chetty et al. (2015). The children whose families decided to receive Section 8 voucher and relocate themselves to neighborhoods with low poverty rates were 9 percent more likely to be employed than the children whose families did not relocate themselves to wealthier neighborhoods (Chyn, 2018). Also, the displaced children earned 602 dollars more annually than the non-displaced children. As mentioned in the previous paragraph, however, Chyn (2018) does not find any differences in these economic benefits by children's age. In his sample, displaced children between age 13 and 18 also experience better economic outcomes (higher earnings and higher chances of being employed) than their counterparts (Chyn, 2018).

The studies by Chetty et al. (2015) and Chyn (2018) are valuable as they show that moving into neighborhoods with lower poverty rates has positive impact on children's long-term economic outcomes. Also, their disagreements on the neighborhood effects on older children make it worthwhile for my study to control for children's age. However, their studies are limited in that they only indirectly control for unobserved characteristics of families that take up MTO voucher or receive Section 8 voucher to relocate to affluent neighborhoods (van Ham et al., 2018). In the study by Chetty et al. (2015), only 48 percent of the families of young children (age below 13) in the experimental group decided to take the MTO voucher; in the study by Chyn (2018), the families in the demolishing units were given three different choices for relocation. Both of the studies use 2SLS estimation method to control for these unobserved characteristics that sort the families into the decision to take up MTO voucher or into the decision to receive Section 8 voucher and relocate to affluent neighborhoods. As it will be discussed in the following subsection on incorporating selection effects in neighborhood-effects models, van Ham et al. (2018) criticizes that instrumental variables control for selection effects only indirectly.

## *2.3 Incorporating Selection Effects*

The three studies mainly discussed in this section propose methodologies to address the endogeneity problem in previous neighborhood effects literature. According to van Ham, Boschman, and Vogel (2018), Sari (2012), and Hedman and Galster (2013), the majority of the previous literature on neighborhood effects on personal outcomes has failed to address the fact that individuals are non-randomly selected into the neighborhoods that they reside. Individuals choose to live in certain neighborhoods based on their preferences, income, the affordability of housing, and sociodemographic characteristics of that neighborhood. Therefore, it is likely that the outcomes of interest that the researchers have examined, such as income, health, and education, are also the factors that derived the individuals to allocate themselves in that neighborhood. Each of the studies suggests different econometric models to include the neighborhood sorting process in the neighborhood-effects models.

First, van Ham et al. (2018) propose a two-step procedure to incorporate the selection process in the neighborhood- effects models, utilizing longitudinal population data and neighborhood-level data produced by Netherlands Statistics. Their sample includes 24,014 individuals from 203 neighborhoods within the Utrecht urban region. These 24,014 individuals moved within the Utrecht region neighborhoods during the 2009 calendar year. The authors limit the sample to only the households who moved within the Utrecht region to control for the neighborhood choices that the households have (van Ham et al., 2018). With this sample and the dataset, the authors examine the neighborhood effects on income of the heads of the households employed in 2013.

In the first step, a conditional logit model is implemented to predict the probability of a household selecting a certain type of neighborhood from a set of neighborhood choices (van Ham et al., 2018). Eight different correction components are derived from this step by using Principal Component Analysis (PCA). In the second step, three different neighborhood-effects models are constructed to capture the neighborhood effects on the income of the heads of the households in 2013: first, a model without control variables; second, a model controlling for individual characteristics of the head of the households; third, a model incorporating the correction components derived from the conditional logit model.

From this two-step process, the authors make several important conclusions. First, the conditional logit model, which reflects the neighborhood selection process, shows that the individual characteristics of the heads of the households, such as ethnicity, marriage status, and age, have significant impacts on the types of neighborhoods that they choose to live. For example, the non-Western minorities were most likely ($\hat{\beta}$=3.6129) to choose to live in a neighborhood with a high share of non-Western minorities (van Ham et al., 2018). Also, the families with children were most likely to choose neighborhoods with a high share of families with children, because it was likely that necessary resources, such as schools, libraries, and playgrounds, for the children were congregated in those neighborhoods.

In addition, all three neighborhood-effects models show that the size of the impact that neighborhood average income has on the average income of the heads of the households decreases when individual characteristics (ethnicity, household type, and age) are controlled and the correction components are incorporated. For example, when the individual characteristics are controlled, the impact of neighborhood income on individual income is 31.8 percent smaller than when the individual characteristics are not controlled. Similarly, when the correction components are incorporated, the impact is reduced by 68.2 percent. Although the size of the impact is reduced, the average neighborhood income maintains to be positively related to the average individual income throughout the three different neighborhood-effects models, and this positive relationship stays statistically significant.

Similarly, Sari (2012) examines the impact of living in a deprived neighborhood on unemployment in Paris. The French Population Census of 1999 is used to sample 46,460 male heads of the households who are in between working age of 16 and 64. These individuals are residents of either Paris or three other sub-regional administrative districts: Seine-Saint-Denis, Val-de-Marne, and Hauts-de-Seine.

Neighborhood deprivation is measured in two ways. First, the neighborhoods in Paris and the three sub-regional districts are ranked according to their socioeconomic characteristics. These socioeconomic characteristics include various indicators such as the percentage of residents with high school diploma or more, the percentage of blue-collar workers in the neighborhood, the percentage of residents with foreign citizenship. After they are ranked according to their characteristics, they are given scores that reflect their ranks; the neighborhoods with less favorable characteristics are given high scores. In the end, a neighborhood is defined as “deprived” if its score belongs to the top 20 percent (Sari, 2012).

In order to check for the robustness of the first deprivation method, Sari (2012) uses an official definition, which is that a neighborhood is deprived if it has one or more Sensitive Urban Zones. Sensitive Urban Zones are areas identified by the government as the primary target of the government policies due to conditions of living or issues faced by the residents in the areas. The deprived neighborhoods by the definition of Sensitive Urban Zones is shown to largely overlap with the deprived neighborhoods identified by the ranking, proving the robustness of the ranks. (Sari, 2012).

Unlike van Ham et al. (2018) who implement a conditional logit model to incorporate the neighborhood selection effects, Sari (2012) uses two-step probit models. First, a bivariate probit model, which includes residential location in deprived neighborhood as an endogenous variable, is used to identify the impact of living in a deprived neighborhood on the head of the household’s employment status. The employment status, which is the outcome variable, takes the value of one if the he is employed and zero otherwise. Below is an elaboration on the first-stage probit model.

$$Y_i = \alpha + \theta_i D_i + \beta_i I_i + \gamma_i S_i + \delta_i Sp_i + \eta_i E_i + \mu_i$$

In this model, $Y_i$ equals to one if the individual is employed; $D_i$ equals to one if the neighborhood is deprived; $I_i$ is a set of individual characteristics, such as age, nationality, and education level; $S_i$ is the characteristics of the spouse; $Sp_i$ is a measure of accessibility to jobs; $E_i$ is an employment area dummy variable; and $\mu_i$ is an error term (Sari, 2012). Using this model, the probability of being employed is predicted as a function of neighborhood deprivation with the control variables.

Then, as a second step, this first-stage probit model is estimated on a sub-sample of heads of households living in public housing. In this second probit model, the assumption is that families in public housing has limited options over the location of the public housing development, which makes it possible to assume that their residential location is exogenous.

The two probit models yield the following three findings. First, residing in a deprived neighborhood hurts an individual's chance of being employed. This negative impact of neighborhood deprivation on employment status stays constant when deprived neighborhoods are defined by their ranks and when they are defined by the presence of Sensitive Urban Zones. Second, the relationship between neighborhood effects and individual labor market outcomes is linear. Previous studies have often suggested that the relationship between neighborhood effects and individual labor market outcomes is non-linear, meaning that one unit decrease in neighborhood quality does not lead to one unit decrease in employment outcomes; there is a threshold at which neighborhood characteristics exert impacts on employment outcomes (Galster, 2012). Sari (2012), however, does not support the non-linearity theories and shows that the probability of being employed decreases with the level of deprivation in neighborhoods. Finally, the probability of being employed increases when an individual is physically mobile.

Although the findings by Sari (2012) are rich, his study is limited in two ways. First, working-age women are excluded from the sample. He explains that women are excluded because his study examines the labor market participation (Sari, 2012). However, considering the increasing percentage of labor market participation by women, this exclusion may result in bias in estimation. Also, residential location may not be exogenous for individuals in public housing. If the individuals have strong preference for public housing developments in certain neighborhoods, they can choose to wait until they get a unit in those public housing and waive other offers. As a result, limiting the model to the sub-sample of public housing residents does not eliminate the endogeneity problem completely (Sari, 2012).

Finally, Hedman and Galster (2013) suggest implementing fixed-effects model with instrumental variables to address the endogeneity problem in neighborhood effects models. Using the annual employment data from GeoSweden, the authors create a sample of 90,438 males of working-age (25-49) living in Stockholem between the years 1994 and 2006. Then, two models are developed. The first model identifies the impact of neighborhood income mix on individual male's income, and the second model explores the impact of individual male's income on the neighborhood income mix. Here, neighborhood income mix is defined as the percentage of high-income males (top 30 percent of the national income distribution) and the percentage of low-income males (bottom 30 percent of the national income distribution) in the neighborhood (Hedman & Galster, 2013).

In their study, Hedman and Galster (2013) draw completely opposite conclusions from van Ham et al. (2018). When the selection effects, modeled by the second model, are incorporated in the neighborhoods-effects model, which is the first model, the magnitude of neighborhood effects on income is amplified. In other words, the endogeneity problem underestimates the impact of neighborhood effects on individuals' incomes (Hedman & Galster, 2013). As noted by van Ham et al. (2018), however, it is more logical if the extent of the neighborhood effects is reduced when selection bias is controlled for. As a result, the results suggested by Hedman and Galster (2013) are counterintuitive (van Ham et al., 2018).

Although the methodologies discussed in this section have their own strengths and weaknesses, they provide valuable considerations for this paper. The conditional logit model employed by van Ham et al. (2018) seems to be most comprehensive and advanced in incorporating the selection effects. The dataset utilized in this paper, however, does not provide detailed census tract statistics to employ the conditional logit model for this study. Due to the lack of neighborhood characteristics variables, the individual characteristics of the youths cannot be matched with the characteristics of their neighborhoods or census tracts. The fixed-effects model by Hedman and Galster (2013), on the other hand, gives results with opposite signs, which casts doubts on the validity of the model. As a result, this study largely follows the two-stage probit model by Sari (2012).

The two-stage probit model best suits this study for two reasons. First, it allows testing for the probability of the youths relocating into safe neighborhoods and the probability of them earning above the median household income in their adulthood. In order to study for the effects of moving out of disadvantaged neighborhoods into relatively advantageous neighborhoods on incomes, the two probabilities need to be tested in consecutive order. Also, the limitations identified in Sari (2012) can be improved with the dataset utilized in this study. The working sample includes both male and female youths, which allows for analyzing neighborhood effects on women's economic outcomes. In addition, the sample includes youths in public housing as well as the youths who are not in public housing, which eliminates the assumption that the neighborhood choice is exogenous for the youths in public housing.

The next section elaborates on data, sampling strategy, and variables used in this study to analyze the long-term impacts of moving out of disadvantaged neighborhoods on youths’ incomes.

## 3. Data

In this paper, the National Longitudinal Survey of Youth 1997 (NLSY97) by the Bureau of Labor Statistics is used to analyze the long-term impact of moving out of a disadvantaged neighborhood on the earnings of the youths. The NLSY97 is a national survey that has been conducted since 1997

(Round 1) on a sample of approximately 9,000 youths in the United States.[1] The most recent data release available is Round 17, which was conducted in 2015 and 2016.[2] From Round 1 to 15, the survey was performed every year; since Round 16, it has been performed biennially.

The primary mode of the survey is personal interviews in which the interviewers visit the respondents. When the respondents are not willing to participate in person, phone interviews are conducted. In Round 17, 73.3 percent of the surveys were conducted through personal interviews (BLS, 1997-2015).

In Round 1in 1997, 8,984 youths were interviewed, and about 80 percent of them were interviewed throughout the seventeen rounds (BLS, 1997-2015). Among these 8,984 youths in Round 1, 51 percent was males, and 51.9 percent was Whites. As of the end of 1996, the youths were 12 to 18 years old.

### *3.1 Sampling Strategy*

The working dataset of this paper consists of the youths who satisfy two criteria. First, they are the youths who have lived in neighborhoods that exhibit disadvantageous characteristics. In order to show the effects of moving out of disadvantaged neighborhoods, it is essential to limit the sample to the youths who were living in deprived neighborhoods in the beginning of the survey. Second, the youths need to have records of their migration history. This criterion is necessary to show that the change in the

[1] Bureau of Labor Statistics. (2018). National Longitudinal Surveys. Retrieved from https://www.bls.gov/nls/nlsy97.htm. Access Date: March 31, 2019.

[2] Bureau of Labor Statistics. (1997-2015). The NLSY97 Sample: An Introduction. Retrieved from https://www.nlsinfo.org/content/cohorts/nlsy97/intro-to-the-sample/nlsy97-sample-introduction-0. Access Date: March 31, 2019.

youths' neighborhood environment from disadvantaged to relatively more advantaged is attributable to their migration decisions.

To sample the youths who satisfy the first criterion, the Physical Environment Risk Index is utilized. The Physical Environment Risk Index is a variable that indicates the level of risks in a youth's home and neighborhood. It incorporates five different questions that assess the risk factors in the youth's surroundings. Each of the answers are given scores that are added up to indicate the overall level of risk. Below is the list of the questions and the scores for each answer. [3]

1. In the past month, has your home usually had electricity and heat when you needed it?
   No= Risk (1)
   Yes= Not coded as Risk (0)
2. How well kept are most of the buildings on the street where the adult/youth resident lives?
   Poorly Kept= High Risk (2)
   Fairly Well Kept = Moderate Risk (1)
   Well Kept= Not coded as Risk (0)
3. How well kept is the interior of the home in which the youth respondent lives?
   Poorly kept= High Risk (2)
   Fairly Well Kept = Moderate Risk (1)
   Well Kept= Not coded as Risk (0)
4. When you went to the respondent's neighborhood/home, did you feel concerned for your safety?
   Yes= Risk (1)
   No= Not coded As Risk (0)
5. In a typical week, how many days from 0 to u7 do you hear gunshots in your neighborhood?
   1 or more days = Risk (1)
   0 days= Not coded as Risk (0)

The numbers in the parentheses indicate the scores. The second, third, and fourth questions are answered by the interviewers who visit the youth respondents for personal interviews. The sum of the scores ranges from zero to seven with seven being the most dangerous home and neighborhood environments for the youth. This Physical Environment Risk Index was collected only in Round 1 in 1997 for the youths between age 12 and 14.

[3] Child Trends, Inc., & Center for Human Resource Research. (1999). NLSY97 Codebook Supplement Main File Round 1. Retrieved from http://www.nber.org/nlsy97/appendix9.pdf. Access Date: March 31, 2019.

To limit the sample to the youths who were living in an environment with risk factors in the beginning of the survey, the youths who has a score of zero for the index are excluded from the working dataset. As a result, 6,047 youths from the original NLSY97 sample are eliminated; the working dataset is left with 2,937 youths who were between 12 and 14 years old and had Physical Environment Risk Index scores one or above in 1997.

In addition to the first criterion, the working dataset satisfies the second criterion by utilizing Migration History variables for every year from 1998 to 2001. In every round after Round 1 in1997, the youths are asked to record their address if it has changed since the date of the last interview. Then, the interviewers categorize the addresses into six groups: move within county, move within state/different county, move between states, move to or from a foreign country, no change in the address, and invalid skip. These categorized responses are publicly available, while the addresses recorded by the youths are private.

In order to limit the sample to the youths who have migration records, the youths who are classified as invalid skip are eliminated. Then, the youths who are classified as move to or from a foreign country are withdrawn. Although these youths have the records of their migration history, they do not serve the purpose of this paper which concentrates on the neighborhood effects in the United States. As a result, the remaining sample consists of 1,575 youths who were living in the neighborhoods with risks in 1997 and either stayed in those neighborhoods or moved out of them between 1998 and 2001.

In the following subsection, the variables utilized in this study are described in depth and their summary statistics are provided.

### *3.2 Variables*

In this paper, the long-term impact of moving out of a disadvantaged neighborhood on the youth's income is analyzed using 11 variables retrieved from the NLSY97 dataset. Table1 provides the summary statistics of these variables.

*Mobility 1998-2001.* Based on the annually collected Migration History variables described in the previous subsection, the variable *Mobility 1998-2001* is created. It is a binary variable that takes the value of one if a youth migrated at least once between 1998 and 2001. The year 2001 is chosen, because it is the last year that the interviewers' remarks on the level of neighborhood deprivation are collected. The Physical Environment Risk Index, which incorporates the youths' and the interviewers' assessments on the neighborhoods, was collected only in 1997. Then, from 1998 to 2001, the interviewers alone evaluated the youths' neighborhoods. After 2001, there is no data available on the level of deprivation in the neighborhoods. Thus, the migration history of a youth after 2001 cannot be studied in regard to its relationship with the youths' neighborhood characteristics. As a result, the migration history between 1998 and 2001 is selected to create the variable *Mobility 1998-2001*.

In order to merge the migration history of the youths between 1998 and 2001 into one variable *Mobility 1998-2001*, a binary mobility variable was generated for each of the four years. These four binary mobility variables took the value of one if the Migration History variable of that year indicated that the youth had migrated. Whether the youth moved within her original county or moved to a different state was not taken into account. Since specific geographic data of the youths, such as to which county they moved, are not publicly available, identifying the types of migration by destination in *Mobility 1998-2001* is not necessary.

As shown in Table 1, 485 youths (30.8 percent) in the working sample migrates to different parts of the counties and states in the United States between 1998 and 2001.

**Table 1**. Descriptive Statistics

| VARIABLES | Total | Mean | SD | Min | Max |
|---|---|---|---|---|---|
| Mobility 1998-2001 | 1,575 | 0.308 | 0.462 | 0 | 1 |
| Moved | 485 | | | | |
| Not Moved | 1,090 | | | | |
| Neighborhood Safety | 1,575 | 0.286 | 0.452 | 0 | 1 |
| Safe | 451 | | | | |
| Not Safe | 1,124 | | | | |
| 1997 HH Income | 1,575 | 34,678 | 30,484 | 0 | 246,474 |
| 1997 Income-Median HH Income | 1,575 | 0.389 | 0.488 | 0 | 1 |
| Below Median | 962 | | | | |
| Above Median | 613 | | | | |
| 2015 HH Income | 1,575 | 62,975 | 58,420 | 1 | 329,331 |
| 2015 Income-Median HH Income | 1,575 | 0.457 | 0.498 | 0 | 1 |
| Below Median | 855 | | | | |
| Above Median | 720 | | | | |
| Race | 1,575 | 0.465 | 0.499 | 0 | 1 |
| White | 842 | | | | |
| Minority | 733 | | | | |
| Sex | 1,575 | 0.502 | 0.500 | 0 | 1 |
| Male | 785 | | | | |
| Female | 790 | | | | |
| 1997 Age | 1,575 | 12.97 | 0.821 | 12 | 14 |
| 2015 Age | 1,575 | 31.93 | 0.887 | 30 | 34 |
| 1997 HH members under 18 | 1,575 | 2.687 | 1.288 | 1 | 8 |
| Highest Grade Completed: Father | 948 | 12.17 | 3.165 | 3 | 20 |
| Highest Grade Completed: Mother | 895 | 12.26 | 3.018 | 1 | 20 |

*Neighborhood Safety*. This variable takes the value of one if a youth was living in a safe neighborhood in 2001. It is generated using three existing variables in the original NLSY97 dataset: Interviewer Remarks on Interior of House Where Respondent Lives, Interviewer Remarks on How Well Buildings Are Kept on Respondent Street, and Interviewer Remarks on Concern for Safety. It is determined that a youth is in a safe neighborhood if: the variable Interviewer Remarks Interior of House

Where Respondent Lives takes the value of one, which means that the house is very well kept and cared for; the variable Interviewer Remarks How Well Buildings Are Kept on Respondent Street takes the value of one, which means that the buildings on the street are very well kept and cared for; and the variable Interviewer Remarks Concern for Safety takes the value of zero, which means that the interviewer is not concerned about her safety in the respondent's neighborhood and home. All three of these criteria must be satisfied for *Neighborhood Safety* to equal to one.

The three Interviewer Remarks variables are collected from 1997 to 2001. The responses for these variables in 1997 are included to generate the Physical Environment Risk Index. As mentioned previously, year 2001 is chosen to generate the variables *Mobility 1998-2001* and *Neighborhood Safety* in this study since it is latest year these three variables are available.

As it is presented in Table 1, 451 youths (28.6 percent) are living in safe neighborhoods in 2001. The rest of 71.4 percent of the youths is in houses and neighborhoods where the interviewers felt unsafe and assessed that the interior of the houses and buildings on the streets needed repairs.

*1997 Household Income* and *1997 Income-Median Household Income*. The variable *1997 Household Income* is gross household income data directly retrieved from NLSY97 dataset. As shown in Table 1, the youths in the working dataset were in a household that earned an annual income of $34,678 on average in 1997.

Based on the *1997 Household Income* variable, the *1997 Income-Median Household Income* is created. This variable is a binary variable that takes the value of one if the household, which a participating youth was part of in 1997, earned an income above the median household income in 1997. The median household income was approximately $37,000 in 1997. This binary income variable is generated to simplify the interpretation of the probit results.

According to van Ham et al. (2018), Sari (2012), and Hedman and Galster (2013), individuals are likely to choose neighborhoods that match their personal characteristics and socioeconomic standards. For example, a head of a household with a high income has a higher probability of sorting himself into an affluent neighborhood than an individual with low income does. As a result, it is hypothesized that the level of household income in 1997 has a positive relationship with the probability of a youth living in a safe neighborhood in 2001, and *1997 Income-Median Household Income* is included in the model as a control variable.

*2015 Household Income and 2015 Income- Median Household Income*. These variables resemble the two income variables created for 1997. The variable *2015 Household Income* is directly retrieved from the NLSY97 dataset and shows the family income of the youths in 2015 when they were 30 to 34 years old. On average, the participating youths earned a family income of $62,975 in their thirties.

The *2015 Income-Median Household Income* variable is generated from the variable *2015 Household Income*. It is a binary variable that takes the value of one if the grown-up youths had family income above the median household income of $56,000 in 2015. It is the ultimate variable of interest that this paper intends to predict with the neighborhood characteristics of the youths in 2001.

*Race*. This variable is a control variable that takes the value of one if a youth is racial minority and the value of zero if she is White. The term racial minority includes Black, American Indian, Asian or Pacific Islander, and others. As presented in Table 1, 46.5 percent of the working sample is racial minority.

*Sex*. This control variable is binary, taking the value of zero for male youths and one for female youths. Approximately 50.2 percent of the sample is females. According to Ludwig et al. (2013), the MTO experiment has larger benefits for female youths than for male youths in terms of the improvements in physical and mental health and educational achievements. Chetty et al. (2015), however, shows that when the experimental outcomes are measured in youths' adulthood, there is no significant difference between the benefits on males and females. Since these past studies show that gender may have impacts on the outcome variables, the variable *Sex* is included as a control variable.

*1997 Age* and *2015 Age.* These control variables indicate the age of the youths in 1997 and in 2015. In 1997, the youths were between 12 and 14 years old; in 2015, they were between 30 and 34 years old. According to Chetty et al. (2015), the benefits of moving out of a disadvantaged neighborhood depends on the years of the youths' exposure to the advantaged neighborhood. They show that the youths who are below 13 at the time of migration is more likely to experience larger gains from the advantaged neighborhoods than the youths who are above 13 at the time of migration.

The working dataset of this paper includes youths who are between age 12 and 14 in 1997, which includes the age groups below 13 and above 13. Therefore, age is controlled for in the models.

*1997 Household Members under 18*. This control variable shows the number of children under age 18 in each household. In other words, this variable indicates the number of siblings that the youths had in 1997. On average, each household had two children under age 18 in 1997, including the participating youths, and the maximum number of children that households had was eight.

Following studies by Dujardin and Goffette-Nagot (2009) and Currie and Yelowitz (2000), Sari (2012) suggests that the number of children in the household is a factor that determines the probability of that household living in a deprived neighborhood. Traditionally, deprived neighborhoods have been predominantly occupied by large families because it is relatively easy for the families to find a large house in low price. Therefore, he predicts that higher number of children in a household increases the probability of that family living in a deprived neighborhood. Following his logic, the variable *1997 Household Members under 18* is included in the models.

*Highest Grade Completed: Father*. This control variable indicates the years of education the residential father of the youth has. On average, the residential fathers completed 12 years of school, and the years of education vary from three years to 20 years. The youths who are not living with a father is excluded from the statistics, which causes the sample size to be slightly smaller than that of the other variables.

According to Huston (1995) and Mauldin, Mimura, and Lino (2001), the level of education received by parents, especially by the head of the household, affects the level of their education spending on their children. Assuming that the marginal increase in the years of education received by an individual increases their marginal income, the number of schooling that the parents receive may have statistically significant impact on the youths. Therefore, the education level of parents is controlled for in the models.

*Highest Grade Complete: Mother*. This control variable shows the years of education that the residential mother of the youth received. The average years of education that the mothers received is 12 years. Along with the variable *Highest Grade Completed: Father*, this variable was collected only in Round 1 in 1997. It is hypothesized that one additional years of education received by residential fathers and mothers increase the probability of the youths living in a safe neighborhood in 2001 and earning above the median household income in 2015.

### *3.3 Descriptive Statistics by Subgroups*

In this subsection, the summary statistics of the youths are studied by two different subgroups. First, the youths are divided according to their migration history: the youths who migrate and the youths who do not migrate. The statistics of these two groups of youths are reported in Tables 2 and 3. Then, the youths are grouped by their neighborhood characteristics in 2001: the youths in safe neighborhoods and the youths in not in safe neighborhoods. Tables 3 and 4 show the statistics of these groups.

**Table 2**. Descriptive Statistics of Non-Migrated Youths

| VARIABLES | Total | Mean | SD |
|---|---|---|---|
| Neighborhood Safety | 1,090 | 0.265 | 0.442 |
| Safe | 289 | | |
| Not Safe | 801 | | |
| 1997 Income | 1,090 | 34,673 | 31,246 |
| 1997 Income- Median HH Income | 1,090 | 0.395 | 0.489 |
| Below Median | 659 | | |
| Above Median | 431 | | |
| 2015 Income | 1,090 | 61,311 | 55,128 |
| 2015 Income-Median HH Income | 1,090 | 0.445 | 0.497 |
| Below Median | 605 | | |
| Above Median | 485 | | |
| Race | 1,090 | 0.477 | 0.500 |
| White | 570 | | |
| Minority | 520 | | |
| Sex | 1,090 | 0.494 | 0.500 |
| Male | 551 | | |
| Female | 539 | | |
| 1997 Age | 1,090 | 12.88 | 0.814 |
| 2015 Age | 1,090 | 31.83 | 0.878 |
| 1997 HH Members under 18 | 1,090 | 2.692 | 1.315 |
| Highest Grade Completed: Father | 665 | 12.08 | 3.244 |
| Highest Grade Completed: Mother | 633 | 12.16 | 3.054 |

There are several notable similarities and differences between the youths who do not migrate and those who migrate between 1998 and 2001. As shown in Table 2, 1,090 youths do not migrate in the given years. Table 3 shows that 485 youths migrate.

**Table 3.** Descriptive Statistics of Migrated Youths

| VARIABLES | Total | Mean | SD |
|---|---|---|---|
| Neighborhood Safety | 485 | 0.334 | 0.472 |
| Safe | 162 | | |
| Not Safe | 323 | | |
| 1997 HH Income | 485 | 34,690 | 28,730 |
| 1997 Income-Median HH Income | 485 | 0.375 | 0.485 |
| Below Median | 303 | | |
| Above Median | 182 | | |
| 2015 HH Income | 485 | 66,716 | 65,122 |
| 2015 Income- Median HH Income | 485 | 0.485 | 0.500 |
| Below Median | 250 | | |
| Above Median | 235 | | |
| Race | 485 | 0.439 | 0.497 |
| White | 272 | | |
| Minority | 213 | | |
| Sex | 485 | 0.518 | 0.500 |
| Male | 234 | | |
| Female | 251 | | |
| 1997 Age | 485 | 13.17 | 0.801 |
| 2015 Age | 485 | 32.15 | 0.868 |
| 1997 HH Members under 18 | 485 | 2.676 | 1.227 |
| Highest Grade Completed: Father | 283 | 12.39 | 2.964 |
| Highest Grade Completed: Mother | 262 | 12.51 | 2.921 |

First, higher percentage of the youths who migrate is in safe neighborhoods than the youths who do not migrate. As shown in Table 2, 26.5 percent of the 1,090 youths who do not migrate (mean= 0.265) is in safe neighborhoods. In Table 3, 33.4 percent of the 485 youths (mean= 0.334) with a history of migration is in safe neighborhoods. To determine the statistically significant difference between the two means, a two-sample t-test is performed. From this test, the t-statistic of -2.8 is obtained, which shows that the mean of 0.265 is less than the mean of 0.334. Thus, it is concluded that a higher percentage of the youths who migrate is in safe neighborhoods in 2001 than the youths who do not migrate.

The statistical difference between the percentages of the youths in safe neighborhoods in the subgroups needs to be examined because it concerns the validity of the assumptions of this paper. To address the research question, the working sample is assumed to be consisted of the youths who are in risky neighborhoods in 1997. In addition, it is assumed that the youths and their families who move out of their risky neighborhoods between 1998 and 2001 are relocating themselves to safe neighborhoods. These assumptions need to be held in order to study the effects of moving from deprived neighborhoods to relatively affluent neighborhoods on children's long-term income. The results from the t-test above support the assumptions by showing that the group of youths with a history of migration has a higher percentage of the youths in safe neighborhoods than the group of non-migrated youths has.

In addition to the percentage of youths in risky and safe neighborhoods, it is interesting to notice the differences in their household income in 1997 and 2015. In 1997, there is no statistically significant difference between the average household incomes of the youths who do not migrate (Table 2) and those who migrate (Table 3). The youths who migrate have average household income that is only 17 dollars higher than that of the youths who do not migrate, and t-statistics for the difference is 0.01.

Similarly, in 2015, the difference between the average household incomes for the youths in these two groups is not statistically significant. The youths who migrate have an average household income of 66,716 dollars in 2015; the youths who do not migrated have an average household income of 61,311 dollars in the same year. The t-statistic for the difference is 1.696, which shows that the difference between the 2015 household income of the youths who migrate is not statistically greater than that of the youths who do not migrate.

Similar to Tables 2 and 3, Tables 4 and 5 examine the characteristics of the youths by their neighborhood characteristics in 2001. Table 4 represents 1,124 youths who were not living in safe neighborhoods in 2001; Table 5 shows the rest of 451 youths who were in safe neighborhoods in 2001.

**Table 4.** Descriptive Statistics of Youths Not in Safe Neighborhoods in 2001

| VARIABLES | Total | Mean | SD |
|---|---|---|---|
| Mobility 1998-2001 | 1,124 | 0.287 | 0.453 |
| Moved | 323 | | |
| Not Moved | 801 | | |
| 1997 HH Income | 1,124 | 30,269 | 26,419 |
| 1997 Income- Median HH Income | 1,124 | 0.318 | 0.466 |
| Below Median | 767 | | |
| Above Median | 357 | | |
| 2015 HH Income | 1,124 | 57,929 | 56,492 |
| 2015 Income-Median HH Income | 1,124 | 0.411 | 0.492 |
| Below Median | 662 | | |
| Above Median | 462 | | |
| Race | 1,124 | 0.495 | 0.500 |
| White | 568 | | |
| Minority | 556 | | |
| Sex | 1,124 | 0.512 | 0.500 |
| Male | 549 | | |
| Female | 575 | | |
| 1997 Age | 1,124 | 12.98 | 0.826 |
| 2015 Age | 1,124 | 31.94 | 0.890 |
| 1997 HH Members under 18 | 1,124 | 2.789 | 1.341 |
| Highest Grade Completed: Father | 641 | 11.73 | 3.183 |
| Highest Grade Completed: Mother | 599 | 11.80 | 3.011 |

First, higher percentage of the youths in safe neighborhoods has a history of migration than the youths in risky neighborhoods in 2001 has ($t = -2.803$). Specifically, 28.7 percent of the youths in risky neighborhoods in 2001 migrates between 1998 and 2001, while 35.9 percent of the youths in safe neighborhoods in 2001 migrates between the years. This result supports the finding discussed previously on the percentage of the youths in safe neighborhoods when the youths are grouped by their migration history.

Unlike Tables 2 and 3, however, Tables 4 and 5 show large differences in the average household incomes of the youths in 1997 and 2015. When the youths were grouped by their migration history in Tables 2 and 3, there were no statistically differences between the average household incomes in 1997 and 2015. When the same youths are grouped by the level of safety in their neighborhoods, however, the average household incomes show large difference in both years. For example, the youths in safe neighborhoods in 2001 (Table 5) have an average of 45,666 dollars for their household incomes in 1997; the youths in risky neighborhoods in the same year (Table 6) have an average that is 15,397 dollars less than their counterparts. The youths in safe neighborhoods in 2001 have families with higher household income in 1997 than the youths not in safe neighborhoods in 2001 have in 1997 ($t = -9.304$). Similarly, in 2015, the youths who are in safe neighborhoods in 2001 have an average household income that is 17,624 dollars more than the youths who are in risky neighborhoods in 2001 ($t = -5.462$).

The significant differences between the average household incomes of the youths who are not in safe neighborhoods and those who are in safe neighborhoods show that the residence in safe neighborhoods is not random. As discussed previously, van Ham et al. (2018), Sari (2012), and Hedman and Galster (2013) argue that individuals select their neighborhoods based on their preferences. These preferences include the demographic characteristics of the neighborhoods, such as the racial and age compositions, and economic characteristics, such as the average household income of the other residents and the affordability of the homes. This claim by the authors is supported by the differences between the average household incomes of the youths found in Tables 4 and 5. The youths who are in safe neighborhoods are born into families that are wealthier than those of the youths in risky neighborhoods, and this difference in household wealth persists in their household incomes in their adulthood.

**Table 5**. Descriptive Statistics of Youths in Safe Neighborhoods in 2001

| VARIABLES | Total | Mean | SD |
|---|---|---|---|
| Mobility 1998-2001 | 451 | 0.359 | 0.480 |
| Moved | 162 | | |
| Not Moved | 289 | | |
| 1997 HH Income | 451 | 45,666 | 36,593 |
| 1997 Income-Median HH Income | 451 | 0.568 | 0.496 |
| Below Median | 195 | | |
| Above Median | 256 | | |
| 2015 HH Income | 451 | 75,553 | 61,248 |
| 2015 Income-Median HH Income | 451 | 0.572 | 0.495 |
| Below Median | 193 | | |
| Above Median | 258 | | |
| Race | 451 | 0.392 | 0.489 |
| White | 274 | | |
| Minority | 177 | | |
| Sex | 451 | 0.477 | 0.500 |
| Male | 236 | | |
| Female | 215 | | |
| 1997 Age | 451 | 12.94 | 0.810 |
| 2015 Age | 451 | 31.90 | 0.882 |
| 1997 HH Members under 18 | 451 | 2.432 | 1.106 |
| Highest Grade Completed: Father | 307 | 13.09 | 2.922 |
| Highest Grade Completed: Mother | 296 | 13.20 | 2.814 |

In addition to their average household incomes, there are interesting differences between the racial composition of the youths and the level of education completed by the parents. First, there are less minority population in safe neighborhoods than in risky neighborhoods ($t = 3.719$). As shown in Table 5, 39.2 percent of the youths in safe neighborhoods is racial minority in 2001. In risky neighborhoods in the same year, 49.5 percent of the youths is racial minority (Table 6). Also, the youths in safe neighborhoods have parents who are more educated than the youths in risky neighborhoods. The average grade completed by residential fathers and mothers of the youths in safe neighborhoods is about 13 years, while that of the youths in risky neighborhoods is 11 years ($t = -6.319, t = -6.686$).

## 4. Methodology

In this paper, probit models are used to study the impact of moving into a safe neighborhood (*Neighborhood Safety*=1) on the income of the youths in 2015. It is hypothesized that if the youths move out of the risky neighborhoods that they reside in 1997, they are more likely to earn income above the median household income in 2015 than the youths who do not move out of the risky neighborhoods.

Before identifying the relationship between the youths living in a safe neighborhood in 2001 and their household income in 2015, it is necessary to identify the relationship between their migration history and the likelihood of being in a safe neighborhood in 2001. As it was explained in the previous section of this paper, the levels of neighborhood safety are subjective judgements of the interviewers. None of the youths in the sample were visited and interviewed by the same interviewer from 1997 to 2001. The fact that the interviewers did not interview the same youths in each round makes it difficult to assume that the youths who were identified as living in a risky environment in 1997 and in a safe environment in 2001 experienced a migration in between those two years. For example, even if a youth had stayed in the same neighborhood, an interviewer who visited her in 1997 could have judged her neighborhood as dangerous and another interviewer who visited her in 2001 could have assessed her neighborhood as safe. Therefore, it is necessary to validate the assumption that the change in the level of neighborhood safety in between 1997 and 2001 is due to the migration of the youths. Without proving the relationship between migration and neighborhood safety in 2001, it is difficult to properly address the research question which asks the impact of moving out of a deprived neighborhood on the youths' long-term earnings. As a result, two-stage probit models are utilized in this study.

In the first stage, Models 1 and 2 test the relationship between migration and neighborhood safety in 2001.

$$\Pr(\text{neighsafe} = 1) = \Phi(\beta_0 + \beta_1 \text{mob4yr}) \quad (1)$$

$$\Pr(\text{neighsafe} = 1) = \Phi(\beta_0 + \beta_1 \text{mob4yr} + \beta_2 \mathbf{X}) \quad (2)$$

In Model 1, the probability of living in a safe neighborhood in 2001 is predicted as a function the migration history of the youths between the years 1998 and 2001. Then, Model 2 expands on the first model by adding a number of control variables (**X**) to the equation. The control variables include the gross household income in 1997, age, race, sex, the number of household members under 18 in 1997, and the highest grade completed by the residential fathers and the mothers.

In the second stage, the assumption is that the youths who are in a safe neighborhood by 2001 are those who migrate to the safe neighborhoods from the risky neighborhoods that they resided in 1997.

$$\Pr(\text{income15} = 1) = \Phi(\beta_0 + \beta_1 \text{neighsafe}) \quad (3)$$

$$\Pr(\text{income15} = 1) = \Phi(\beta_0 + \beta_1 \text{yhat}) \quad (4)$$

$$\Pr(\text{income15} = 1) = \Phi(\beta_0 + \beta_1 \text{neighsafe} + \beta_2 \mathbf{X}) \quad (5)$$

$$\Pr(\text{income15} = 1) = \Phi(\beta_0 + \beta_1 \text{yhat} + \beta_2 \mathbf{X}) \quad (6)$$

Model 3 predicts the probability of the youths having family income above the median household income in 2015 as a function of their neighborhood safety level in 2001. In Model 4, the same probability is estimated using a predicted neighborhood safety variable (*yhat*) from Model 2. Model 5 and 6 add to the equations the control variables, which include age, race, sex, the number of household members under 18 in 1997, and the highest grades completed by the residential father and mother.

In addition to the two-stage probit models, OLS regressions are conducted to analyze the differences in neighborhood effects on the youths' income by subgroups. These OLS models follow Model 6, which shows the predicted neighborhood effects on youth's income in 2015 with the control variables.

First, OLS is utilized on all of the youths in working dataset as shown in Model 7 below.

$$\log(income15) = \beta_0 + \beta_1 yhat + \beta_2 \mathbf{X} + \epsilon \tag{7}$$

As in Model 6, the predicted neighborhood safety variable (*yhat)* is included in the model as an independent variable. **X** is a set of control variables that includes the youths' age in 2015, race, sex, the number of household members under 18 in 1997, and the highest grades completed by residential fathers and mothers. Also, the dependent variable *income15*, is the original income variable retrieved from NLSY97 instead of the modified binary variable used for the probit models. All of the OLS models in this study utilize this original income variable.

After Model 7, OLS analyses are conducted on different subgroups. First, in Model 8, the effects of living in safe neighborhoods on income is analyzed by the youths' race. In Model 9, the same effect is studied by the youths' sex, and in Model 10, the youths are grouped by their age in 2015. Finally, Model 11 shows the influence of the number of household members under 18 on the model.

$$\log(income15) = \beta_0 + \beta_1 yhat + \beta_2 age15 + \beta_3 sex + \beta_4 memundr18 + \beta_5 hgcfthr + \beta_6 hgcmthr + \epsilon \tag{8}$$

$$\log(income15) = \beta_0 + \beta_1 yhat + \beta_2 age15 + \beta_3 race + \beta_4 memundr18 + \beta_5 hgcfthr + \beta_6 hgcmthr + \epsilon \tag{9}$$

$$\log(income15) = \beta_0 + \beta_1 yhat + \beta_2 race + \beta_3 sex + \beta_4 memundr18 + \beta_5 hgcfthr + \beta_6 hgcmthr + \epsilon \tag{10}$$

$$\log(income15) = \beta_0 + \beta_1 yhat + \beta_2 age15 + \beta_3 race + \beta_4 sex + \beta_5 hgcfthr + \beta_6 hgcmthr + \epsilon \tag{11}$$

In Models 8 and 9, there are two groups identified for each model: whites and minorities for Model 8, and males and females for Model 9. In Model 10, the youths in age 31 and 33 are analyzed primarily due to the sample size. The youngest of the sample in 2015 is 30, and the oldest of the sample is 34. However, there are only 25 youths who are 30, and there are 12 youths who are 34. The majority of the youths are in between age 31 and 33: 325 youths are 31, and 250 youths are 33. Thus, the age groups of 31 and 33 are chosen for the analysis. Similarly, based on the sample size, the youths with no sibling (one household member under 18), one sibling (two household members under 18), and two siblings (three household members under 18) are chosen for analysis in Model 11.

## 5. Results

### *5.1 First- Stage Models*

The results from the first-stage models, which are Models 1 and 2, are reported in Table 2. The reported coefficients are marginal effects. First, in Model 1, the probability of living in a safe neighborhood in 2001 is predicted without the control variables. From this model, it is found that the youths who move between 1998 and 2001 are 6.8 percent points more likely than the youths who do not migrate to live in safe neighborhoods in 2001. Then, in Model 2, the control variables are added to estimate the probability with increased robustness. Migration is still a statistically significant factor that increases the likelihood of the youths living in safe neighborhoods. Holding other variables constant, the youths who migrate between 1998 and 2001 are 8.5 percent points more likely to be in safe neighborhoods than the youths who do not migrate.

In addition to the migration history of the youths, the results from Model 2 show that the chances of living in advantageous neighborhoods significantly depend on the following factors: the level of household income in 1997, the number of children in each household, and the level of education completed by residential mothers. For example, having a household income above the median household income in 1997 increases the probability of living in a safe neighborhood by 17.2 percent points, while one-year increase in the years of education received by residential mothers increases the probability by 0.4 percent points. Supporting the findings by Dujardin and Goffette-Nagot (2009), Currie and Yelowitz (2000), and Sari (2012), the results also show that having an additional household member under 18 decreases the probability of living in advantageous neighborhoods by 3.8 percent points.

**Table 6**. Probability of Living in a Safe Neighborhood in 2001

| VARIABLES | Model 1 | Model 2 |
|---|---|---|
| Mobility 1998-2001 | 0.0689*** | 0.0856*** |
| | (0.0252) | (0.0260) |
| 1997 Income-Median HH Income | | 0.172*** |
| | | (0.0279) |
| 1997 Age | | -0.0182 |
| | | (0.0142) |
| Race | | -0.0130 |
| | | (0.0243) |
| Sex | | -0.0196 |
| | | (0.0230) |
| 1997 HH members under 18 | | -0.0388*** |
| | | (0.00957) |
| Highest Grade Completed: Father | | 0.00225 |
| | | (0.00161) |
| Highest Grade Completed: Mother | | 0.00413** |
| | | (0.00207) |
| Observations | 1,575 | 1,575 |

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
Reported Coefficients are Marginal Effects

Both Models 1 and 2 show that the migrations of the youths have a statistically significant positive effect on their probability of residing in safe neighborhoods in 2001. Thus, the results from the first- stage models reflect that the change in the neighborhood characteristics from risky to safe between

1997 and 2001 can be attributed to the migrations of the youths into the safe neighborhoods, rather than to the change in subjective opinions of the interviewers.

### *5.2 Second- Stage Models*

The second- stage models predict the impact of living in a safe neighborhood in 2001 on the probability of the youths earning a family income above the median in 2015. First, Model 3 shows that the youths who are in safe neighborhoods in 2001 are 16.1 percent points more likely to earn a household income above the median than the youths who are not in safe neighborhoods. The magnitude of the impact that the neighborhood safety has on household incomes enlarges in Model 4. In this model, the probability of earning above the median in 2015 is estimated using the predicted variable (*yhat*) obtained from Model 2. The result shows that the youths in safe neighborhoods are 106.9 percent points more likely than the youths in risky neighborhoods to earn above the median in 2015. The large discrepancy between the magnitudes of the neighborhood effects measured in Models 3 and 4 shows that utilizing two-stage probit models, as it is used in Sari (2012), is necessary. Measuring the neighborhood effects with the predicted value *yhat* gives results that are robust.

When the control variables are added in Models 5 and 6, the size of the neighborhood effects on the youths' probability of earning above the median in 2015 decreases. In Model 5, living in a safe neighborhood increases the probability by 11.8 percent points. In Model 6, the probability is increased by 81.5 percent points. In both models, race is a statistically significant factor that affects the probability of earning above the median household income in 2015. The youths who are racial minorities, which include Blacks, American Indians, Asians, and Pacific Islanders, are 15.2 percent points (Model 5) and 12.8 percent points (Model 6) less likely to earn above the median household income in 2015 than those who are White. In Model 5, the number of children in a household in 1997 and the years of education received by the fathers and mothers are also significant contributing factors to the level of income that the youths earn in 2015. Growing up with one additional sibling decreases the youths' likelihood of earning an income above the median by 3.1 percent points, while one additional years of education the parents received increases the probability by 0.5 percent points.

**Table 7**. Probability of Earning Above the Median Household Income in 2015

| VARIABLES | Model 3 | Model 4 | Model 5 | Model 6 |
|---|---|---|---|---|
| Neighborhood Safety | 0.161*** | | 0.118*** | |
| | (0.0275) | | (0.0287) | |
| *yhat* | | 1.069*** | | 0.815*** |
| | | (0.105) | | (0.155) |
| 2015 Age | | | -0.00500 | -0.00205 |
| | | | (0.0145) | (0.0145) |
| Race | | | -0.152*** | -0.128*** |
| | | | (0.0262) | (0.0269) |
| Sex | | | -0.0158 | -0.00327 |
| | | | (0.0257) | (0.0259) |
| 1997 HH members under 18 | | | -0.0312*** | -0.00422 |
| | | | (0.0104) | (0.0119) |
| Highest Grade Completed: Father | | | 0.00546*** | 0.00113 |
| | | | (0.00164) | (0.00189) |
| Highest Grade Completed: Mother | | | 0.00593*** | 0.00165 |
| | | | (0.00227) | (0.00244) |
| Observations | 1,575 | 1,575 | 1,575 | 1,575 |

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
Reported Coefficients are Marginal Effects

## *5.3 OLS Regressions by Subgroups*

Table 8 below shows the results from the OLS analysis for all groups of the youths in the dataset. First, the results show that the youths in safe neighborhoods in 2001 earn 221.2 percent points more than the youths in risky neighborhoods in 2015. In addition, race and the number of household members under 18 in 1997 have statistically significant impacts on the level of youths' household incomes in 2015. For example, the youths who are of racial minority earn 75.3 percent points less than the youths who are white in 2015. Also, one additional household member under 18 decreases the youths' incomes by 20.0 percent points in 2015.

**Table 8.** OLS Regression for All Groups

| VARIABLES | Model 7 |
|---|---|
| *yhat* | 2.212*** |
| | (0.807) |
| 2015 Age | 0.0430 |
| | (0.0751) |
| Race | -0.753*** |
| | (0.142) |
| Sex | 0.0885 |
| | (0.134) |
| 1997 HH Members under 18 | -0.200*** |
| | (0.0606) |
| Highest Grade Completed: Father | 0.0188* |
| | (0.00981) |
| Highest Grade Completed: Mother | 0.00195 |
| | (0.0128) |
| Constant | 8.789*** |
| | (2.446) |
| Observations | 1,575 |
| R-squared | 0.074 |

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
Reported Coefficients are in Percentage

Tables 9 to 12 below present the results from the OLS analyses by different subgroups. First, Table 9 shows the results from Model 8, which examines the neighborhood effects on youths' incomes by race. If the youths are of racial minorities, then living in a safe neighborhood increases their incomes in 2015 by 491.9 percent points. For them, neighborhood safety is the variable that exerts the most significant impacts on the level of their household incomes. If the youths are white, however, living in a safe neighborhood does not have statistically significant impacts on their household incomes. Rather than the neighborhood characteristics, the number of household members under 18 in 1997 and the years of education completed by the residential fathers exert more significant impacts on their incomes. For example, having an additional household member under 18 when they are growing up decreases their adulthood incomes by 17.8 percent points. Also, having a residential father who has completed one additional year of schooling increases their incomes by 2.78 percent points.

**Table 9.** OLS Regression by Race

| VARIABLES | White | Minority |
|---|---|---|
| *yhat* | 0.425 | 4.919*** |
| | (0.836) | (1.483) |
| 2015 Age | -0.110 | 0.243* |
| | (0.0788) | (0.135) |
| Sex | 0.0180 | 0.226 |
| | (0.142) | (0.237) |
| 1997 HH Members under 18 | -0.178** | -0.172* |
| | (0.0716) | (0.0978) |
| Highest Grade Completed: Father | 0.0278*** | 0.00531 |
| | (0.0106) | (0.0171) |
| Highest Grade Completed: Mother | 0.00970 | -0.00896 |
| | (0.0152) | (0.0204) |
| Constant | 14.08*** | 1.011 |
| | (2.562) | (4.393) |
| Observations | 842 | 733 |
| R-squared | 0.030 | 0.051 |

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
Reported Coefficients are in Percentage

In Table 10, the results from Model 9 are reported. For both male and female youths, being racial minorities decreases their household incomes by 84.6 percent points and 63.6 percent points, respectively. Living in a safe neighborhood, however, has a significant impact only on the level of females' incomes. For the female youths, the residence in a safe neighborhood increases their household incomes by 291.3 percent points. For the male youths, it increases their incomes by 162.3 percent point, but this effect is statistically insignificant. Finally, the number of household members under 18 in youths' families in 1997 has a statistically significant impacts on the incomes of the males.

Having an additional household member under 18 reduces their 2015 incomes by 27.0 percent points. The number of children in the household decreases the females' incomes by 12.4 percent points, but this impact is statistically insignificant. Unlike the results from Model 8, the years of education completed by the fathers do not have statistically significant impacts on the incomes of the neither group.

**Table 10.** OLS Regression by Sex

| VARIABLES | Male | Female |
|---|---|---|
| *yhat* | 1.623 | 2.913** |
| | (1.153) | (1.134) |
| 2015 Age | -0.0230 | 0.120 |
| | (0.109) | (0.104) |
| Race | -0.846*** | -0.636*** |
| | (0.205) | (0.198) |
| 1997 HH Members under 18 | -0.270*** | -0.124 |
| | (0.0902) | (0.0818) |
| Highest Grade Completed: Father | 0.0163 | 0.0205 |
| | (0.0145) | (0.0133) |
| Highest Grade Completed: Mother | -0.0134 | 0.0257 |
| | (0.0174) | (0.0191) |
| Constant | 11.48*** | 5.689* |
| | (3.529) | (3.394) |
| Observations | 785 | 790 |
| R-squared | 0.072 | 0.084 |

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
Reported Coefficients are in Percentage

The results from Model 10 are reported in Table 11. In Model 10, the impact of neighborhood safety levels on the youths' household incomes is studied by their age. The residence in safe neighborhoods has a statistically significant impacts on incomes of the youths who are 33 years old in 2015. Their 2015 household incomes increase by 331.2 percent points if they are in safe neighborhoods in 2001. For the youths who are 31 years old, the residence in the safe neighborhoods increases their household incomes by 1792. Percent points. This effect, however, is statistically insignificant.

**Table 11.** OLS Regression by Age

| VARIABLES | 31 | 33 |
|---|---|---|
| *yhat* | 1.792 | 3.312** |
| | (1.355) | (1.451) |
| Race | -1.116*** | -0.572** |
| | (0.232) | (0.260) |
| Sex | 0.125 | 0.0635 |
| | (0.222) | (0.243) |
| 1997 HH Members under 18 | -0.202** | -0.101 |
| | (0.0990) | (0.111) |
| Highest Grade Completed: Father | 0.0247 | 0.0200 |
| | (0.0162) | (0.0180) |
| Highest Grade Completed: Mother | 0.0251 | 0.00205 |
| | (0.0239) | (0.0203) |
| Constant | 10.18*** | 9.583*** |
| | (0.571) | (0.589) |
| Observations | 540 | 464 |
| R-squared | 0.115 | 0.076 |

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
Reported Coefficients are in Percentage

The difference between the neighborhood effects on incomes of the youths aged 31 and 33 contradicts the findings by Chetty et al. (2015). According to Chetty et al. (2015), the youths who are younger (below 13) are more likely to benefit from the advantageous circumstances of their neighborhoods than the youths who are older (above 13). The results from Model 10, however, contradict the findings by showing that the older youths who spent less time in their safe neighborhoods experience larger and more significant benefits from the neighborhoods than the younger youths.

In addition to the neighborhood safety, race has a statistically significant impacts on both groups of the youths. For the youths who are 31, being racial minorities reduces their household incomes by 111.6 percent points. For the 33 years old youths, being racial minorities decreases their household incomes by 57.2 percent points.

**Table 12.** OLS Regression by the Number of HH Members under 18

| VARIABLES | 1 member | 2 members | 3 members |
|---|---|---|---|
| *yhat* | 2.699* | 3.884*** | 0.628 |
| | (1.595) | (1.049) | (1.620) |
| 2015 Age | -0.202 | 0.0781 | -0.0526 |
| | (0.160) | (0.0996) | (0.155) |
| Race | -0.687** | -0.463** | -0.753*** |
| | (0.294) | (0.198) | (0.283) |
| Sex | 0.000441 | 0.132 | -0.470* |
| | (0.282) | (0.183) | (0.269) |
| Highest Grade Completed: Father | -0.00957 | -0.00832 | 0.0310 |
| | (0.0195) | (0.0138) | (0.0193) |
| Highest Grade Completed: Mother | -0.000348 | -0.00480 | 0.00245 |
| | (0.0256) | (0.0190) | (0.0217) |
| Constant | 16.33*** | 6.865** | 12.03** |
| | (5.173) | (3.230) | (4.972) |
| Observations | 252 | 563 | 390 |
| R-squared | 0.057 | 0.055 | 0.050 |

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
Reported Coefficients are in Percentage

Finally, the results from Model 11 are reported in Table 12. For the youths who grow up without a sibling and the youths who grow up with one sibling experience large increases in their incomes for living in safe neighborhoods. For example, the youths who grow up without any siblings (one household member under 18) experience 269.9 percent point gains in their household incomes. Similarly, the youths who grow up with one sibling (two household members under 18) experience 388.4 percent point increases in their incomes. The incomes of the youths who have more than one sibling increases by 62.8 percent points, and this increase is statistically insignificant.

These results largely support the findings by Dujardin and Goffette-Nagot (2009), Currie and Yelowitz (2000), and Sari (2012). They suggest that the large number of children in a household increases the probability of the household living in a deprived neighborhood and thus increases the probability of the children being unemployed in their adulthood. Table 12 shows that having more than one sibling decreases the magnitude and significance of the positive effects that living in safe neighborhoods has on the youths' 2015 incomes.

In addition to the neighborhood effects, race continues to have statistically significant impacts on the youths' household incomes in 2015. For the youths who grow up without any siblings, being racial minorities decreases their incomes by 68.7 percent points. Similarly, for the youths who grow up with two siblings, being racial minorities decreases their incomes by 75.3 percent points. Therefore, it can be concluded that having more than one sibling increases the negative impacts of being racial minorities on the youths' incomes.

## 6. Discussion

This study contributes to the existing literature on neighborhood circumstances and individual economic outcomes by using a unique set of neighborhood characteristics. The majority of past studies on long-term neighborhood effects on youths' earnings define neighborhood deprivation using census tract statistics such as average income, poverty rate, and the number of job opportunities. However, as mentioned previously, geographic information in the NLSY97 dataset was not available for the public. Any information about the youths' state, county, and ZIP code was private. Also, the variables that describe the neighborhood characteristics, such as the average income, poverty rate, and demographics, were not accessible. Therefore, this study solely relied on the interviewers' remarks on the level of safety and the conditions of the buildings in youths' neighborhoods. If the interviewers expressed that they felt unsafe in the neighborhoods or determined that the buildings needed significant renovations, the neighborhoods were defined to be disadvantaged. As a result, this study contributes to the past studies by showing that their findings that living in affluent neighborhoods have positive impacts on adulthood outcomes are robust, even if different criteria are applied to define neighborhood characteristics.

While this study contributes to the existing literature by using unique definitions of neighborhood deprivation, the biggest challenge is that neighborhood safety scores are subjective opinions of the interviewers, rather than measured characteristics of the neighborhoods.

The fact that the judgment on the level of neighborhood deprivation solely depends on the interviewers' subjective remarks on neighborhoods may lead to problems that reduce the validity of this study. For example, an "improvement" in the level of safety in a youth's neighborhood may be attributable to factors other than the migration history of the youth. To study the effects of moving out of a disadvantaged neighborhood, this study assumed that if a youth was in a risky neighborhood in 1997 and in a safe neighborhood in 2001, then this change in the level of safety is due to the youth moving into a safe neighborhood. The first stage models tested for the probability of living in a safe neighborhood in 2001 as a function of migration history to show that the assumption was valid. The results from these models were statistically significant but the marginal effects were small. As a result, it is valid to assume that there can be other contributing factors, such as gentrification or family characteristics, to the probability of the youth living in a safe neighborhood or that there are better ways to measure the level of neighborhood safety. However, due to the lack of geographic variables, it is impossible to test for the alternatives.

## 7. Conclusion

In this study, the long-term impacts of moving out of a disadvantaged neighborhood on youths' earnings are analyzed using the NLSY97 dataset by the Bureau of Labor Statistics. It was hypothesized that the youths who moved out of disadvantaged neighborhoods would have a higher probability of earning an income above the median household income in adulthood than the youths who did not move out of the disadvantaged neighborhoods. In order to test for the hypothesis, the original sample of approximately 9,000 youths was reduced to 1,575 youths who were living in a neighborhood with risks in 1997 and had valid record of their migration history between 1998 and 2001.

The research question was investigated with two stage probit models. In the first stage, the probability of a youth living in a safe neighborhood in 2001 was predicted as a function of his migration history between 1998 and 2001. It was shown that holding other variables constant, the youths who had migrated between 1998 and 2001 were 8.5 percent more likely to live in a safe neighborhood in 2001.

In the second stage, the probability of the youths earning above the median household income in 2015 was predicted with the youths who lived in a safe neighborhood in 2001 and those who did not. The results suggested that the youths who were living in a safe neighborhood was 81.5 percent more likely to earn above the median household income in their adulthood than those who were not living in a safe neighborhood in 2001.

Overall, this study showed that youth's neighborhood circumstances have statistically significant impacts on their long-term economic outcomes. This has several implications for policymakers. First, there needs to be active efforts to help individuals and families in poverty to move into safe and resourceful neighborhoods. As shown in the previous studies by van Ham, Boschman, and Vogel (2018), Sari (2012), and Hedman and Galster (2013), individuals and families sort themselves into certain neighborhoods based on their preferences. For individuals in poverty, it is most likely that the preference is on whether the housing and the cost of living is affordable, which keeps them in cheap, risky, and resource-deprived neighborhoods. Therefore, the government programs, such as Section 8 vouchers, that assist the housing price and the cost of living need to be expanded to help those in poverty to choose to live in wealthy and resourceful neighborhoods.

Another implication for policymakers concerns the plausibility of social mobility theory. In this paper, the first stage models showed that the families with household income above the median household income in 1997 are 17.2 percent more likely to live in a safe neighborhood in 2001 than the families with household income below the median. Then, the second stage models showed that the youths who were in safe neighborhoods in 2001 were 81.5 percent more likely to earn above the median household income themselves in 2015 than those who were not in safe neighborhoods in 2001.

These two results together show that the youths who were born into families with income above the median household income are more likely to have family income above the median than the youths who were born into families with income below the median. In other words, the youths who were born into wealthy families maintain the wealth in their adulthood, and the youths who were born into poor households stay to be poor in their adulthood. Moreover, results from Model 5 suggest that the level of education received by the parents has statistically significant effects on the level of income that the youths make in their adulthood. These results suggest that the youths tend to stay in economic strata that they are born into and the mobility across the economic strata, especially upward movement, is rare. Therefore, there needs to be policy implementation that aims at helping those children and youths who are born into poor families to find proper education opportunities and other resources in their neighborhoods to lift them out of poverty.

Future researches with comprehensive set of neighborhood and individual characteristics will allow us to understand what kinds of policy interventions can be effective to address the problem of intergenerational poverty.

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