The Receipt of Subsidized Housing across Generations

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Abstract

In this paper, I ask whether children who grow up in subsidized housing return to the program as adults. I use the Panel Study of Income Dynamics (PSID) and adopt the potential outcome approach using Inverse Probability of Treatment Weighting to compare children who lived in subsidized housing before age 18 and those who did not live in subsidized housing before age 18. I find that children who grow up in subsidized housing are statistically more likely to return to the program as adults, however, the absolute probabilities of returning to subsidized housing as an adult are fairly small.

Keywords: subsidized housing; intergenerational transmission

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INTRODUCTION

A persistent controversy in academic and policy circles has been whether government programs aimed at helping the poor undermine the upward mobility of those who receive assistance. The importance of the issue can hardly be overstated, especially when it concerns the federal subsidized housing program. Currently the U.S. government spends $34.8 billion on low-income housing assistance, supporting 4.7 million households across traditional public housing, mixed-income housing, Housing Choice Vouchers, housing for the elderly and people with disabilities. There are roughly 2 million families with children in subsidized housing; median length of stay for these families is between 3 and 5 years, but lengths of stay up to 25 years do occur (Lubell, Shroder, & Steffen, 2003). Therefore, it is important to know if the subsidized housing program is not only helping to meet immediate shelter needs, but also does not hinder the socioeconomic prospects of children who grow up in subsidized housing.

Although there has been a long standing interest in the transmission of welfare receipt from mothers to daughters (Gottschalk, 1996; Rank & Cheng, 1995), we know little about what happens to children who grow up in subsidized housing beyond employment outcomes and earnings outcomes in adulthood (Newman & Harkness 2002; Aratani 2010). Moreover, while there is ethnographic evidence that some families remain in subsidized housing for generations (Venkatesh, 2002), we do not know the degree to which the subsidized housing program is reproducing itself and whether the strong intergenerational component is only a feature of the most distressed public housing projects or the program as a whole.

My project is a detailed examination of how often children who grew up in subsidized housing return to the program as adults. I use counterfactual analysis for longitudinal data to compare children who grew up in subsidized housing to those who did not but were eligible to receive the subsidy. I find that children who grew up in subsidized housing are more likely to return to the program as adults to form their own households. Nevertheless, the absolute probabilities of returning to subsidized housing as an adult are fairly small.

SUBSIDIZED HOUSING PROGRAMS

Over the course of its 80-year history, the main goal of the subsidized housing program in the United States has been to help poor households live in physically sound affordable housing (Newman 2008). Over and above serving the immediate shelter needs of low-income households, an important but not always explicit justification for the program has been the belief that upgrading the housing conditions of the poor will yield broader benefits of social and economic advancement to its occupants (Vale 2002). Moreover, unlike other forms of government assistance, such as food stamps and Medicaid, subsidized housing for the poor is not an entitlement and only a quarter of eligible households receive it (HUD 2008). The various forms that the subsidized housing program has taken over the years have been closely linked to attitudes towards the proper responses to address poverty (Harloe 1995; Vale 2002). At the heart of the uneasy relationship between providing support for the poor and providing subsidies for housing has been the debate about the need to care for the poor versus the desire to only reward worthy behavior, especially with the promise of homeownership (Vale 2002).

Currently the U.S. government spends $34.8 billion on low-income housing assistance, supporting 4.7 million households across traditional public housing, mixed-income housing, Housing Choice Vouchers, housing for the elderly and people with disabilities. This represents a larger government expenditure serving more people than TANF (Temporary Assistance to

Needy Families), the successor to Aid to Families with Dependent Children (AFDC) (Newman 2008). While 49 percent of all renter households have incomes low enough to be considered eligible for housing assistance, only 26 percent of all income-eligible renters actually receive rental subsidies (HUD 2008). Out of the total number of subsidized households, approximately 1.3 million live in public housing units, operated by local Public Housing Authorities, approximately 1.8 million receive assistance through vouchers that can be used on the private housing market, and approximately 1.7 million live in privately built and managed subsidized units (HUD 2008).

Compared to all income-eligible renters, subsidized households are more likely to be headed by a female and by an African American (HUD 2008). Heads of household in subsidized housing are also more likely to have lower income and lower educational levels compared to all income-eligible renters (HUD 2008). Neighborhoods with public housing are significantly poorer than the average environment experienced by a household with income below the poverty line (Newman and Schnare 1997). While the voucher program appears to be successful in moving recipients out of the lowest-income areas, it has not been successful in promoting moves to middle-class neighborhoods (Newman and Schnare 1997). More than half of all public housing units are located in minority census tracts where at least 50 percent of the households have a black or Hispanic head, and 38 percent are located in tracts that are 80 to 100 percent minority (Newman and Schnare 1997). Voucher users do enjoy more integrated environments than public housing residents. However, they are not more likely than the poor in general to live in neighborhoods where the percent minority is less than 50 (Newman and Schnare 1997).

All subsidized housing programs share some general eligibility requirements. Applicants must have an annual income adjusted for family size that is no more than 80 percent of the median income for the metropolitan area or non-metropolitan part of each state where the applicant resides (HUD 2003). Moreover, local Public Housing Authorities must admit on an yearly basis no less than 40 percent of households with extremely low income, or income that is less than 30 percent of the median local area income (HUD 2003). In addition to these requirements, local housing authorities can establish priority categories for selection of subsidy recipients, such as whether the applicant household is a single-parent household, whether the applicant household lives in substandard housing, whether there is a working adult in the household, or whether there are people with disabilities in the household (HUD 2003).

THE INTERGENERATIONAL ASSOCIATION IN THE RECEIPT OF GOVERNMENT ASSISTANCE

An overwhelming majority of the research that concerns the intergenerational transmission in the receipt of government assistance concerns the association between a mother receiving AFDC and her daughter receiving AFDC. Daughters who grew up in a household that received welfare are more likely to receive welfare themselves, controlling for a variety of socioeconomic characteristics (McLanahan 1985; Duncan, Hill, and Hoffman 1988; Solon et al. 1988; Antel 1992; Gottschalk 1992, 1996; Pepper 1995). Nevertheless, there is evidence that childhood socioeconomic disadvantage is a better predictor of receiving welfare in adulthood compared to childhood welfare receipt (Rank and Cheng 1995). Moreover, as much as three-quarters of the intergenerational association in the receipt of AFDC could be due to the intergenerational association in poverty (Levine and Zimmerman 1996).

While the intergenerational transmission of AFDC from mother to daughter has received substantial attention from scholarly circles, there is little evidence regarding the degree to which children who grow up in subsidized housing return to the program as adults. Ethnographic evidence of some of the most distressed public housing projects suggests that many families live in subsidized housing for generations (Venkatesh 2002). The one nationally representative quantitative study of the intergenerational transmission of subsidized housing only examines teenage children who lived in public housing between 1979 and 1981 (Aratani 2010). The study finds that in their late 20s and early 30s black children, but not white children, who lived in subsidized housing in their teenage years are significantly more likely to receive a housing subsidy. The statistically significant effect for black children disappears by the time respondents reach their late 30s and early 40s.

MECHANISMS OF THE INTERGENERATIONAL TRANSMISSION OF SUBSIDIZED HOUSING RECEIPT

How does living in a subsidized apartment as a child influence the decision of adult offspring to return to the subsidized housing program after age 18? Drawing on the literature of the intergenerational transmission of welfare (McLanahan 1985; Rank and Cheng 1995; Gottschalk 1992, 1996; Levine and Zimmerman 1996) and the literature on the effects of subsidized housing (Meyers et al. 1995, 2005; Currie and Yelowitz 2000; Newman and Harkness 2002; Jacob 2004; Newman 2008; Newman, Holupka, and Harkness 2009; Aratani 2010), I identify six possible mechanisms: a selection mechanism, an income mechanism, a housing stability mechanism, a neighborhood mechanism, an information mechanism, and a welfare trap mechanism.

Selection Mechanism. Compared to all income-eligible renters, subsidized households are more likely to be female-headed, to have lower incomes, and to rely on income from Social Security, TANF, and food stamps (HUD 2008). Therefore, given their more disadvantaged socioeconomic backgrounds, I expect children in subsidized housing to have lower incomes as adults, thus, making them more likely to receive subsidized housing as adults. It should be noted, however, that the participation in subsidized housing as an adult through this particular socioeconomic mechanism is due to the selection of disadvantaged households into the program rather than any features of the program itself.

Income Mechanism. As rents in subsidized housing are lower than rents in the private sector, parents may have more disposable income to invest in their children (Newman 2008). In fact, children in subsidized housing are less likely to have been held back in school (Currie and Yelowitz 2000) and less likely to be undernourished (Meyers et al. 1995, 2005) compared to children of similar socioeconomic backgrounds who did not grow up in subsidized housing. These findings suggest that even though children in subsidized housing grow up in families that are more disadvantaged, some of the negative effects of growing up in a poor family may be mitigated by access to affordable housing that leaves parents with more disposable income.

Housing stability mechanism. Subsidized housing residents are less likely to experience overcrowding, more likely to stay in their apartments longer, and more likely to have access to higher quality housing than they would otherwise afford in the private market (HUD 2008; Newman and Schnare 1997). Therefore, as subsidized tenants have access to housing that is appropriate for their family size and in better condition than what is available for the same price on the private market, children may grow up in less stressful and healthier environments. Moreover, since families in subsidized housing do not move as often compared to similar families, children would not need to adjust to new schools as frequently compared to children from households of similar incomes. Therefore, the quality and stability of subsidized housing may help in the process of socioeconomic attainment making children less likely to need the program as adults.

Neighborhood mechanism. Taking up the subsidy may lead to suboptimal residential location choices if the only available subsidized housing is in neighborhoods with poor schools and low levels of safety. In some cases families would have to make a choice between living in affordable housing versus living in a better neighborhood but in more expensive housing. In fact, compared to other rental housing and to housing occupied by welfare recipients, public housing is far more likely to be located in racially segregated areas with high concentrations of households in poverty (Newman and Schnare 1997). The poor schools in segregated neighborhoods may not prepare children for future college attendance, while the social networks in poor neighborhoods may not give children access to good job networks (Wilson 1987). Therefore, the location of subsidized housing might interfere with the socioeconomic attainment of children making them more likely to need the program as adults.

Information mechanism. It could be the case that parents pass information to children regarding the process of entering subsidized housing. Therefore, children who grew up in subsidized housing may be better informed about the program compared to children who never lived in subsidized housing. In this case, as Gottschalk (1996) has observed with respect to welfare, the intergenerational transmission of subsidized housing status resembles the process of the intergenerational transmission of occupations. In other words, as the costs of obtaining information about the subsidized program are lower for children living in subsidized households, these children will have higher probabilities of participating in the program as adults should they qualify for it.

Welfare trap mechanism. Finally, proponents of the welfare trap mechanism argue that children could acquire a taste for or preference for welfare assistance by virtue of their parents participating in the program (Murray 1984). While there is conflicting evidence whether participating in government assistance programs lowers the stigma associated with receiving assistance or changes the attitudes of children towards welfare (Moffitt 1983; Garfinkel and McLanahan 1986; Bartholomae, Fox, and McKenry 2004), if children who receive subsidized housing feel less stigmatized in applying for it, then that would increase their participation in the program. This argument is related to the neighborhood mechanism above. However, it hinges on the assumption that the intergenerational transmission of subsidized housing happens not because subsidized housing exacerbates the economic disadvantages of poor families because it is located in very disadvantaged neighborhoods. Rather it is the parents and neighbors of subsidized children that serve as bad role models when it comes to job market behavior and that by being exposed to bad role models, children change their tastes for government assistance income over labor market income.

In sum, the mechanisms specified above have an ambiguous effect on the intergenerational transmission of subsidized housing status. If parents choose to live in affordable housing that is in disadvantaged neighborhoods, the gains to children due to good housing quality and stability might be counteracted by the bad quality of the local environments, especially in terms of schools and safety. Moreover, to the extent that children receive information from their parents regarding the process of entering subsidized housing or if children indeed develop a taste for living in subsidized housing, then children who grew up in subsidized housing would return to the program as adults. It should be noted that I am not able to test directly the operation of all mechanisms that link the receipt of subsidized housing in childhood to the receipt of subsidized housing in adulthood. While my statistical procedures correct for the selection of households into the subsidized housing program based on an extensive list of observable socioeconomic characteristics, I do not have a direct test for the rest of the mechanisms although they do inform the interpretation of my results.

The primary contribution of my paper is to provide estimates of the degree to which the housing program has a tendency to reproduce itself by having those who were subsidized as children remain in the program as adults. My study is only the second one to my knowledge to quantify the intergenerational continuity in the receipt of housing assistance (Aratani 2010) and the first one to do so without restricting the sample only to teenage children and without restricting the period in which children were in subsidized housing only to the late 1970s and early 1980s.

DATA

This study uses data from the Panel Study of Income Dynamics (PSID), which is an ongoing nationally representative, longitudinal survey of U.S. households. The PSID was conducted annually between 1968 and 1997 and biennially thereafter. The PSID contains a rich set of household structure and socioeconomic variables with an oversample of low-income and minority families. Attrition from the PSID has not compromised the representativeness of the data (Lillard and Panis 1994; Fitzgerald, Gottschalk, and Moffitt 1998). In addition to using the PSID demographic and socioeconomic data on respondents, I also incorporate into my analysis the PSID-geocode files, which provide a crosswalk between the addresses of PSID respondents and the corresponding metropolitan areas, counties, and census tracts in which PSID families live. I use these geocode files to attach census-tract-level and metropolitan-level information to every respondent at each interview year. Although census tracts are only an approximation of the concept of a neighborhood, their use in this capacity is widespread in sociological research. I use the Geolytics Neighborhood Change Database (NCDB) to access U.S. Census data for 1970, 1980, 1990, and 2000 in constant 2000 census tract boundaries. The consistency of census tracts across decades allows me to employ linear interpolation to compute the census tract characteristics of PSID respondents during intercensal years.

The PSID has been asking household heads whether they live in public housing or whether they receive any other help from federal, state, or local sources in paying their rent in every wave of the survey since 1986. Moreover, out of concern for the quality of information obtained by asking respondents about their receipt of housing subsidies (Shroder and Martin 1996), each PSID family in every year through 1995 has been identified as living in a subsidized unit by matching its address to HUD and local Public Housing Agencies' administrative records (Newman and Schnare 1997; Newman and Harkness 1999). The subsidized status of voucher recipients has not been matched to administrative records, as HUD does not maintain a database with the addresses of those subsidized through the voucher program.

In order to identify children who have lived in a home with a low-income housing subsidy I use both the self-reports of household heads regarding their receipt of housing assistance as well as the information matched to administrative records. This allows me to use the full span of PSID data from 1968 through 2007 and follow children from birth until they are old enough to apply for their own subsidized housing apartment. I cannot disaggregate building-based subsidies (public housing and privately managed subsidized housing) from person-based subsidies (vouchers) as the wording of the self-report questions in the PSID until 2005 did not allow respondents to explicitly identify whether or not they received a voucher. I also do not have information on the receipt of vouchers before 1986, as the addresses of voucher recipients are not present in administrative sources and 1986 is the first year in which respondents could self-identify as using a housing subsidy other than public housing. What this means is that some children may have lived in a home that received a voucher before 1986, but I would not observe that receipt. To the extent that the "control" sample in my analysis includes "treated" children and those children of voucher homes are more similar to the "treated" children as opposed to the "control" children, the estimates in my paper are biased downward.

My study uses the longitudinal life histories of all children who were born into the PSID. Some of these children, however, either leave the PSID before they are old enough to form their own households in subsidized housing or are still in the survey but are not old enough in the last wave of follow-up to be at risk of forming their own households. Therefore, my analyses estimate the probability of returning to subsidized housing as an adult only for children who were continuously observed at least until age 18, or a total of 1,045 black children and 1,646 non-black children. I describe how I deal with attrition from the sample in the *Methods* section below.

METHODS

I use recent advances in counterfactual analysis for longitudinal data to estimate the effect of living in subsidized housing before age 18 on forming one's own household in subsidized housing after age 18. Since the treatment of living in subsidized housing is not a discrete event such as losing one's job or becoming a parent, it is important to properly account for the duration of stays in subsidized housing as well as for the sequencing of living in subsidized housing and not living in subsidized housing over a person's entire childhood from birth until age 18. Specifically, I use a method pioneered by Robins and colleagues (Robbins 1999; Hernán, Brumback, and Robins 2000; Robins, Hernán, and Brumback 2000) called Inverse Probability of Treatment Weighting (IPTW) that accounts for the longitudinal nature of the treatment of living in subsidized housing over one's childhood. The IPTW method involves a two-step procedure in which I first use discrete-time survival logistic regressions to model the process of living in subsidized housing from age 1 until age 17. These discrete-time logistic models have several advantages over conventional regression models as they properly adjust for time-varying covariates that affect assignment to treatment. Second, I fit a discrete-time logistic regression to model whether a person forms their own household in subsidized housing after age 18. I weight that model using the IPT weights estimated in the first part of the analysis. Weighting the logistic regression with IPT weights creates a pseudo-population in which the treatment is not confounded by observed covariates (Robbins 1999; Hernán et al. 2000; Robins et al. 2000). The use of IPT weights in this context is similar to the use of survey sampling weights that make it possible to weight samples so that they are representative of a specific population (Morgan and Todd 2008; Austin 2011). The logistic regression weighted by IPT weights produces unbiased and consistent estimates of the causal effect of living in subsidized housing as a child under assumptions described below.

Estimation of the Inverse Probability of Treatment Weights

The Inverse Probability of Treatment Weights at each time *k* is the inverse probability that a child received the treatment that they received given prior treatment history, baseline time-invariant covariates, and time-varying covariates. Intuitively, at each time *k* the IPTW creates a pseudo-population in which the treatment behaves as it were sequentially randomized with respect to prior observed covariates (Sampson, Laub, and Wimer 2006; Wodtke, Harding, and Elwert 2011). In other words, at each time *k* the IPTW "balances" the assignment to treatment with respect to prior stays in subsidized housing, baseline time-invariant covariates, and time-varying covariates (Wodtke et al. 2011).

Formally, the IPTW is defined as:

$$W_i = \frac{1}{\prod_{k=1}^{K} f[A_i(k) \mid \overline{A}_i(k-1),\ \overline{L}_i(k)]} \tag{1}$$

where $A_i(k)$ is child *i*'s treatment status at time *k*, $\overline{A}_i\ (k-1)$ is child *i*'s treatment history up to time $k-1$, and $\overline{L}_i(k)$ is a vector of time-invariant and time-varying covariates (see Barber, Murphy, and Verbitsky (2004) for a more detailed discussion of the IPTW logic within the context of survival analysis). The time-invariant covariates are all measured at birth. All time-varying covariates are lagged one year with respect to experiencing the treatment of living in subsidized housing and are measured yearly from birth until age 17. There are a total of seventeen treatment periods *k* between age 1 and age 17 during which a child can experience the treatment of living in subsidized housing.[1]

Using the weights as defined above can lead to inefficient and unstable estimates if some children have very low probabilities of receiving the treatment that they actually received given their observed characteristics (Robins et al. 2000). Therefore, in my analysis I use stabilized IPT weights, defined as:

$$SW_i = \frac{f[A_i(k) \mid \overline{A}_i(k-1), \overline{L}_i(0)]}{\prod_{k=1}^{K} f[A_i(k) \mid \overline{A}_i(k-1),\ \overline{L}_i(k)]} \tag{2}$$

where the denominator is the same as the one in Equation (1); however, the numerator represents the probability that a child received their own treatment at time *k*, given their past treatment history and baseline covariates but not adjusting for time-varying covariates (Robins et al. 2000).

As mentioned in the *Data* section above, I estimate the probability of forming one's own household in subsidized housing only for children who are observed at least until age 18 in the PSID. This type of restriction can be problematic if children with certain characteristics are more likely to drop out of the survey. Therefore, in addition to calculating the stabilized IPT weights, I also calculate stabilized censoring weights, which represent the probability of attrition in each wave of the PSID. I estimate the stabilized censoring weights using the same method I outline for the stabilized IPTWs in Equation (2) above. In this case, instead of estimating the probability of being treated, I estimate the probability of being censored at each time *k* given each child's treatment history, baseline covariates, and time-varying covariates. After I derive the stabilized censoring weights, I multiply them by the stabilized IPT weights to arrive at the final weights that I use in the second part of the analysis.[2]

IPTW model covariates

My IPTW models include an extensive list of baseline and time-varying covariates that predict the treatment of living in subsidized housing. The covariates include household size, whether the child lives in a single-headed household, number of children under age of 6 in the household, the educational attainment of the household head, whether there are extended family members present, and whether there is a sibling of a different gender present in the household. I include the covariate that describes the gender composition of the sibship because of a subsidized housing regulation that states that children of opposite genders above the age of 5 need to have their own bedrooms. This rule could make households with children of opposite genders less likely to live in a subsidized apartment if there are no units available that are big enough to accommodate the family given the gender composition of the sibship.

In addition to these household characteristics, I also include variables that describe the income sources of the household, such as labor income, transfer income, whether the household receives food stamps, whether the household receives AFDC/TANF, and whether the household head has a disability that prevents work. In addition, I also include a dummy variable of whether the family's total income is less than 30 percent of the MSA median income as families with extremely low incomes usually have priority in receiving a housing subsidy.

In my models, I also control for a number of MSA and neighborhood characteristics, such as the MSA population size, the local county unemployment rate, and the Fair Market Rent for a two-bedroom apartment as calculated by HUD.[3] I also include neighborhood characteristics that describe the racial composition of the neighborhood, the percent in poverty, the percent unemployed, the percent receiving welfare, the percent female-headed households, and the density of children. The neighborhood characteristics that I am using in my analysis correspond to the scale of neighborhood concentrated disadvantage developed by Sampson, Raudenbush, and Earls (1997) to study the effect of neighborhoods on children's outcomes. In the context of my study, it is important to use these metropolitan-level and neighborhood-level characteristics because that makes the IPT weights reflect the disadvantage that children are facing not only with respect to their family environments but also with respect to their neighborhood environments prior to entering subsidized housing.

All covariates that I describe above are measured at baseline (or the year that the child was born into the sample) and with a one-year lag with respect to the dependent variable (or at time $k-1$). In addition to using these demographic and socioeconomic covariates, I also include several variables that describe a child's treatment history of being in subsidized housing, namely whether a child was in subsidized housing at time $k-1$ and the cumulative years a child has been in subsidized housing up to time $k-1$. These two variables vary over time. I also construct variables that show the first year in which each child became eligible to receive the subsidy and the age at which each child first became eligible to receive the subsidy. Both of these variables are constant over time.

Estimating the effect of living in subsidized housing as a child on the probability of forming a household in subsidized housing after age 18

Each child in my study has a total of 17 chances before age 18 to be observed in subsidized housing. The sequence of living arrangements inside subsidized housing and outside subsidized housing can formally be expressed as $a_k = (a_1,..., a_k)$, where $\overline{a} = a_k$ represents a child's complete treatment history from age 1 to age 17. For example, $a_k = (1,1, \ldots ,1)$ is the treatment history of a child who spent their entire childhood in subsidized housing, while $a_k = (0,0, \ldots ,0)$ is the treatment history of a child who never was in subsidized housing before age 18.

The average effect of a child's specific treatment history before age 18 on the outcome of forming one's own household in subsidized housing can be defined as the expected difference in outcomes if that particular child experienced treatment history $\overline{a}$ versus treatment history $\overline{a}'$. Formally that relationship is:

$$E\left(Y_{\overline{a}} - Y_{\overline{a}'}\right) = P(Y_{\overline{a}} = 1) - P\left(Y_{\overline{a}'} = 1\right) \qquad (3)$$

where $P(Y_{\overline{a}} = 1)$ is the probability of forming a household in subsidized housing had all children experienced the treatment history $\overline{a}$, and $P(Y_{\overline{a}'} = 1)$ is the probability of forming a household in subsidized housing had all children experienced an alternate treatment history $\overline{a}'$. Because the same child can only experience a single sequence of treatments, it is necessary to estimate Equation (3) using data on the observed treatment histories of different children. Equation (3) can be identified from observational data if at each time *k* the treatment is independent of the outcome given each child's treatment history, observed time-invariant baseline covariates, and time-varying covariates. Formally, this condition can be expressed as:

$$Y_{\bar{a}} \perp A_k \mid \bar{L}_k, \bar{A}_{k-1} \tag{4}$$

where $\bar{L}_k$ is a vector of observed covariates up to time *k* and $\bar{A}_{k-1}$ is the treatment history through time $k-1$.

Since there are a total of 2^{17} (or 131,072) different possible treatment histories with a dichotomous treatment variable and seventeen treatment periods, it is necessary to impose some simplifying assumptions about the relationship between the treatment and the outcome (Wodtke et al. 2011). Therefore, following Wodtke et al. (2011), I estimate the effect of living in subsidized housing before age 18 on the probability of forming a household in subsidized housing after age 18 using a duration-weighted measure of the proportion of years that each child spent in subsidized housing before age 18, or $\sum_{k=1}^{17} \frac{a_k}{17}$. I fit the average effect of the treatment variable using a second-order polynomial of the form $\delta_1(\sum_{k=1}^{17} \frac{a_k}{17}) + \delta_2(\sum_{k=1}^{17} \frac{a_k}{17})^2$, as sensitivity analyses revealed that the treatment variable has a nonlinear relationship with the outcome. Therefore, the discrete time logistic regression of the probability of returning to subsidized housing as an adult takes the following form:

$$log\left(\frac{f_{it}}{1-f_{it}}\right) = \alpha_t + \delta_1\left(\sum_{k=1}^{17} \frac{a_k}{17}\right) + \delta_2\left(\sum_{k=1}^{17} \frac{a_k}{17}\right)^2 + \beta\bar{L}_i(0) + \lambda\bar{A}_{it} \tag{5}$$

where f_{it} is a binary variable equal to 1 if a respondent *i* forms their own household in subsidized housing at time t and 0 otherwise. The regression also includes a vector of childhood socioeconomic characteristics measured at birth, $\overline{L}_i(0)$, and a series of splines, $\overline{A}_{it}$, which fit the baseline hazard time parameter. As mentioned above household heads in subsidized housing are more likely to be African American and more likely to be female. Therefore, I implement all of my analyses separately by both race and gender.

Assumptions of IPTW models

It is important to note that all IPTW models have several strong assumptions that allow for the effects from these models to be interpreted as causal and for the coefficients in the models to be unbiased and consistent. First, IPTW models assume that children with the same combination of treatment histories up to time *k* and the same combination of observed baseline and time-varying covariates do not select into treatment based on unobserved factors that also predict the outcome (Cole and Hernán 2008; Robins et al. 2000). This assumption is also known in the causal literature as "exchangeability" or non-confounding on unobserved covariates (Cole and Hernán 2008; Robins et al. 2000). While in practice this assumption cannot be verified using observational data, all causal interpretations of the coefficients in my models hinge on having controlled for all baseline and time-varying covariates that predict the treatment.

Second, IPTW models assume that the model used to estimate the IPT weights and the censoring weights is correctly specified (Cole and Hernán 2008; Robins et al. 2000). As with the assumption of "exchangeability" described above, this assumption cannot be verified using observational data. Therefore, following Sampson et al. (2006), as a test of sensitivity to different model specifications, I also re-estimate my models using different combinations of the independent variables and omitting independent variables that have a p-value greater than 0.2.

These models do not produce substantively different results.

Third, IPTW models require that all subjects in the study have a non-zero probability of experiencing the treatment, also known as the "positivity" assumption (Cole and Hernán 2008; Robins, Hernán, and Brumback 2000). Therefore, it is important to estimate the IPT weights only from periods in childhood when a child was actually at risk of entering subsidized housing. HUD calculates the income limit by household size on a yearly basis, using the median family income within a metropolitan area or within the non-metropolitan portion of each state. HUD supplies official estimates of the income limits by family size only for the period 1991-2012. For years before 1991, I estimated the income limits within metropolitan and non-metropolitan areas using a procedure as close as possible to HUD's official estimates. HUD sets the income limit for a four-person household at 80% of the median family income within a metropolitan area or the remainder non-metropolitan area for a state. I used the 1960, 1970, 1980 and 1990 U.S. Census to compute the respective values of median family income for every metropolitan area in the US and for non-metropolitan parts of states. I used a linear interpolation to arrive at values between census years. Then, I multiplied the respective income limits by HUD's official family-size factors to arrive at the income limit by family size by metropolitan/non-metropolitan area. In my analysis, I only used children who lived in families that had total income under the respective HUD income limit. Therefore, my analyses estimate IPT weights given the treatment history of children who were actually eligible to enter subsidized housing.

Comparisons with conventional regression models

The advantage of IPTW models compared to conventional regression models is that they address problems that arise from estimating causal effects using time-varying treatments. As mentioned above, the treatment of receipt of a housing subsidy varies over time and is affected by prior time-varying covariates. However, once a child receives a housing subsidy, that treatment in turn affects future time-varying covariates and time-varying treatments. Therefore, at each period in childhood, stays in subsidized housing have both a direct effect on the outcome of receiving the subsidy as an adult and an indirect effect on the outcome through future levels of time-varying covariates (Robbins 1999; Hernán et al. 2000; Robins et al. 2000). Conventional regression models condition on these time-varying covariates, which are on the causal path between past treatment and the outcome. Therefore, conventional regressions over-control for the indirect pathways between past treatment and the outcome because they remove from the total effect of the treatment on the outcome the indirect effect of the treatment on the outcome that operates through time-varying covariates (Sampson et al. 2002).

The second problem with conventional regression models is that they condition on potential "collider" variables, which is also known as collider-stratification bias (Greenland 2003). "Collider" variables are time-varying covariates that are common effects of prior treatments and unobserved covariates. Conditioning on a collider produces an association between its common causes – the prior treatment and the unobserved covariates – even if that association does not exist (Pearl 1995, 2000). If unobserved covariates affect the outcome through time-varying observed covariates, conditioning on a time-varying observed covariate creates an association between the unobserved covariate and the outcome that biases the estimate of the effect of the treatment on the outcome.

In sum, conventional regression models fail to produce consistent and unbiased estimates of the effects of time-varying covariates on the outcome when these time-varying covariates are affected by past treatment. The solution to this problem does not simply involve modeling the outcome without taking account of time-varying covariates, as removing the effect of time-varying covariates on the association between the treatment and outcome produces biased estimates. What IPTW models do instead is to first estimate the probability that each person received the treatment that they received given past treatment history and time-varying covariates and use that probability to create a pseudo-population where under the assumptions described above the treatment behaves as if it were randomized at every age with respect to past treatment and past time-varying covariates. That pseudo-population can then be used to compare the effect of living in subsidized housing as a child on the outcome of returning to subsidized housing as an adult without the need to control for time-varying covariates. By separating the estimation of the treatment probability and the estimation of the effect of the treatment on the outcome, IPTW models, therefore, allow for the comparison between treated and untreated children without making distributional assumptions about the causal pathways between time-varying covariates and the outcome (Ko, Hogan, and Mayer 2003; Sampson et al. 2006).

RESULTS

Descriptive Statistics

Tables 1 and 2 describe my outcome variable, the distribution of duration weighted-spells in subsidized housing and the distributions of the baseline covariates in the models.[4] The covariates include socioeconomic characteristics associated with the household, the neighborhood, and the metropolitan area of each child and characteristics that may make some households more likely to participate in the subsidized housing program given the administrative rules of the program.

[Tables 1 and 2 about here]

The descriptive statistics show that 19 percent of black males and 32 percent of black females end up in subsidized housing after age 18 as a head of household given that they either were in subsidized housing before age 18 or were eligible for the program before age 18. The respective numbers for nonblack males and females are 10 percent and 13 percent. Black males and females also spend higher proportions of their childhoods in subsidized housing compared to nonblack males and females. Black males spend about 19 percent of their childhood in subsidized housing; black females spend about 22 percent; non-black children spend about 3 percent of their childhoods in subsidized housing. In addition, black children compared to white children come from slightly larger households, households with extended family members present, households with lower levels of total income but higher levels of transfer income. Black children are also more likely to come from neighborhoods with higher percent black neighbors, higher percent of people in poverty, higher percent of households receiving welfare, and higher percent of female-headed households.

IPTW models

Table 3 shows the discrete-time logistic regression results of being exposed to the treatment of subsidized housing given eligibility for receiving the subsidy disaggregated by race and gender. I use these models to estimate the denominator of the IPT weight. Models showing the estimation of the numerator of the IPT weight that do not include the time-varying covariates are available upon request.

[Table 3 about here]

The log odds in Table 3 show that previous treatment history – both recent subsidized housing receipt and cumulative subsidized housing receipt – is a large and statistically significant predictor of current subsidized housing receipt. Other variables in the logit regressions have the expected sign but are not always statistically significant. For example, having siblings of a different gender at time $k-1$ reduces the probability of being in subsidized housing at time k. Living in a household with a better educated head at time $k-1$ also reduces the probability of being in subsidized housing at time k. On the other hand, living in a household with a greater number of children under the age of 6 or participating in other government transfer programs such as food stamps or AFDC/TANF at time $k-1$ increases the probability of being in subsidized housing at time k.

[Table 4 about here]

Table 4 shows the distributions of the estimated stabilized treatment weights, stabilized censoring weights, and the product of the two that I use to weight the analyses linking the treatment to the outcome. The weights in Table 4 are the cumulative product of year-specific weights between age 1 and age 17. All weights have means close to one with small variances and approximately normal distributions. I implemented a sensitivity test of my results to the variance of the treatment weights by trimming the estimated weights at the 1st and 99th percentiles (Cole and Hernán 2008). Since the treatment effects did not change when using the trimmed distribution of the IPT weights, I present results that use the full distribution of the estimated weights.

Estimates of the Effect of Living in Subsidized Housing as a Child on Forming a Household in Subsidized Housing as an Adult

Figure 1 shows the smoothed baseline hazard of forming one's own household in subsidized housing after age 18. Black females have the largest hazard of forming their own households in subsidized housing followed by black males, white females, and white males. For all respondents, the shape of the hazard is about the same with a peak in the early to mid-twenties.

[Figure 1 about here]

Table 5 shows estimates of the discrete time logit regressions linking stays in subsidized housing as a child and returning to the program as an adult. All models in Table 5 use a series of splines to express parametrically the baseline hazard presented in Figure 1. In addition, all models in Table 5 include a series of baseline socioeconomic covariates measured at birth. As discussed above, the parameter of the duration-weighted stays in subsidized housing before age 18 is a second-order polynomial. For easier interpretations of the results and comparisons across race and gender, I converted the estimates from Table 5 into predicted probabilities. Figure 2 shows these predicted probabilities and associated standard errors over the distribution of the duration-weighted treatment parameter for black males and females. Figure 3 shows the respective probabilities for nonblack males and females.

[Table 5 about here]

Figure 2 shows that a black female who never was in subsidized housing as a child has about 5 percent probability of forming her own household in subsidized housing as an adult. On the other hand, a black female who spent her entire childhood in subsidized housing has about 8 percent probability of forming her own household in subsidized housing as an adult. The respective numbers for black males are 3 percent and 7 percent. Figure 2 also shows that for black females the probability of returning to subsidized housing tapers off for females who spent more than 60 percent of their childhood in subsidized housing. This non-linearity in the effect of living in subsidized housing as a child indicates that the cumulative effect of being in subsidized housing as a child is about the same for those black females who spent a majority of their childhood in subsidized housing.

[Figures 2 and 3 about here]

Figure 3, on the other hand, shows that non-black males and females who spent no time in subsidized housing in childhood have about 1.5 percent probability of returning to subsidized housing as an adult. The probability of returning to subsidized housing as an adult for both non-black males and females follows a similar shape as the probability for black females where the cumulative effect of living in subsidized housing tapers off at high values in the distribution. Please note, however, that for nonblack children, in particular, there are very few individuals who spent more than 80 percent of their childhoods in subsidized housing and that part of the distribution has large confidence intervals around it.

A different way to look at the probabilities in Figures 2 and 3 is to ask what the expected probability of return to subsidized housing is for an individual who spent the median amount of time in subsidized housing before age 18. In the PSID, the median length of stay in subsidized housing in childhood is seven years for black children and four years for non-black children. Therefore, a black female who spent 7 years of her childhood in subsidized housing has an expected probability of returning to subsidized housing of about 10 percent. The respective expected probabilities for black males, non-black males and non-black females are 4 percent, 5 percent, and 4 percent. Taken together, the estimates from Table 5 and the probabilities from Figures 2 and 3 show that children who spent time in subsidized housing are statistically more likely to return to the program as adults; however, the probability of returning to subsidized housing as a head of household exceeds 10 percent only for black females who spent more than 40 percent of their childhood in subsidized housing.

Sensitivity Analyses

I use several different sensitivity analyses to evaluate my treatment estimates. First, I exclude from my IPTW equation all variables that have a p-value of more than 0.2 to evaluate the possibility that I am over-controlling for factors that predict the probability of being in subsidized housing as a child (Sampson et al. 2006). Second, I trim the IPT weights at the 1st and 99th percentiles to explore the influence of outliers in the analysis (Cole and Hernán 2008). Third, I estimate the effect of subsidized housing using only the data matched to administrative records. As I mention above, there has been some concern over the quality of information obtained by asking respondents about their receipt of housing subsidies (Shroder and Martin 1996). Therefore, since the estimates from Table 5 come from both the administrative data and the self-reported data, it is important to evaluate how different these estimates are from ones that rely only on the administrative data of receipt of subsidized housing.

[Table 6 about here]

Table 6 shows a summary of the predicted probabilities of forming a household in subsidized housing after age 18 using the sensitivity analyses described above across the distribution of duration-weighted stays in subsidized housing in childhood. A majority of the predicted probabilities are very close to each other with the exception of some of the probabilities coming from the administrative data model. In the administrative data model, black females who spend their entire childhood in subsidized housing have lower probabilities of returning to subsidized housing as an adult. It is important to mention, however, that these probabilities in the administrative data model are estimated off of very few cases and have large confidence intervals around them since administrative data are available only through 1995, which significantly restricts the sample of children old enough to be at risk of forming their own households in subsidized housing. In sum, the results of my sensitivity analyses give me confidence that my conclusions hold under a different specifications of the treatment model, when outliers are trimmed from the distribution, and when I use data that only relies on the administrative portion of the PSID.

DISCUSSION

In this paper, I ask whether children who grow up in subsidized housing return to the program as adults. I use nationally representative longitudinal data and adopt the potential outcome approach using Inverse Probability of Treatment Weighting to compare children who lived in subsidized housing before age 18 and those who did not live in subsidized housing before age 18. I find that children who grow up in subsidized housing are more likely to return to the program as adults to form their own households. Nevertheless, the absolute probabilities of returning to subsidized housing as an adult are relatively small with the exception of the probabilities for black females who spend at least 40 percent (or about 7 years) of their childhoods in subsidized housing.

The main limitation to my findings being interpreted as causal as opposed to associational is the assumption of "exchangeability" based on observed covariates, which implies that I have adequately controlled for all covariates that influence the probability to be in subsidized housing in childhood. While this is not an assumption that is verifiable using observational data, it is crucial to interpreting the effects I find as causal as opposed to just associational. Even though I have access to extensive measures on family and neighborhood characteristics for every child in the PSID, it could still be the case that children who never were in subsidized housing are different in unmeasured ways from those who did have experience with the program. Any unmeasured family and neighborhood characteristics might be responsible for some of the statistically significant effects of subsidized housing.

Moreover, I assume that the treatment of subsidized housing is equivalent across children. This may very well not be the case if for example children who lived in a family using a housing voucher experienced better housing quality than children who lived in public housing. Unfortunately, the wording of the subsidized housing question in the PSID does not yet allow for long-term longitudinal comparisons between building-based subsidies and person-based subsidies.

Despite these limitations, my study is an important first step in understanding the implications of subsidized housing for the intergenerational transmission of disadvantage. I show that children who grew up in subsidized housing are statistically more likely to return to subsidized housing as adults not because their parents are providing housing for them but rather because these children grow up to form their own households in the subsidized housing program. The policy implications of these conclusions depend on the underlying mechanisms that link the subsidized housing program to the behaviors of children who grow up in it. On one hand, it could be the case that parents pass information to children regarding the process of entering subsidized housing. If that indeed is the mechanism that links parental and offspring receipt of subsidized housing, any policy that changes the participation rates of the parental generation would not change the participation rates in the children's generation, as children who grow up in subsidized housing would still have the informational advantage.

On the other hand, if subsidized parents are not able to transmit the needed human and social capital to the next generation because of their participation in the subsidized program, then the consequences of growing up in subsidized housing might be amenable to policy changes. Nevertheless, the specific policy changes would have to target the mechanism that produces the association in the receipt of subsidized housing between the parental and offspring generations. It could be the case that the program interferes with the transition to adulthood of children who grow up in subsidized housing by, for example, lowering the age of first birth or reducing the probability of high school graduation. It could also be the case that the geographic location of subsidized units in some of the most segregated neighborhoods with high percent poverty and unemployment (Newman and Schnare 1997) makes children less prepared for good job opportunities. If the first mechanism is at work that would imply changing the behaviors of children who grow up in subsidized housing. If the second mechanism is at work that would imply changing the geographic placement of subsidized units. Therefore, a valuable next step in this research is to test further the causality link between being in subsidized housing as a child and returning to the program as an adult and to investigate the specific life transitions, such as having a child at an early age or not being able to graduate from high school, which might link the receipt of the subsidy across generations.

Endnotes

1. Please note that I do not estimate the probability of living in subsidized housing at birth, as there are no appropriate lagged time-varying covariates to estimate that probability.

2. For a detailed explanation of how to compute the stabilized IPT weights and censoring weights within the Stata statistical package see Fewell et al. (2004).

3. Official annual Fair Market Rents are only available for the period 1983-2012. HUD sets the Fair Market Rent for a two-bedroom apartment at 40% of the median rent for recent movers. For metropolitan areas, the rent is set within the boundary of the respective metropolitan region. For non-metropolitan areas, the rent is set at 40% of the median rent for that particular state's non-metropolitan regions. For the period before 1983, I use the 1960, 1970, and 1980 decennial census public IPUMS files to arrive at metropolitan area Fair Market Rents, following HUD's procedure for calculating the cut-offs (HUD 2012). I used a linear interpolation to arrive at the values between census years.

4. The group of nonblack children is overwhelmingly non-Hispanic white. Even though the PSID has made an effort to fold in a sample of Latinos after 1990, their numbers are not large enough to warrant a separate group for analysis.

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REFERENCES

Antel, J. (1992). The Intergenerational transfer of welfare dependency: Some statistical evidence. *Review of Economics and Statistics*, 74(3), 467–473.

Aratani, Y. (2010). Public housing revisited: Racial differences, housing assistance, and socioeconomic attainment among low-income families. *Social Science Research*, 39, 1108-1125.

Austin, P.C. (2011). An introduction to propensity score methods for reducing the effects of confounding in observational studies. *Multivariate Behavioral Research*, 46, 399-424.

Barber, J.S., Murphy, S.A., & Verbitsky, N. (2004). Adjusting for time-varying confounding in survival analysis. *Sociological Methodology*, 34, 163-192.

Bartholomae, S., Fox, J. J., & McKenry, P. C. (2004). The legacy of welfare—economic endowments or cultural characteristics. *Journal of Family Issues*, 25(6), 783–810.

Cole, S.R., & Hernán, M.A. (2008). Constructing inverse probability weights for marginal structural models. *American Journal of Epidemiology*, 168, 656-664.

Currie, J., & Yelowitz, A. (2000). Are public housing projects good for kids? *Journal of Public Economics* 75, 99-124.

Duncan, G. J., Hill, M. S., & Hoffman, S. D. (1988). Welfare dependence within and across generations. *Science*, 239, 467–471.

Fewell, Z., Hernán, M.A., Wolfe, F., Tilling, K., Choi, H., & Sterne, J.A.C. (2004). Controlling for time-dependent confounding using marginal structural models. *The Stata Journal*, 4, 402-420.

Fitzgerald, J., Gottschalk, P., & Moffitt, R. (1998). An analysis of the impact of sample attrition on the second generation of respondents in the Michigan Panel of Income Dynamics. *Journal of Human Resources* 33, 300–343.

Garfinkel, I., & McLanahan, S. (1986). *Single mothers and their children: A new American dilemma*. Washington D.C.: The Urban Institute.

Gottschalk, P. (1992) The Intergenerational Transmission of Welfare Participation: Facts and Possible Causes. *Journal of Policy Analysis and Management*, 11(2), 254-272.

Gottschalk, P. (1996). Is the correlation in welfare participation across generations spurious? *Journal of Public Economics* 63, 1–25.

Greenland, S. (2003). Quantifying biases in causal models: Classical confounding vs collider-stratification bias. *Epidemiology,* 14, 300-306.

Harloe, M. (1995). The people's home? Social rented housing in Europe and America. Oxford: Blackwell Publishers.

Hernán, M.A., Brumback B., & Robins, J.M. (2000). Marginal structural models to estimate the causal effect of zidovudine on the survival of HIV-positive men. *Epidemiology,* 11, 561-570.

Jacob, B. (2004). Public housing, housing vouchers, and student achievement: Evidence from public housing demolitions in Chicago. *The American Economic Review*, 94(1), 233-258.

Ko, H., Hogan, J.W., & Mayer, K.H. (2003). Estimating causal treatment effects from longitudinal HIV natural history studies using marginal structural models. *Biometrics*, 59, 152-162.

Levine, P. B., & Zimmerman, D. J. (1996). The intergenerational correlation in AFDC participation: Welfare trap or poverty trap? Institute for Research on Poverty Discussion Paper #1100-96, July.

Lillard, L., & Panis, C. (1994). Panel attrition from the PSID: Household income, marital status, and mortality. Working paper series 94–16, Rand Labor and Population Program, Santa Monica, CA.

Lubell, J., Shroder, M., & Steffen, B. (2003). Work participation and length of stay in HUD-assisted housing. *Cityscape*, 6, 207–223.

McLanahan, S. (1985). Family structure and the reproduction of poverty. *American Journal of Sociology*, 90(4), 873–901.

Meyers, A., Cutts, D., Frank, D., Levenson, S., Skalicky, A., Heeren, T., Cook, J., Berkowitz, C., Black, M., Casey, P., & Zaldivar, N. (2005). Subsidized housing and children's nutritional status: Data from a multi-site surveillance study. *Archives of Pediatric Adolescent Medicine* 159, 551–556.

Meyers, A., Frank, D., Roos, N., Peterson, K., Casey, V., Cupples, A., & Levenson, S. (1995). Housing subsidies and pediatric undernutrition. *Archives of Pediatric and Adolescent Medicine* 149, 1079–1084.

Moffitt, R. (1983). An Economic Model of Welfare Stigma. *American Economic Review*, 1023-1035.

Morgan, S.L., & Todd, J.L. (2008). A diagnostic routine for the detection of consequential heterogeneity of causal effects. *Sociological Methodology*, 38, 231-281.

Murray, C. (1984). *Losing ground: American social policy 1950–1980*. New York: Basic Books.

Newman, S. (2008). Does housing matter for poor families? A critical summary of research and issues still to be resolved. *Journal of Policy Analysis and Management*, 27(4), 895-925.

Newman, S., & Harkness, J. (1999). The effects of welfare reform on housing: A national analysis. In S. Newman (Ed.), *The home front* (pp. 29–80). Washington, DC: The Urban Institute Press.

Newman, S., & Harkness, J. (2002). The long-term effects of public housing on self-sufficiency. *Journal of Policy Analysis and Management*, 21, 21–43.

Newman, S., & Schnare, A. (1997). ". . . and a suitable living environment": The failure of housing programs to deliver on neighborhood quality. *Housing Policy Debate*, 8, 703–741.

Newman, S., Holupka, C.S., & Harkness, J. (2009). The long-term effects of housing assistance on work and welfare. *Journal of Policy Analysis and Management*, 28(1), 81-101.

Pearl, J. (1995). Causal diagrams for empirical research. *Biometrika,* 82, 669-710.

Pearl, J. (2000). *Causality: Models, reasoning, and inference*. Cambridge, UK: Cambridge University Press.

Pepper, J. V. (1995). The intergenerational transmission of welfare receipt: A nonparametric bounds analysis. *Review of Economics and Statistics*, 82(3), 472–488.

Rank, M., & Cheng, L. (1995). Welfare use across generations: How important are the ties that bind. *Journal of Marriage and Family*, 57(3), 673–684.

Robins, J. (1999). Marginal structural models versus structural nested models as tools for causal inference." In E. Halloran (Ed.) *Statistical Models in Epidemiology* (pp. 95-134). New York: Springer-Verlag.

Robins, J. M., Hernán, M.A., & Brumback, B. (2000). Marginal structural models and causal inference in epidemiology. *Epidemiology,* 11, 550-560.

Sampson, R.J., Laub, J.H., & Wimer, C. (2006). Does marriage reduce crime? A counterfactual approach to within-individual causal effects. *Criminology*, 44(3), 465-508.

Sampson, R.J., Raudenbush, S., & Earls, F. (1997). Neighborhoods and violent crime: A multilevel study of collective efficacy. *Science*, 277, 918–924.

Shroder, M., & Martin, M. (1996). *New results from administrative data: Housing the poor, or what they don't know might hurt somebody*. Washington, DC: U.S. Department of Housing and Urban Development, Office of Policy Development and Research.

Solon, G., Corcoran, M., Gordon, R., & Larsen, D. (1988). Sibling and intergenerational correlations in welfare program participation. *Journal of Human Resources*, 23(3), 388–396.

U.S. Department of Housing and Urban Development. (2003). Public Housing Occupancy Guidebook. http://www.hud.gov/offices/pih/programs/ph/rhiip/phguidebooknew.pdf. Cited July 11, 2013.

U.S. Department of Housing and Urban Development. (2008). Characteristics of HUD-assisted renters and their units in 2003. http://www.huduser.org/portal/publications/pdf/Hud_asst_renters_report_p1.pdf. Cited May 15, 2012.

U.S. Department of Housing and Urban Development. (2012). Fair Market Rents. http://www.huduser.org/datasets/fmr.html. Cited December 15, 2012.

Vale, L. (2000). *From the puritans to the projects: Public housing and public neighbors.* Cambridge, MA: Harvard University Press.

Venkatesh, S. (2002). *American project: The rise and fall of a modern ghetto*. Cambridge, MA: Harvard University Press.

Wilson, W.J. (1987). *The truly disadvantaged: The inner city, the underclass, and public policy*. Chicago, IL: University of Chicago Press.

Wodtke, G.T., Harding, D.J., & Elwert, F. (2011). Neighborhood Effects in temporal perspective: The Impact of Long-Term Exposure to Concentrated Disadvantage on High School Graduation. *American Sociological Review*, 76(5), 713-736.

Table 1. Sample statistics (Blacks)

	Males		Females	
	Mean	St. Dev	Mean	St. Dev.
In subsidized housing after age 18 (as head of household)	0.185	0.388	0.320	0.467
Duration weighted spells in subsidized housing	0.194	0.286	0.217	0.298
Year enter risk set for entry into subsidized housing	1979	7.412	1979	7.541
Age enter risk set for entry into subsidized housing	1.722	2.406	1.891	2.589
Household structure (baseline)				
Sibling of different gender	0.527	0.500	0.552	0.498
Household size	5.062	2.476	5.188	2.526
Single-headed household	0.426	0.495	0.455	0.498
Number of children under age 6	1.947	1.137	1.980	1.159
Extended family members present	0.312	0.464	0.307	0.462
Education of household head (baseline)				
Less than 8th grade	0.161	0.368	0.194	0.396
Some high school	0.279	0.449	0.294	0.456
High School Diploma	0.297	0.457	0.276	0.447
Some college and above	0.263	0.440	0.236	0.425
Income (baseline)				
Family labor income (in '000s)	16.010	14.506	15.031	14.475
Family total income less than 30% MSA median	0.541	0.499	0.596	0.491
Family transfer income (in '000s)	3.906	5.886	4.227	6.090
Whether receiving food stamps	0.322	0.467	0.396	0.489
Whether receiving AFDC/TANF	0.167	0.373	0.184	0.388
Disability preventing work	0.108	0.311	0.103	0.304
Disability (not in universe)	0.124	0.329	0.120	0.326
MSA characteristics (baseline)				
Unemployment rate	6.017	2.420	6.212	2.597
Fair Market Rent	518.197	168.279	511.554	175.409
MSA population (baseline)				
Less than 250,000	0.065	0.246	0.058	0.233
250,000-500,000	0.181	0.386	0.183	0.387
500,000-1,000,000	0.075	0.264	0.068	0.251
1,000,000-5,000,000	0.463	0.499	0.462	0.499
5,000,000+	0.216	0.411	0.230	0.421
Neighborhood Characteristics (baseline)				
Percent non-Hispanic black	57.158	37.135	56.691	38.498
Percent in poverty	23.277	15.621	23.475	16.451
Percent unemployed	8.677	6.877	8.684	7.009
Percent receiving welfare	14.126	11.790	14.565	12.395
Percent female-headed households	33.507	21.379	33.593	21.825
Density of children	29.085	13.124	28.307	13.631
N	849		797	

Note: Statistics reported for children not lost to follow-up before age 18.

Table 2. Sample statistics (Non-blacks)

	Males		Females	
	Mean	St. Dev	Mean	St. Dev.
In subsidized housing after age 18 (as head of household)	0.095	0.294	0.126	0.332
Duration weighted spells in subsidized housing	0.034	0.125	0.033	0.127
Year enter risk set for entry into subsidized housing	1980	7.863	1980	8.007
Age enter risk set for entry into subsidized housing	2.933	3.647	2.878	3.651
Household structure (baseline)				
Sibling of different gender	0.446	0.497	0.471	0.499
Household size	4.223	1.425	4.178	1.428
Single-headed household	0.147	0.355	0.163	0.369
Number of children under age 6	1.619	0.966	1.577	0.968
Extended family members present	0.066	0.248	0.062	0.242
Education of household head (baseline)				
Less than 8th grade	0.082	0.274	0.076	0.264
Some high school	0.187	0.390	0.167	0.373
High School Diploma	0.297	0.457	0.261	0.440
Some college and above	0.434	0.496	0.497	0.500
Income (baseline)				
Family labor income (in '000s)	22.604	13.242	21.578	13.138
Family total income less than 30% MSA median	0.310	0.463	0.336	0.473
Family transfer income (in '000s)	2.272	4.605	2.964	5.519
Whether receiving food stamps	0.120	0.326	0.139	0.346
Whether receiving AFDC/TANF	0.047	0.212	0.051	0.220
Disability preventing work	0.069	0.254	0.061	0.240
Disability (not in universe)	0.099	0.299	0.092	0.289
MSA characteristics (baseline)				
Unemployment rate	5.673	2.278	5.658	2.217
Fair Market Rent	515.490	159.790	516.657	163.478
MSA population (baseline)				
Less than 250,000	0.103	0.304	0.112	0.315
250,000-500,000	0.122	0.328	0.114	0.318
500,000-1,000,000	0.109	0.312	0.136	0.343
1,000,000-5,000,000	0.281	0.450	0.271	0.445
5,000,000+	0.384	0.487	0.367	0.482
Neighborhood Characteristics (baseline)				
Percent non-Hispanic black	10.159	23.845	9.002	22.221
Percent in poverty	10.023	9.900	9.376	8.819
Percent unemployed	4.997	4.149	4.996	4.132
Percent receiving welfare	5.676	6.575	5.441	6.255
Percent female-headed households	14.182	12.712	13.896	11.874
Density of children	24.531	12.746	24.727	12.615
N	1038		1045	

Note: Statistics reported for children not lost to follow-up before age 18.

Table 3. Discrete-time logit regression of the probability of entering subsidized housing before age 18 by race and gender

	Black males		Black females		Non-black males		Non-black females	
Household composition (baseline)								
Sibling of different gender	0.015		0.324	**	0.461	*	0.553	*
	(0.114)		(0.120)		(0.233)		(0.274)	
Household size	0.055		0.001		0.065		-0.050	
	(0.033)		(0.034)		(0.081)		(0.082)	
Single-headed household	0.094		0.180		0.915	***	0.365	
	(0.133)		(0.142)		(0.233)		(0.243)	
Number of children under age 6	-0.135	*	-0.009		-0.205	*	0.072	
	(0.055)		(0.054)		(0.101)		(0.114)	
Extended family members present	-0.117		0.014		0.249		0.061	
	(0.141)		(0.139)		(0.324)		(0.262)	
Education of Head (baseline)								
Less than 8th grade	omitted		omitted		omitted		omitted	
Some high school	0.327	*	0.078		0.107		-0.000	
	(0.155)		(0.171)		(0.326)		(0.304)	
High School Diploma	0.301		0.204		0.599		-0.055	
	(0.181)		(0.191)		(0.351)		(0.356)	
Some college and above	0.086		0.022		0.317		-0.220	
	(0.173)		(0.197)		(0.391)		(0.377)	
Income (baseline)								
Family labor income (in '000s)	-0.003		0.011	*	0.020		0.003	
	(0.005)		(0.006)		(0.010)		(0.011)	
Total family income less than 30% of MSA median	-0.123		-0.045		0.224		0.276	
	(0.120)		(0.132)		(0.196)		(0.224)	
Family transfer income (in '000s)	0.005		0.008		0.044	*	0.004	
	(0.009)		(0.010)		(0.021)		(0.016)	
Whether receiving food stamps	0.146		0.036		-0.180		-0.155	
	(0.110)		(0.107)		(0.206)		(0.224)	
Whether receiving AFDC/TANF	-0.114		0.021		-0.058		0.141	
	(0.130)		(0.132)		(0.268)		(0.271)	
Disability preventing work	-0.015		0.087		-0.138		-0.614	*
	(0.156)		(0.159)		(0.282)		(0.309)	
Disability (not in universe)	-0.416	*	0.125		-0.213		-0.156	
	(0.178)		(0.176)		(0.312)		(0.324)	
MSA population (baseline)								
More than 5,000,000	omitted		omitted		omitted		omitted	

Less than 250,000	-0.255		-1.366	***	-0.144		-0.493	
	(0.339)		(0.386)		(0.464)		(0.404)	
250,000-500,000	-0.390		-1.167	**	-0.299		-0.335	
	(0.317)		(0.356)		(0.584)		(0.473)	
500,000-1,000,000	0.378		-0.758	*	-0.510		0.069	
	(0.349)		(0.324)		(0.628)		(0.405)	
1,000,000-5,000,000	0.188		-0.997	***	-0.199		-0.945	**
	(0.273)		(0.251)		(0.372)		(0.364)	
<u>MSA characteristics (baseline)</u>								
Unemployment rate	-0.016		0.023		0.027		-0.030	
	(0.032)		(0.029)		(0.055)		(0.052)	
Fair Market Rent	-0.000		0.000		-0.001		0.000	
	(0.000)		(0.000)		(0.001)		(0.001)	
<u>Neighborhood Characteristics (baseline)</u>								
Percent non-Hispanic black	0.002		0.003		-0.005		-0.012	*
	(0.002)		(0.002)		(0.005)		(0.005)	
Percent in poverty	0.019	*	0.012		0.037	*	0.013	
	(0.008)		(0.008)		(0.016)		(0.023)	
Percent unemployed	0.018		0.026		-0.004		0.038	
	(0.016)		(0.017)		(0.038)		(0.040)	
Percent receiving welfare	-0.038	**	-0.050	***	-0.036		-0.038	
	(0.012)		(0.011)		(0.024)		(0.025)	
Percent female-headed households	0.001		0.012		-0.007		0.020	
	(0.006)		(0.007)		(0.016)		(0.015)	
Density of children	-0.006		-0.003		-0.003		0.004	
	(0.007)		(0.007)		(0.011)		(0.010)	
<u>Household composition (k-1)</u>								
Sibling of different gender	-0.054		-0.378	**	-0.402		-0.373	
	(0.122)		(0.123)		(0.268)		(0.282)	
Household size	-0.062		-0.059		-0.013		-0.164	
	(0.041)		(0.040)		(0.097)		(0.124)	
Single-headed household	-0.368	**	0.045		-0.218		-0.209	
	(0.130)		(0.138)		(0.235)		(0.273)	
Number of children under age 6	0.255	***	0.295	***	0.197		0.189	
	(0.048)		(0.053)		(0.117)		(0.101)	
Extended family members present	-0.115		0.170		0.008		0.207	
	(0.131)		(0.135)		(0.340)		(0.393)	
<u>Education of Head (k-1)</u>								
Less than 8th grade	omitted		omitted		omitted		omitted	
Some high school	-0.029		-0.073		0.021		-0.262	

	(0.166)		(0.198)		(0.367)		(0.300)	
High School Diploma	-0.113		-0.087		-0.051		-0.355	
	(0.181)		(0.219)		(0.348)		(0.363)	
Some college and above	-0.046		-0.088		-0.098		-0.339	
	(0.174)		(0.210)		(0.414)		(0.371)	
<u>Income (k-1)</u>								
Family labor income (in '000s)	0.012	*	0.015	**	0.007		0.007	
	(0.005)		(0.005)		(0.004)		(0.006)	
Family total income less than 30% MSA median	-0.086		0.291	*	-0.353		-0.098	
	(0.114)		(0.119)		(0.187)		(0.195)	
Family transfer income (in '000s)	0.003		0.007		-0.028		-0.004	
	(0.007)		(0.006)		(0.020)		(0.012)	
Whether receiving food stamps	0.209		0.267	*	0.547	**	0.314	
	(0.129)		(0.114)		(0.196)		(0.252)	
Whether receiving AFDC/TANF	0.134		-0.125		0.625	*	0.164	
	(0.149)		(0.148)		(0.287)		(0.290)	
Disability preventing work	-0.096		-0.103		-0.088		-0.302	
	(0.151)		(0.147)		(0.280)		(0.356)	
Disability (not in universe)	1.091	***	0.732	*	1.881	***	1.195	*
	(0.275)		(0.305)		(0.478)		(0.510)	
<u>MSA population (k-1)</u>								
More than 5,000,000	omitted		omitted		omitted		omitted	
Less than 250,000	0.105		1.339	**	-0.155		-0.309	
	(0.439)		(0.409)		(0.521)		(0.411)	
250,000-500,000	0.262		1.146	**	-0.203		-0.433	
	(0.348)		(0.353)		(0.600)		(0.498)	
500,000-1,000,000	-0.270		0.785	*	-0.483		-0.649	
	(0.350)		(0.330)		(0.652)		(0.448)	
1,000,000-5,000,000	0.002		0.589	*	-0.298		-0.203	
	(0.280)		(0.246)		(0.372)		(0.346)	
<u>MSA characteristics (k-1)</u>								
Unemployment rate	-0.038		-0.051		0.057		0.109	*
	(0.026)		(0.031)		(0.044)		(0.050)	
Fair Market Rent	-0.000		0.001	*	0.001		0.000	
	(0.000)		(0.000)		(0.001)		(0.000)	
<u>Neighborhood Characteristics (k-1)</u>								
Percent non-Hispanic black	-0.010	***	-0.013	***	0.006		0.001	
	(0.003)		(0.003)		(0.007)		(0.007)	
Percent in poverty	-0.014		-0.015		-0.011		-0.026	
	(0.008)		(0.008)		(0.020)		(0.028)	
Percent unemployed	-0.068	***	-0.075	***	-0.103	**	-0.002	

	(0.015)		(0.016)		(0.037)		(0.038)	
Percent receiving welfare	0.055	***	0.056	***	0.024		0.003	
	(0.012)		(0.012)		(0.030)		(0.028)	
Percent female-headed households	0.020	**	0.031	***	0.025		0.028	
	(0.007)		(0.008)		(0.015)		(0.018)	
Density of children	0.009		-0.005		0.022		-0.012	
	(0.008)		(0.009)		(0.013)		(0.013)	
Subsidized housing								
In subsidized housing (k-1)	4.097	***	3.966	***	4.179	***	4.200	***
	(0.112)		(0.127)		(0.235)		(0.382)	
Cumulative years in subsidized housing up to (k-1)	0.203	***	0.218	***	0.415	***	0.475	***
	(0.023)		(0.022)		(0.085)		(0.136)	
Year enter risk set for entry into subsidized housing	0.063	***	0.061	***	0.083	***	0.040	*
	(0.011)		(0.012)		(0.017)		(0.020)	
Age enter risk set for entry into subsidized housing	-0.087		-0.149	**	-0.076		0.016	
	(0.048)		(0.048)		(0.042)		(0.059)	
Time parameters								
Spline: Age 1-2	0.230	*	0.051		0.436	**	0.401	*
	(0.095)		(0.087)		(0.160)		(0.190)	
Spline: Age 3-5	0.085		0.131	**	-0.020		0.085	
	(0.048)		(0.049)		(0.079)		(0.092)	
Spline: Age 6-8	0.024		-0.020		-0.121		0.051	
	(0.054)		(0.057)		(0.107)		(0.117)	
Spline: Age 9-11	0.151	*	0.098		-0.003		0.070	
	(0.068)		(0.075)		(0.132)		(0.158)	
Spline: Age 12-14	-0.055		-0.047		0.381		0.076	
	(0.077)		(0.100)		(0.230)		(0.226)	
Spline: Age 15-17	0.031		-0.042		0.614		0.488	
	(0.161)		(0.172)		(0.353)		(0.399)	
Intercept	-128.351	***	-124.907	***	-171.817	***	-84.376	*
	(22.029)		(23.203)		(32.691)		(39.253)	
N person-years	10,030		9,756		7,179		7,532	
N individuals	849		797		1038		1,045	
X^2	3,746.36 64 d.f., p<.000		3,420.58 64 d.f., p<.000		1774.46 64 d.f., p<.000		1,966.44 64 d.f., p<.000	
Log-likelihood	-2248.40		-2189.80		-766.08		-720.72	

Notes: Numbers in parentheses are robust standard errors, adjusted for clustering of years within individuals.
* p <.05 ** p < .01 *** p < .001 (two-tailed tests)

Table 4. Stabilized treatment and censoring weights

			Percentiles			
Weight	Mean	St. Dev.	1st	25th	75th	99th
Black Males (n=849)						
Stabilized treatment weight (STW)	0.981	0.182	0.409	0.945	1.013	1.712
Stablizied censoring weight (SCW)	1.002	0.029	0.946	0.984	1.015	1.098
STWxSCW	0.983	0.187	0.408	0.938	1.021	1.742
Black Females (n=797)						
Stabilized treatment weight (STW)	1.005	0.342	0.317	0.938	1.012	2.843
Stablizied censoring weight (SCW)	1.002	0.029	0.946	0.984	1.015	1.098
STWxSCW	1.007	0.342	0.318	0.937	1.023	2.818
Non-black Males (n=1,038)						
Stabilized treatment weight (STW)	0.997	0.138	0.606	0.987	1.003	1.401
Stablizied censoring weight (SCW)	1.003	0.025	0.929	0.993	1.013	1.085
STWxSCW	1.000	0.140	0.606	0.983	1.014	1.446
Non-black Females (n=1,045)						
Stabilized treatment weight (STW)	0.995	0.092	0.651	0.990	1.003	1.182
Stablizied censoring weight (SCW)	1.003	0.025	0.929	0.993	1.013	1.085
STWxSCW	1.000	0.101	0.650	0.987	1.015	1.212

Table 5. Discrete-time logit regression of the probability of entering subsidized housing before age 18 by race and gender

	Black males		Black females		Non-black males		Non-black females	
Duration-weighted stay in subsidized housing before age 18	0.794		2.877	***	6.299	**	6.853	***
	(0.938)		(0.871)		(2.018)		(1.881)	
Duration-weighted stay (Squared)	0.137		-2.274	*	-5.756	*	-6.411	**
	(1.075)		(1.051)		(2.778)		(2.465)	
<u>Household composition (baseline)</u>								
Sibling of different gender	-0.042		0.108		-0.316		-0.534	*
	(0.212)		(0.165)		(0.278)		(0.227)	
Household size	-0.012		-0.017		0.119		0.074	
	(0.071)		(0.046)		(0.097)		(0.086)	
Single-headed household	-0.084		-0.290		-0.107		-0.260	
	(0.263)		(0.205)		(0.424)		(0.334)	
Number of children under age 6	0.019		0.051		-0.084		0.029	
	(0.119)		(0.083)		(0.145)		(0.142)	
Extended family members present	-0.263		-0.045		0.231		-0.310	
	(0.281)		(0.202)		(0.431)		(0.456)	
<u>Education of Head (baseline)</u>								
Less than 8th grade	omitted		omitted		omitted		omitted	
Some high school	0.205		0.292		0.116		-0.041	
	(0.285)		(0.204)		(0.375)		(0.378)	
High School Diploma	-0.051		0.037		-0.002		-0.090	
	(0.312)		(0.221)		(0.375)		(0.385)	
Some college and above	-0.642		-0.051		-0.401		0.043	
	(0.343)		(0.259)		(0.393)		(0.381)	
<u>Income (baseline)</u>								
Family labor income (in '000s)	-0.024	*	0.011		-0.005		0.032	
	(0.011)		(0.011)		(0.015)		(0.017)	
Total family income less than 30% of MSA median	-0.079		0.554	*	-0.260		0.832	**
	(0.218)		(0.224)		(0.323)		(0.301)	
Family transfer income (in '000s)	-0.025		-0.003		-0.041		0.036	
	(0.022)		(0.019)		(0.041)		(0.026)	
Whether receiving food stamps	0.335		-0.090		0.325		0.679	*
	(0.216)		(0.166)		(0.389)		(0.289)	
Whether receiving AFDC/TANF	-0.298		0.256		0.616		-0.418	
	(0.280)		(0.229)		(0.482)		(0.417)	
Disability preventing work	-0.266		0.102		-0.400		-0.402	
	(0.302)		(0.246)		(0.484)		(0.479)	

Disability (not in universe)	-0.258		-0.037		-0.278		0.325	
	(0.268)		(0.203)		(0.340)		(0.302)	
MSA population (baseline)								
More than 5,000,000	omitted		omitted		omitted		omitted	
Less than 250,000	-0.406		0.269		-0.738		0.478	
	(0.428)		(0.355)		(0.482)		(0.298)	
250,000-500,000	-0.339		0.041		-0.016		0.361	
	(0.358)		(0.287)		(0.380)		(0.321)	
500,000-1,000,000	-0.268		0.856	**	0.132		0.194	
	(0.423)		(0.294)		(0.393)		(0.320)	
1,000,000-5,000,000	-0.191		0.128		0.206		-0.133	
	(0.308)		(0.231)		(0.306)		(0.296)	
MSA characteristics (baseline)								
Unemployment rate	-0.009		0.032		0.014		0.035	
	(0.056)		(0.042)		(0.056)		(0.055)	
Fair Market Rent	-0.000		-0.001		0.001		-0.000	
	(0.001)		(0.001)		(0.001)		(0.001)	
Neighborhood Characteristics (baseline)								
Percent non-Hispanic black	-0.003		0.006		-0.008		0.008	
	(0.004)		(0.003)		(0.005)		(0.006)	
Percent in poverty	0.002		-0.001		0.012		0.035	
	(0.013)		(0.011)		(0.024)		(0.020)	
Percent unemployed	0.005		0.014		0.071		-0.008	
	(0.028)		(0.023)		(0.051)		(0.036)	
Percent receiving welfare	-0.006		0.002		-0.009		0.001	
	(0.019)		(0.016)		(0.035)		(0.026)	
Percent female-headed households	0.001		-0.005		-0.024		-0.009	
	(0.011)		(0.010)		(0.019)		(0.016)	
Density of children	0.013		-0.013		-0.013		-0.017	
	(0.011)		(0.009)		(0.012)		(0.010)	
Subsidized housing								
Year enter risk set for entry into subsidized housing	0.038		0.027		-0.039		-0.024	
	(0.025)		(0.019)		(0.029)		(0.024)	
Age enter risk set for entry into subsidized housing	-0.021		-0.058		0.023		0.080	
	(0.049)		(0.048)		(0.052)		(0.047)	
Time parameters								
Spline: Wave 1-2	0.413	*	0.444	***	0.766	***	0.296	*
	(0.167)		(0.108)		(0.218)		(0.145)	
Spline: Wave 3-5	0.376	***	0.063		-0.046		-0.078	
	(0.100)		(0.081)		(0.121)		(0.105)	
Spline: Wave 6-8	-0.108		-0.087		-0.239		-0.356	*

	(0.119)	(0.127)	(0.172)		(0.165)
Spline: Wave 9-11	-0.216	0.001	-0.708	*	-0.209
	(0.204)	(0.212)	(0.355)		(0.209)
Spline: Wave 12-14	-0.510	-0.008	0.713	*	0.397
	(0.619)	(0.266)	(0.360)		(0.211)
Spline: Wave 15-17	0.516	0.408			-0.070
	(0.277)	(0.362)			(0.631)
Intercept	-78.210	-58.772	70.378		41.886
	(49.678)	(38.310)	(57.389)		(46.907)
N person-years	4,401	4,005	6,691		6,286
N individuals	849	797	1,038		1,045
X^2	106.09 37 d.f., p<.000	103.30 37 d.f., p<.000	86.30 37 d.f., p<.000		185.82 37 d.f., p<.000
Log-likelihood	-632.05	-934.21	-482.79		-585.15

Notes: Numbers in parentheses are robust standard errors, adjusted for clustering of years within individuals.
* p <.05 ** p < .01 *** p < .001 (two-tailed tests)

Table 6. Predicted probabilities of forming a household in subsidized housing after age 18

	Duration-weighted stay in subsidized housing in childhood	Model from Table 5	Select variables	Trimmed weights	Only administrative data
Black males	0	0.030	0.030	0.030	0.008
	0.25	0.037	0.036	0.037	0.020
	0.5	0.046	0.044	0.046	0.042
	0.75	0.057	0.057	0.058	0.076
	1	0.072	0.077	0.074	0.119
Black females	0	0.049	0.049	0.050	0.012
	0.25	0.083	0.084	0.083	0.074
	0.5	0.108	0.107	0.108	0.145
	0.75	0.109	0.104	0.113	0.107
	1	0.085	0.077	0.095	0.027
White males	0	0.013	0.013	0.013	n.a.
	0.25	0.043	0.037	0.043	
	0.5	0.067	0.054	0.075	
	0.75	0.055	0.044	0.073	
	1	0.023	0.019	0.040	
White females	0	0.018	0.018	0.018	0.005
	0.25	0.062	0.065	0.064	0.044
	0.5	0.098	0.106	0.100	0.059
	0.75	0.076	0.085	0.074	0.013
	1	0.028	0.032	0.024	0.0003

Notes: Analyses based on children not lost to follow-up before age 18. Only 27 out of 813 white males return to subsidized housing in adulthood in the administrative data models; therefore, there are not enough data to estimate the respective logistic models for white males.

Figure 1. Smoothed hazard estimates of forming a household in subsidized housing by age

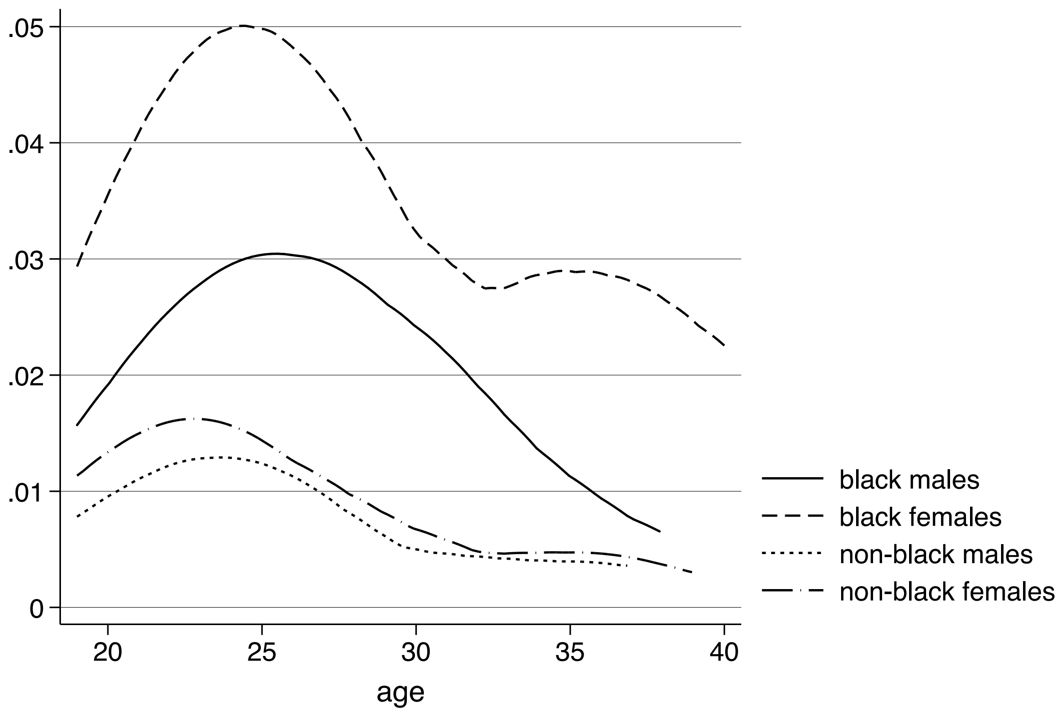

Figure 2. Predicted probabilities of forming a household in subsidized housing after age 18 by duration-weighted stays in subsidized housing before age 18 (Blacks)

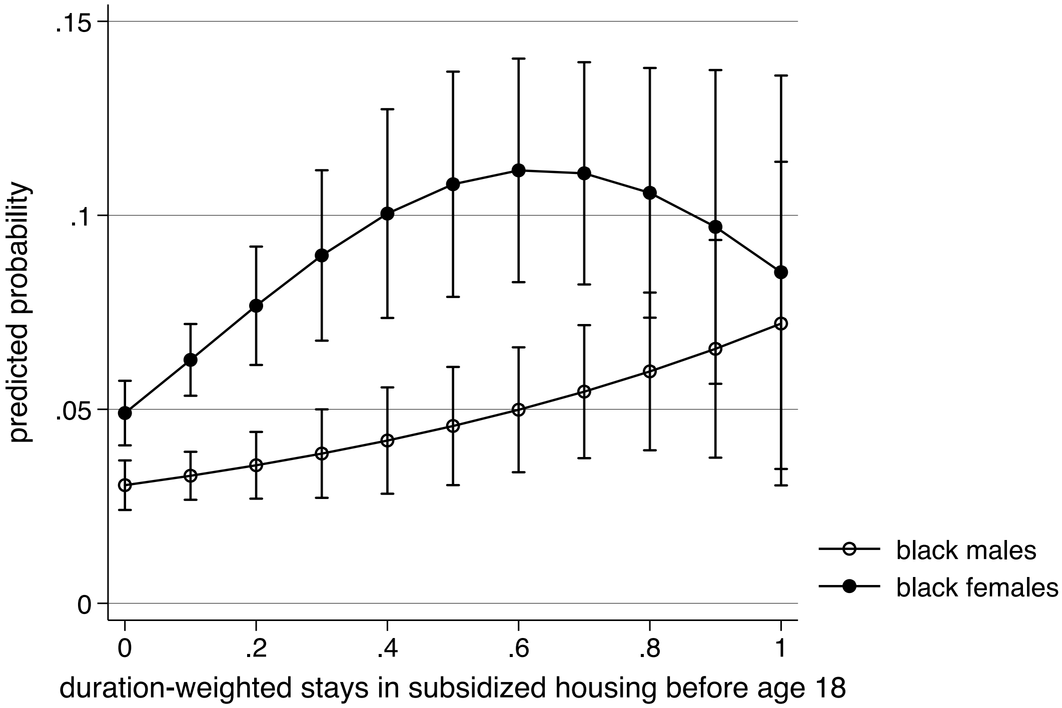

Figure 3. Predicted probabilities of forming a household in subsidized housing after age 18 by duration-weighted stays in subsidized housing before age 18 (Non-blacks)