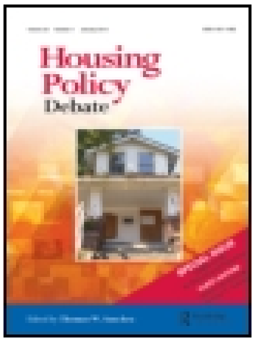

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Losing Your Home Is Bad for Your Health: Short- and Medium-Term Health Effects of Eviction on Young Adults

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ABSTRACT

U.S. cities are increasingly adopting antieviction policies predicated on the belief that evictions have negative consequences for families and communities. Yet the nature and duration of many of these consequences are relatively unknown. We add to the literature on the consequences of evictions by assessing the enduring effects of eviction on the self-reported health of young adults. Using the National Longitudinal Study of Adolescent to Adult Health (Add Health), we find evictions have both short-term (12 months) and medium-term (7–8 years) negative impacts on multiple measures of health. Individuals who experience an eviction are more likely to report being in poor general health or experiencing mental health concerns, even many years after an eviction. As state and local governments develop policies to reduce evictions, it is worth noting that any resulting decrease in evictions may have a positive impact on population health, making health professionals effective potential policymaking partners.

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eviction; health; housing policy; rental housing

Whereas involuntary mobility has been a concern of researchers for decades, until recently, the true scope of evictions in the United States was unknown. Groups such as Princeton University's Eviction Lab, the Anti-Eviction Mapping Project, and scholars examining narrower geographic regions answered Hartman and Robinson's (2003) call for a comprehensive eviction database, estimating more than 850,000 families[1] are evicted annually (The Eviction Lab, 2018). The advent of these new data sources as well as the success of Matthew Desmond's (2016) award-winning book *Evicted: Poverty and Profit in the American City* elevated evictions to the top of the agenda in many jurisdictions. Local governments raced to adopt policies to address the problem. Cities such as New York City adopted right-to-counsel laws, which provide lawyers to tenants facing eviction. More recently, San Jose, California, proposed halting evictions resulting from the COVID-19 virus, with many cities and states adopting similar policies shortly thereafter. These policies are predicated on the idea that evictions have negative consequences for the families who are forced to leave their homes. Without a clear counterfactual—an understanding of what happens when a family is evicted—it is difficult to evaluate how successful antieviction policies are at keeping families in their homes and preventing negative outcomes. Because of a paucity of data on evictions across multiple jurisdictions, the nature and duration of many consequences are relatively unclear.

A developing literature suggests eviction can lead to housing instability and homelessness (Kenna, Benjaminsen, Busch-Geertsema, & Nasarre-Aznar, 2018; Sandel et al., 2018), job loss (Desmond & Gershenson, 2016), criminal justice system involvement (Gottlieb & Moose, 2018), problems in school (Ersing, Sutphen, & Loeffler, 2009), and poor health. Housing instability, which can be caused by evictions among other factors, can lead to risky health behaviors as well as decreased adult and child mental and physical health. Families experiencing housing instability

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are more likely to delay medical care and medications (Ma, Gee, & Kushel, 2008) and less likely to have a healthcare provider (Kushel, Gupta, Gee, & Haas, 2006). Whereas much of the research examines housing instability and mobility broadly, a few studies investigate the health effects of evictions specifically. Counties with high eviction rates are more likely to have higher substance-use-related mortality rates (Bradford & Bradford, 2020). Desmond and Kimbro (2015) find mothers who were evicted are more likely to report poor health for themselves and their children, an effect that remains 2 years after the eviction. In fact, even the threat of eviction can lead to poor health (Vásquez-Vera et al., 2017). We build on this literature by assessing the short- and medium-term effects of eviction on the self-reported health of young adults.

We evaluate the relationship between eviction and health with the restricted-use version of the Longitudinal Study of Adolescent to Adult Health (Add Health) survey (Harris, 2009), which follows 15,701 children through four survey waves, starting when they were in grades 7–12 through early adulthood (when they are between 24 and 34 years old; Harris et al., 2009). We use data from more than 11,000 individuals in waves III and IV of the survey (when respondents were 18 to 27 years old and 24 to 34 years old, respectively), identifying whether the respondent experienced an eviction in the 12 months prior to each survey wave, and their health in wave IV. We measure health three ways: self-reported general health, the presence of two mental health disorders (depression and anxiety/panic disorder), and a composite of general and mental health. Using binary and multinomial logistic regression, we find that evictions are negatively associated with health in both the short term (12 months) and the medium term (7–8 years).[2] Whereas the relationship between poor health and a recent eviction is stronger than health and an eviction years ago, both types of eviction are associated with poorer general and mental health. When comparing the relationship between eviction and health by sex and race, we find evictions are generally associated with poor health more in the short term for White people and men, and more in the medium term for non-White people and women, suggesting the relationship between eviction and health is not homogeneous across demographic groups.

Our research provides evidence that evictions do more than force a family to move. Individuals who experience an eviction are more likely to report being in poor general health or experiencing mental health concerns, even 8 years after an eviction. As state and local governments develop policies to reduce evictions, it is worth noting that any resulting decrease in evictions may have a positive impact on population health. Therefore, advocates and decision makers in New York City, San Jose, California, and other jurisdictions concerned with addressing evictions in their community would do well to collaborate with the public health community to develop effective antieviction policies.

Eviction and Its Consequences

Eviction Definition and Prevalence

A formal eviction occurs when a family is compelled to leave their home through a court order. It may involve the forceable removal of their belongings from the premises, or the occupant may leave on their own after the court order. This is in contrast to informal evictions, which are much more common and do not involve the judicial system (Desmond, 2016). Landlords telling their tenant they will file an eviction with the courts if the tenant does not move out of the unit, changing the locks, or paying the tenant to leave are all forms of informal eviction. Thus, formal evictions are just one of several types of forced mobility (Hatch, 2020). When asked if they have ever been evicted, many families will say no unless they experienced a formal eviction ending in a court order, even if they have been informally evicted (Desmond, 2016). Therefore, most studies underestimate the true frequency of evictions.

Nonetheless, several studies approximate the prevalence of evictions in the United States. The Eviction Lab (2018) estimates a 2016 national eviction rate (evictions divided by renting households) of 2.34%. In their interview-based study of 128 African American families with low incomes in two cities, DeLuca, Wood, and Rosenblatt (2019) observe 7.2% of recent moves were because of an eviction. This rate is nearly identical to that found in another study in Milwaukee, Wisconsin, between 2003 and 2007, that estimated 1 in 14 renter households (7.1%) were evicted annually in predominantly Black inner-city neighborhoods. Consistent with the conclusion that families with children are more likely to be evicted (Desmond, An, Winkler, & Ferriss, 2013; Desmond & Gershenson, 2017), a study using the Fragile Families and Child Wellbeing Study estimates 1 in 7 children (more than 14%) born in large U.S. cities between 1998 and 2000 experienced at least one eviction by age 15 (Lundberg & Donnelly, 2019).

Families who are evicted are more likely to have low incomes (Hartman & Robinson, 2003). There are also racial disparities in eviction rates. Desmond (2012b) observes Black women with low incomes are more likely to be evicted than Black men or White individuals. This is consistent with other studies observing Hispanic and Black families are more likely than White families to move involuntarily (Holupka & Newman, 2011). There is also evidence of discrimination against Hispanic tenants in evictions (Greenberg, Gershenson, & Desmond, 2016). Therefore, whereas evictions happen in large numbers, certain demographic and economic factors—income, sex, race, and parental status—are associated with higher eviction rates, meaning eviction can increase existing socioeconomic inequalities.

Consequences of Eviction

Previously, the relative lack of accurate data on evictions and the problem of varying conceptions of what it means to be evicted led scholars to focus on housing instability broadly instead of evictions specifically. Therefore, much of what we know about the consequences of evictions are from assuming evictions have many of the same outcomes as housing instability. This is a reasonable assumption, because evictions often lead to housing instability and homelessness. In their study of more than 22,000 families interviewed at urban medical centers, Sandel et al. (2018) found 14% of families experiencing homelessness and 15% of families experiencing multiple moves had been evicted in the previous 5 years.

When facing an eviction, families may turn to their relatives (DeLuca et al., 2019) or informal disposable ties with people who were previously strangers (Desmond, 2012a, 2016) for new housing arrangements. The new neighborhoods that evicted families move to are likely to have higher crime rates, and its residents lower average incomes, than their previous neighborhood (Desmond & Shollenberger, 2015). Likewise, these families often move into lower quality homes (Desmond, 2016), which helps explain why these families are prone to move again soon (Desmond, Gershenson, & Kiviat, 2015).

The consequences of eviction are financial as well. Whereas financial stress may lead to the initiation of the eviction, the subsequent eviction may negatively impact a family's access to credit (Humphries, Mader, Tannenbaum, & van Dijk, 2019). In addition, individuals facing eviction are more likely to lose their job (Desmond & Gershenson, 2016). It should therefore come as no surprise that mothers report financial hardship even 2 years after an eviction (Desmond & Kimbro, 2015).

Evictions also take a social toll. Mothers who have been evicted are more likely to be involved in the criminal justice system (Gottlieb & Moose, 2018). This is consistent with research in Sweden that eviction is associated with higher crime conviction rates (Alm & Bäckman, 2020). Children also suffer the consequences of eviction. In general, children experiencing high rates of housing mobility are more likely to be disciplined in school and involved in child protective services (Ersing et al., 2009). Using the same survey data as this study, Fowler, Henry, and Marcal (2015) find housing instability in adolescence is associated with higher arrest rates.

Given these personal, financial, and social consequences, it is anticipated that housing instability and evictions lead to negative health outcomes. Families experiencing housing instability are more likely to report adult and child fair/poor health relative to families not facing housing instability (Sandel et al., 2018), whereas housing instability in adolescence increases the probability of depression in young adulthood (Fowler et al., 2015). Using the same data as this study, Grace et al. (2019) find youth homelessness is associated with a higher lifetime prevalence of mental health disorders. These relationships are likely partially explained by the relationship between housing instability and postponed medical care and medications (Kushel et al., 2006; Ma et al., 2008). In general, families experiencing housing instability are less prone to have a healthcare provider (Kushel et al., 2006).

Studies relating housing instability and health are consistent with Singh, Daniel, Baker, and Bentley's (2019) meta-analysis of 12 longitudinal studies, which finds a positive association between housing disadvantage and poor mental health. Veterans who are worried about having enough money to pay their rent or mortgage are more likely to express mental distress and suicidal ideation (Bossarte, Blosnich, Piegari, Hill, & Kane, 2013). In general, families with high rent burdens report worse health (Meltzer & Schwartz, 2016). Pfeiffer (2018) provides further evidence of this relationship with her observation that families with housing assistance spend less on healthcare than families with similar incomes but no housing assistance, suggesting housing stability and lower costs provide health benefits. In addition to cost burdens, low housing quality contributes to negative feelings of well-being and mental health (Marquez, Dodge Francis, & Gerstenberger, 2019).

Another branch of literature examines the relationship between housing foreclosure and health. In a study of people living in the United Kingdom, Pevalin (2009) observes homeowners who experienced a foreclosure were significantly more likely to report a mental illness. Perhaps counter-intuitively, the author does not find the same effect for a rental eviction. In the United States, Downing (2016) detects an association between foreclosure and anxiety. Inasmuch as foreclosure is a stressful financial and emotional experience, we might expect a similar effect from eviction.

The research on evictions and health, although less developed than the research on housing instability and health, also suggest a link between evictions and poor health. Although many of these studies are in the United States, scholars also observe relationships between evictions and health in Europe (Bolívar Muñoz et al., 2016; Kenna et al., 2018), India (Emmel & Souza, 1999), and Africa (Ochola, 1996), among other places. In a cross-national meta analysis, Vásquez-Vera et al. (2017) observe that even the threat of eviction has negative physical and mental health effects. Within the United States, high county eviction rates are associated with higher substance use-related mortality rates, an effect that is primarily driven by urban counties (Bradford & Bradford, 2020). The study most closely related to our research is Desmond and Kimbro (2015). Using a propensity score analysis of mothers with low incomes from urban areas from the Fragile Families and Child Wellbeing Study, the authors find that mothers who were evicted are more likely to report worse health for themselves and their children, an effect that lasts at least 2 years after the eviction. We also want to understand the relationship between eviction and health, but depart from Desmond and Kimbro (2015) by examining longer term health effects experienced by individuals who experienced eviction in early adulthood, rather than focusing solely on urban mothers and their children. Understanding this relationship will provide clarity regarding the health consequences of evictions specifically, rather than housing instability generally, on young adults.

Methodology

Data and Sample

We used data from waves I (n = 20,745), III (n = 15,197), and IV (n = 15,701) of Add Health (Harris, 2009) to evaluate the relationship between eviction and health in young adults. This longitudinal in-home interview survey follows a nationally representative sample of U.S. adolescents who were in grades 7 through 12 in 1994–1995 through early adulthood in 2008 when they were approximately 24 to 34 years old (Chen & Chantala, 2014; Harris et al., 2009). Our initial sample size was 13,034 respondents who were interviewed in wave I (1994–1995), wave III (2001–2001), and wave IV (2008). We used wave I for basic demographic information such as biological sex and race and previous self-reported general health, and waves III and IV for key dependent and independent variables. We did not include data from wave II in our sample because it was deployed only 1 year after wave I and therefore the variables we were interested in were either unlikely to have changed or did not exist. For example, wave II does not contain a question about eviction. We dropped 746 of the initial 13,034 observations because of the lack of sampling weights and an additional 774 observations because of missing variables. The total sample size for this research was 11,514 for all analyses except for the multinomial logistic regression, which was 11,513. This translates to a weighted sample size of 16,923,811.[3]

We chose to drop observations with missing data because multiple imputation with weighted data from complex surveys is problematic and may introduce bias (Kim, Brick, Fuller, & Kalton, 2006). However, as a robustness check, we repeated our analysis with multiple imputation for the missing variables and did not find substantively different results.[4]

Measures

Dependent Variable

Our dependent variables were measures of self-reported[5] general and mental health in early adulthood (ages 24-34) as measured in wave IV of the Add Health survey in 2008. Respondents answered a series of questions related to their health, on general health and diet, illness, medications, and physical disabilities. We constructed a measure of general health from responses to the question: *In general, how is your health?* Respondents could answer excellent, very good, good, fair, or poor. The survey also asked respondents about their mental health: *Has a doctor, nurse or other health care provider ever told you that you have or had depression?* and *Has a doctor, nurse or other health care provider ever told you that you have or had anxiety or a panic disorder?* To these questions, respondents simply answered yes or no.

Dependent Variable for Binary Logistic Regression. Our first analysis used binary logistic regression and a dichotomous dependent variable to measure the relationship between eviction and poor health. We used three dummy dependent variables to measure poor health: combined general and mental health, general health, and mental health. For combined general health and mental health, we coded respondents who indicated excellent, very good, or good on the general health question and no on the mental health questions (regarding depression and anxiety/panic disorder) as not having poor combined health. We coded respondents who marked fair or poor on the general health question or answered yes to either mental health question as having poor combined health. For the general health dependent variable, we coded respondents who indicated their general health was excellent, very good, or good as not having poor general health, and those who answered fair or poor as having poor general health. For the mental health variable, we coded respondents who answered no to both mental health questions as not having poor mental health, and those who answered yes to either or both mental health questions as having poor mental health. Thus, for each dependent variable, a 1 signifies poor health in that category and a 0 means the respondent did not have poor health.

Dependent Variable for Multinomial Logistic Regression. Although the binary logistic regressions allow us to examine the relationship between good/poor health and evictions, they may mask the relationship between eviction and various levels of health. To see gradations in general and mental health in relation to housing eviction, we next performed a multinomial logistic regression with three dependent variables: combined general and mental health, general health, and mental health.

Following Lopez (2004), we divided health into three groups: excellent, good, and poor. For the combined general and mental health dependent variable, we coded those respondents who answered excellent or very good on the general health question and no on both mental health questions (depression and anxiety/panic disorder) as having excellent combined general and mental health, those who responded good to the general health question and no to both mental health questions as having good combined general and mental health, and those who responded fair or poor on the general health question or yes on either mental health question as having poor combined general and mental health. For the categorical dependent variable general health, we coded respondents who answered excellent or very good to the general health question as having excellent general health, those who answered good as having good general health, and those who marked fair or poor as having poor general health. For mental health, we coded respondents who answered no to both the depression and anxiety/panic disorder questions as haing excellent mental health, those who indicated yes to one of the depression and anxiety/panic disorder questions as having good[6] mental health, and those who answered yes to both the depression and anxiety/panic disorder questions as having poor mental health.

Key Explanatory Variable: Eviction

Waves III and IV of the Add Health data measured whether respondents had recently experienced an eviction, our key explanatory variable. The survey asked respondents the following question: *In the past 12 months, was there a time when (you were/your household was) evicted from your house or apartment for not paying the rent or mortgage?* We coded respondents who answered yes as having been evicted and those answering no as not having been evicted. We included separate variables for eviction in wave III and wave IV to measure the medium- and short-term effects of eviction, respectively. Only three people in the unweighted sample were evicted in both waves III and IV. Curry (2017) also uses this variable in her study of the relationship between various measures of childhood mistreatment and adult housing insecurity, although she combines eviction with other housing insecurity variables because of the small sample size. We did not do that because eviction, rather than housing insecurity generally, is our variable of interest.

Control Variables

Drawing from the literature, we included several control variables associated with health. These covariates were biological sex and race (from wave I), previous self-reported general health (from wave I), health insurance (from wave III), educational attainment (from wave IV), and personal income (from waves III and IV). Previous research indicates women are more likely to report poor health than men (Franks, Gold, & Fiscella, 2003). Black and Hispanic people are more likely to report being in fair or poor health (Lopez, 2004), although the relationship between race and health may disappear after controlling for socioeconomic context (Bell, Thorpe, & LaVeist, 2018). Women, particularly women of color, are more likely to be evicted than men (Desmond, 2012b, 2016). Women may also be treated more leniently by the courts than men (Doerner & Demuth, 2014). Therefore, both race and sex are likely to affect the relationship between eviction and health. We coded biological sex as a dummy variable equal to 1 if the respondent was female and 0 if the respondent was male. Respondents were asked *What is your race?*, and we created a dummy variable for race equal to 1 if the respondent said they were White,[7] and zero otherwise. Although age is associated with health (Franks et al., 2003), we do not control for age because of the small age differences between respondents.

We constructed a measure of previous self-reported general health in wave I from responses to the following question: *In general, how is your health?* Respondents could answer excellent, very good, good, fair, or poor. Since there were no mental-health related questions in wave I, we measured only self-reported general health as the respondent's previous health. This variable is a proxy for overall childhood health. We coded respondents who answered excellent, very good, or good to the general health question in wave I as not having poor previous general health. We coded respondents who marked fair or poor on the general health question as having poor previous general health. We did not include health in wave II in the model because that wave of the survey was only 1 year after wave I; nor did we include health in wave III, because of its high and significant correlation with eviction in wave III. However, in models available upon request, we included health in wave III and the results did not change substantively.

We included whether the respondent had health insurance in our model because health insurance is associated with access to health services and consequently better health (Hoffman & Paradise, 2008; Nyman, 1999). The Add Health survey asked participants in wave III the question: *Which of the following best describes your current health insurance situation?* Response categories included no health insurance, covered by parents' insurance, covered by husband's or wife's insurance, get insurance through work, get insurance through school, covered because of active-duty military, buy private insurance yourself, on Medicaid, and covered through the Indian Health Service, and various iterations of don't know. We coded respondents who indicated their insurance was covered in any way as having insurance, and everyone else as not having insurance.[8] In wave IV, all respondents in our sample said they were covered by some form of insurance. Because of the lack of variation, we did not include insurance status in wave IV as a control variable in our models.

We measured educational attainment in wave IV, which was when respondents were approximately 24 to 34 years old. We included this variable as a control because less education is associated with fair/poor self-reported health (Lopez, 2004). The effects of education on health vary by income group (Schnittker, 2004), suggesting income or education alone would not be a sufficient control variable. We chose education in wave IV instead of education in wave III because we wanted to capture respondents' level of education at the time they were reporting their health, and because respondents were more likely to still be pursuing their education in wave III when they were approximately 18 to 27 years old than in wave IV when they were 24 to 34 years old. We created three groups from the possible answers: (a) less than high school, including 8th grade or less and some high school; (b) high school, including high school graduate, some vocational/technical training (after high school), completed vocational/technical training (after high school), and some college; and (c) bachelor's degree or more, including completed college (bachelor's degree), some graduate school, completed a master's degree, some graduate training beyond a master's degree, completed a doctoral degree, some post baccalaureate professional education (e.g., law school, med school, nurse), and completed post baccalaureate professional education (e.g., law school, med school, nurse). The reference group in our analysis was high school graduates.

We measured personal income in waves III and IV to capture financial resources when the respondent was evicted and reported their health. People with lower incomes are more likely to be evicted, relative to those with higher incomes (Desmond, 2012b; Hartman & Robinson, 2003). In addition, higher income is statistically associated with better health (Lopez, 2004). We constructed a measure of personal income from responses to the question: *How much income did you receive from personal earnings before taxes, that is, wages or salaries, including tips, bonuses, and overtime pay, and income from self-employment?* Respondents answered in dollars or in a range of dollars. To have the most complete data and the largest sample size possible, we first used the range data, supplemented with the dollar amounts which we fit into the ranges. We recoded categories to achieve equal intervals: less than \$10,000; \$10,000 to \$19,999; \$20,000 to \$29,999; \$30,000 to \$39,999; \$40,000 to \$49,999; and \$50,000 or more. Less than \$10,000 was our reference category. We included separate variables in our analyses for income in each survey wave. Another advantage of this variable is that it captures—although not perfectly[9]—unemployment. This is important because wave IV was in the middle of the Great Recession, where unemployment was high.

Statistical Analysis

We performed two main analyses in this research. First, we used binary logistic regression to examine the relationship between eviction and three health outcomes: combined general and mental health, general health, and mental health. The equation for this analysis is:

$$\text{Poor health}_{t2} = \beta_0 + \beta_1 \text{eviction}_{t1} + \beta_2 \text{eviction}_{t2} + \beta_3 X + \beta_4 \text{health}_{t1-2} + \beta_5 Z_{t2} + \beta_6 W_{t2} + \varepsilon \quad (1)$$

The dependent variable *poor health* is each health category where a 1 is poor health and a 0 is good health. The subscript *t1* represents variables from wave III, whereas the subscript *t2* represents variables from wave IV. The key explanatory variable is *eviction*, where the coefficient β_1 is the medium-term effect of eviction on health and β_2 is the short-term effect. *X* is a vector of time-invariant demographic information (whether the respondent is White or female), *Z* is a vector of control variables from wave III (no health insurance and personal income), and *W* is a vector of control variables from wave IV (personal income and educational attainment). *Health* is previous general health, taken from wave I. A value of 1 means poor health, whereas a value of 0 is good or excellent health. The error term is represented by ε, and β_0 is the intercept. The reference group is non-White males with a high school degree, good general health in wave I, health insurance in wave III, and personal income less than $10,000 in each survey wave, who did not experience a housing eviction in either wave.

Second, we used multinomial logistic regression to examine the relationship between evictions and the categorical dependent variables (combined general and mental health, general health, and mental health). The identification strategy was the same as for Equation (1), but with the dependent variable for each measure of health being two categories compared with a third reference group instead of two possible outcomes, as discussed in the section above on the Dependent Variable for Multinomial Logistic Regression. The reference dependent variable for the multinomial logistic regression is people in poor health.

As a preliminary subgroup analysis, we repeated the binary logistic regression adding interaction variables between sex and eviction and race and eviction to examine whether evictions have a differential effect on specific groups in both the medium and short term. We chose these two demographic characteristics because Black women are more likely than White individuals or Black men to be evicted (Desmond, 2012b). We included all four interaction terms in one model, but the results were generally substantively the same if we only included interactions for one demographic category (sex or race) in the model.

To avoid bias from oversampled groups (Harris et al., 2009), Add Health provides weights for each respondent. We used the cross-sectional weights for wave IV because the dependent variable was always from one wave of data, wave IV (Chen & Chantala, 2014; Curry, 2017). We also performed all the analyses without weights. The results were substantively the same, as shown in Appendix Tables A1 and A2.[10] We present the weighted analyses here to ensure unbiased coefficient and standard error estimates (Chen & Chantala, 2014).

Results

Sample Overview

Table 1 shows the summary statistics of the weighted sample. Our study was based on sample respondents who were interviewed in waves I, III, and IV of the Add Health. Whereas the unweighted sample size was 11,514, the weighted sample size was 16,923,811.[11] Of the 16.9 million individuals in the sample, 1.8% experienced housing eviction in wave III or wave IV. A weighted sample size of 9,137 observations (about 0.0005%) experienced eviction in both waves.

The weighted sample roughly reflects the general population: 49% were male and 51% were female. Twenty-five percent were non-White and 75% were White. In wave III, 25% reported not having insurance. About 92% had more than a high school diploma, with 32% having a bachelor's degree or more. In wave III (when respondents were 18 to 27 years old, and the average age was approximately 22), 54% of the weighted individuals earned less than $10,000 annually. Twenty-five percent earned in the range of $10,000 to $19,999, whereas 14% earned between $20,000 and $29,999. Only 6% earned $30,000 or more annually. In wave IV (when respondents were 24 to 34 years old, and the average age was approximately 28), 18% of the weighted sample earned less than $10,000 annually, 13% earned $10,000 to $19,999, 18% earned $20,000 to $29,999, 18% earned $30,000 to $39,999, 12% earned $40,000 to $49,999, and 20% earned $50,000 or more a year. The higher incomes in wave IV likely reflect an increase in education and work experience between the two waves.

Table 1. Summary statistics (weighted sample).

Variable	Mean	*SD*
Health-related indicators		
Multinomial logistic regression		
Combined general and mental health in wave IV		
Excellent health	0.48	1
Good health	0.25	1
Poor health	0.28	1
General health in wave IV		
Excellent health	0.58	1
Good health	0.33	1
Poor health	0.09	1
Mental health in wave IV		
Excellent health	0.78	1
Good health	0.14	1
Poor health	0.08	1
Binary logistic regression		
Combined general and mental health in wave IV		
(0 = excellent health, 1 = poor health)	0.28	1
General health in wave IV		
(0 = excellent health, 1 = poor health)	0.09	1
Mental health in wave IV		
(0 = excellent health, 1 = poor health)	0.22	1
General health in wave I		
(0 = excellent health, 1 = poor health)	0.07	1
No health insurance in wave III	0.25	1
(0 = insurance covered, 1 = no insurance)		
Housing eviction		
Evicted in wave III	0.01	0.10
(0 = no experience of eviction, 1 = experience of eviction)		
Evicted in wave IV	0.01	0.10
(0 = no experience of eviction, 1 = experience of eviction)		
Personal income in wave III		
Less than $10,000	0.54	0.50
$10,000 to $19,999	0.25	0.43
$20,000 to $29,999	0.14	0.34
$30,000 to $39,999	0.04	0.20
$40,000 to $49,999	0.02	0.13
$50,000 or more	0.01	0.11
Personal income in wave IV		
Less than $10,000	0.18	0.38
$10,000 to $19,999	0.13	0.34
$20,000 to $29,999	0.18	0.39
$30,000 to $39,999	0.18	0.39
$40,000 to $49,999	0.12	0.32
$50,000 or more	0.20	0.40
Demographics		
Less than a high school degree	0.08	0.27
High school degree	0.60	0.49
Bachelor's degree or more	0.32	0.47
White (0 = non-White, 1 = White)	0.75	0.43
Female (0 = male, 1 = female)	0.51	0.50

Note. SD = standard deviation. The all-weighted sample size in table was 16,923,811, except mental health for multinomial logistic regression which was 16,923,611.
The unweighted sample size was 11,514 (mental health for multinomial logistic regression sample size was 11,513).
The minimum was 0 and maximum was 1 for all variables.

Binary Logistic Analyses

We employed binary logistic regression (Equation 1) to analyze the relationship between evictions in two time periods and three measures of poor health (combined general and mental health, general health, and mental health). The results from the binary logistic regression are summarized in Table 2, with full results given in Appendix Table A3. The coefficients for each dependent variable are the changes in log odds of reporting poor health.

Column 1 shows the effect of a housing eviction experience on combined general and mental health. An eviction in wave III and an eviction in wave IV had significantly ($p < .01$) positive effects on the likelihood of early adulthood poor combined general and mental health. In other words, respondents who experienced housing eviction reported significantly poorer combined general and mental health than individuals who did not experience eviction. The coefficient of eviction in wave IV (which is a more recent experience) was larger than this experience in wave III, which is consistent with an eviction having a greater short-term than medium-term influence on health.

Column 2 shows the effect of housing eviction on poor general health, and column 3 displays the effect on poor mental health. The coefficients and significance levels for eviction in both waves are similar to those for combined general and mental health. It is worth noting the coefficient of eviction in wave III on poor general health (Column 2) was smaller than for combined poor general and mental health (Column 1) and poor mental health (Column 3), suggesting much of the medium-term effect of eviction on health was driven by mental health.

Across all three measures of poor health (see Columns 1–3 of Appendix Table A3), the effects of the control variables were nearly identical. Respondents without health insurance in wave III, with previous poor health in wave I, and with less than a high school education were generally more likely to report poor health. Respondents who reported education levels of a bachelor's degree or higher and higher incomes were less likely to report poor general health. An unexpected coefficient was race and sex. For general poor health (Column 2), being White was associated with a lower probability of poor general health, but being White was associated with higher levels of poor combined general and mental health (Column 1) and mental health (Column 3). For combined general and mental health (Column 1) and for mental health (Column 3), females were generally more likely to report poor health, which is similar to previous results in the literature; but females were less likely to report poor general health.

Multinomial Logistic Analyses

Multinomial logistic regression allowed us to compare excellent health with poor health (reference category) and good health with poor health, thus providing a fuller picture of the relationship between eviction and poor health (see Table 3 and the full results in Appendix Table A4). As in Table 2, Column 1 in Table 3 displays the effects of housing eviction on combined general and mental health, Column 2 is the dependent variable general health, and Column 3 is mental health. The base category in each case is poor health. Because this is a multinomial logistic regression, a positive coefficient indicates that

Table 2. Binary logistic regression.

	(1) Combined poor general and mental health	(2) Poor general health	(3) Poor mental health
Evicted in wave III	0.878***	0.372***	0.897***
	(0.005)	(0.007)	(0.005)
Evicted in wave IV	1.270***	1.100***	1.048***
	(0.005)	(0.006)	(0.006)
No health insurance in wave III	0.113***	0.254***	0.046***
	(0.001)	(0.002)	(0.001)
Poor general health in wave I	0.841***	1.119***	0.579***
	(0.002)	(0.002)	(0.002)

Note. The unweighted sample size was 11,514; the weighted sample size was 16,923,811.
All models include control variables and a constant term.
The reference group is non-White males with a high school degree, health insurance in wave III, good general health in wave I, and personal income less than $10,000 in each survey wave, who did not experience a housing eviction in either survey wave.
Standard errors are given in parentheses.
*$p < .1$. **$p < .05$. ***$p < .01$.

increasing that variable by one unit would increase the log odds of reporting being in excellent health relative to reporting poor health. Likewise, a negative coefficient would indicate thaat increasing that variable by one unit would decrease the log odds of reporting being in excellent health relative to poor health.

The first half of Table 3 shows the relationship between housing eviction and excellent health compared with poor health. The signs and significance of the coefficients for the key explanatory variable, eviction, were the same for all three measures of poor health, so we discuss them together. Respondents who said they had experienced an eviction were significantly ($p < .01$) less likely to report being in excellent health versus poor health. The effect size was larger for eviction in wave IV than eviction in wave III, once again indicating stronger short-term effects of evictions.

The second part of the multinomial logistic regression compares respondents who marked their health as good versus poor. The signs and significance ($p < .01$) of the key explanatory variable were the same across all three measures of poor health. As with the comparison between excellent and poor health in the first half of the table, respondents who reported an eviction in either wave were significantly less likely to report good health than poor health. This increase in log odds was greater for an eviction in wave IV than in wave III. As expected, the coefficients on the evicted variables were larger when comparing excellent health with poor health than when comparing good health with poor health. The relationships between the control variables and the measures of health are generally consistent with the results from Appendix Table A3 and the literature (see Appendix Table A4 for full results).

Subgroup Analysis

To examine whether evictions have a differential effect on specific groups in both the short and the medium term, we repeated the binary logistic regression, interacting race and sex with eviction in waves III and IV (see Table 4). The results are not consistent across all three measures of poor health,

Table 3. Multinomial logistic regression of eviction on poor health.

		(1) Combined general and mental health	(2) General health	(3) Mental health
Excellent	Evicted in wave III	− 0.977***	− 0.539***	− 0.988***
		(0.006)	(0.008)	(0.007)
	Evicted in wave IV	− 1.560***	− 1.660***	− 1.407***
		(0.007)	(0.007)	(0.007)
	No health insurance in wave III	− 0.182***	− 0.346***	− 0.129***
		(0.001)	(0.002)	(0.002)
	Poor general health in wave I	− 1.160***	− 1.497***	− 0.631***
		(0.002)	(0.003)	(0.003)
Good	Evicted in wave III	− 0.740***	− 0.214***	− 0.156***
		(0.007)	(0.007)	(0.008)
	Evicted in wave IV	− 0.967***	− 0.680***	− 0.628***
		(0.006)	(0.006)	(0.008)
	No health insurance in wave III	− 0.005***	− 0.138***	− 0.133***
		(0.002)	(0.002)	(0.003)
	Poor general health in wave I	− 0.468***	− 0.746***	− 0.083***
		(0.002)	(0.003)	(0.003)

Note. The unweighted sample size was 11,514 for combined general and mental health and only general health, and 11,513 for only mental health. The weighted sample size for combined general and mental health and only general health was 16,923,811, whereas it was 16,923,611 for only mental health.
All models include control variables and a constant term.
The reference group is non-White males with a high school degree, health insurance in wave III, good general health in wave I, and personal income less than $10,000 in each wave, who did not experience a housing eviction in either wave.
The reference dependent variable is people in poor health.
Standard errors are given in parentheses.
*$p < .1$. **$p < .05$. ***$p < .01$.

but there are general patterns. Being female or evicted in either wave was associated with a higher probability of having all three measures of poor health. Females who were evicted in wave III were even more likely ($p < .01$) to be in poor health. Females who were evicted in wave IV were less likely than their male counterparts to be in poor health, an effect that appears to be driven by poor general health, because females who were evicted in wave IV were more likely than males to express having poor mental health. This suggests eviction has a particularly strong negative medium-term effect on females, whereas the short-term negative effects of an eviction on health are less for women than for men.

Being White was associated with poor combined general and mental health and mental health, and with better reported general health, in comparison with non-White individuals. Across all three measures of poor health, White people who were evicted in wave IV were more likely to report poor health than their non-White counterparts. White individuals who were evicted in wave III were less likely to report being in poor combined general and mental health or poor general health, but more likely to report poor mental health. This suggests eviction has less of a medium-term impact on the health of White individuals but more of a short-term effect on health than for non-White individuals. Taken together, the subgroup analyses indicate the relationship between health and eviction likely varies across demographic groups.

Discussion and Conclusion

Hundreds of thousands of families in the United States are evicted every year. Women, families with children, Black families, families with low incomes, and families living in urban areas are more likely to be evicted than their counterparts (Desmond, 2012a, 2012b; Desmond et al., 2013; Hartman & Robinson, 2003; Lundberg & Donnelly, 2019), raising concerns that eviction exacerbates existing social and economic inequalities. Although increasing inequality alone is reason to be concerned about the scope of evictions, researchers find evictions are associated with myriad other negative housing (DeLuca et al., 2019; Desmond, 2016; Sandel et al., 2018), financial (Desmond & Gershenson,

Table 4. Binary logistic regression with interaction terms.

	(1) Combined poor general and mental health	(2) Poor general health	(3) Poor mental health
Evicted in wave III	1.051***	1.263***	0.657***
	(0.014)	(0.015)	(0.017)
Evicted in wave IV	1.280***	1.605***	0.271***
	(0.009)	(0.010)	(0.012)
White	0.503***	− 0.343***	0.934***
	(0.001)	(0.002)	(0.002)
Female	0.639***	0.032***	0.848***
	(0.001)	(0.002)	(0.001)
White evicted in wave III	− 0.302***	− 1.409***	0.270***
	(0.014)	(0.016)	(0.017)
White evicted in wave IV	0.385***	0.622***	0.829***
	(0.011)	(0.013)	(0.013)
Female evicted in wave III	0.139***	0.361***	− 0.006
	(0.011)	(0.014)	(0.011)
Female evicted in wave IV	− 0.479***	− 2.238***	0.476***
	(0.011)	(0.014)	(0.012)

Note. The unweighted sample size was 11,514; the weighted sample size was 16,923,811.
All models include control variables and a constant term.
The reference group is non-White males with a high school degree, health insurance in wave III, good general health in wave I, and personal income less than $10,000 in each survey wave, who did not experience a housing eviction in either survey wave.
Standard errors are given in parentheses.
*$p < .1$. **$p < .05$. ***$p < .01$.

2016; Desmond & Kimbro, 2015; Humphries et al., 2019), and social outcomes (Gottlieb & Moose, 2018). Of particular concern is the observed relationship between eviction and mental and physical health (Desmond & Kimbro, 2015; Vásquez-Vera et al., 2017). We ask what effect eviction has on three measures of health—combined general and mental, general, and mental—as well as whether those relationships lasted in the short term (12 months) and the medium term (7–8 years). Using the National Longitudinal Study of Adolescent to Adult Health (Add Health) and binomial and multinomial regression, we obtained three main findings. First, a housing eviction experience is negatively associated with general and mental health, increasing the likelihood of someone reporting poor health. Second, the relationship between health and eviction is greater for a recent eviction than an eviction years ago. Third, the negative association between evictions and health is greatest in the short term for White people and men and in the medium-term for non-White people and women.

These results add to the literature that uses stress proliferation models to explain the relationship between childhood experiences and adult health (Pearlin, Schieman, Fazio, & Meersman, 2005). Similarly to how children's and young adults' neighborhood influences their adult outcomes (Chetty, Hendren, Kline, & Saez, 2014; Ludwig et al., 2012), we find housing experiences in young adults are associated with their health years later. Both housing experiences and health are likely a reflection of specific events and the accumulation of factors over time. For example, family income in childhood, educational attainment, and adult wages all influence each other. Similarly, eviction could be a consequence of a challenging life course as well as a cause of future problems. Individuals who experienced housing eviction in both wave III and wave IV were more likely to describe their general and mental health as poor. Self-reported poor general health and depression or anxiety/panic disorders may have adverse effects on individuals' personal relationship with family or friends, their work, and their happiness. This is what Desmond (2016, p. 299) means when he writes "eviction is a cause, not just a condition, of poverty."

Although this study focused on evictions in the United States, our findings are relevant to other countries as well. Researchers have observed relationships between evictions and health and health-related behaviors in Europe (Bolívar Muñoz et al., 2016; Kenna et al., 2018), Canada (Pilarinos et al., 2017), India (Emmel & Souza, 1999), and Africa (Ochola, 1996). Our research suggests these relationships may be sustained even after the person finds a new home. Because the laws governing evictions, the prevalence of eviction, and the housing safety net vary among countries (Kenna et al., 2018), future research could take a comparative approach to see whether and to what extent these unique contexts act as protective forces against eviction and poor health.

This research is not without limitations. Because of data constraints, we only captured eviction experiences within a 1-year period of each survey wave. Thus, if a respondent experienced one or more evictions more than a year prior to the survey, but not in the prior 12 months, they would report not having been evicted. Combined with this is the problem that the definition of eviction is somewhat unclear, and often people do not think they were evicted unless they experienced a formal court eviction (Desmond, 2016), even though evictions are often informal or do not reach the stage of a court decision (Desmond, 2016; Hatch, 2020). These undercounts of evictions likely bias our results toward zero, because some eviction experiences will be recorded as not having experienced an eviction. This bias toward zero is a common problem in the literature evaluating the consequences of eviction (Desmond & Kimbro, 2015).

Another limitation of the Add Health data is that it does not collect housing-related information that would be useful for understanding the relationship between evictions and health. For example, there is no question about whether a person rents or owns the home they live in. If a person was evicted, we do not know how quickly they found a new place to live; we only know whether they were currently homeless (13 out of 11,514) in wave IV. People who experience longer spells of housing instability are likely to have poorer health than those who move to a home immediately. The question we use for eviction also includes evictions as a result of not paying a mortgage. Whereas a homeowner-related eviction is still a forceable removal from one's home, it is unknown whether the consequences of such an eviction are different than the consequences of an eviction from a rented home, although some research suggests they may be (Pevalin, 2009). There are public and private programs that work with homeowners to prevent foreclosure and that are not available to renters (and these programs were particularly active during the housing bubble burst and the foreclosure crisis). Thus, the financial situation leading to a foreclosure is likely different from the financial situation leading to an eviction, which may impact the consequences of the event. The Add Health data also do not include information about housing burden, which is associated with poor health and housing instability (Meltzer & Schwartz, 2016; Pfeiffer, 2018; Sandel et al., 2018).

The limitations and findings of this study suggest at least four possible future lines of research. First, to obtain a better understanding of the medium- and long-term effects of evictions, data regarding the eviction experience should be collected throughout the life course. Similarly, housing instability and homelessness should be evaluated in the same way. Housing instability can be measured by housing eviction as well as living in a high crime rate neighborhood, a low-income neighborhood, or a low-quality housing environment, or moving multiple times. The consequences of housing instability may change over the life course and may be influenced by the number of evictions and one's age at the time of eviction. Second, just as the causes and consequences of eviction are likely cumulative, eviction is actually a process rather than an event (Garboden & Rosen, 2019). Future research should explore the effects of the various stages of an eviction, as well as a series of eviction filings with or without the culmination of a formal eviction. Third, our research covers the beginning of the bursting of the housing bubble and foreclosure crisis in the United States: wave IV was in 2008 and asked about evictions in the previous year. Although we expected more evictions in wave IV than in wave III, the eviction rates remained relatively stable at less than 1% of the sample. This could be due to the timing of the Add Health survey, the age of the respondents, or policies aimed at protecting tenants when their landlords foreclosed. Research into this unexpected pattern may provide insight into other factors that prevent eviction. Fourth, the subgroup analyses suggest the relationship between eviction and health varies in the short term and medium term by demographic group. This relationship should be explored further, perhaps through qualitative methods, to determine what causes and consequences of evictions in particular affect women and people of color, who are more likely to be evicted.

Policymakers are rapidly developing policies to address evictions in their jurisdictions. This study provides further evidence of the negative and lasting consequences of evictions. Given the health implications, public health experts may be a good source of coalition-building and policy design ideas for those policymakers. It is clear that a wide variety of policies, including social and economic policies, impact public health (Rigby & Hatch, 2016), and evictions are an important addition to the health-in-all-policies agenda. As policymakers adopt policies such as right to counsel in eviction cases, future research should evaluate these policies along a variety of dimensions, including health. In general, there is a need for systematic evaluation of antieviction policies, because evidence what of what works is scant (Holl, van den Dries, & Wolf, 2016). Our research indicates that when thinking about what works, evaluators should consider the short- and medium-term health effects of evictions and prevented evictions on young adults. By focusing on eviction, we do not mean to imply that it is the only aspect of housing that affects health. Rather, we agree with Baker et al. (2017) that a broad approach to housing is necessary to improve public health. Housing and public health experts need to work together to solve these serious problems.

Notes

1. Throughout this article, we use *families* synonymously with *households* and *individuals*.
2. This duration is 7–8 years because wave III was in 2001–2002 and wave IV (when we measure health) was in 2008, making a range of 6–7 years. The question asked about evictions in the previous 12 months, increasing that range to 7–8 years.
3. The weighted sample size is the same for all analyses except the multinomial logistic regression of mental health, where it is 16,923,611. The sample sizes for the multinomial logistic regression vary because one unweighted observation did not respond to the question about depression and had to be dropped from the analysis.

4. The effects of the eviction variables in both waves and most of the control variables are nearly identical in our preferred model specifications and in the robustness check using multiple imputation.
5. Despite concerns that self-reported measures of health are too subjective, researchers often use self-reports as predictors of future health care and mortality rates (Idler & Benyamini, 1997).
6. We are not implying it is normatively good to have depression or anxiety/panic disorder. Rather, we use the word *good* here to be consistent with our other variables, and it should only be taken as a middle category between excellent and poor health.
7. Add Health does not distinguish between Hispanic White and non-Hispanic White.
8. We included people who said they did not know if they had insurance as not having insurance. In another analysis not shown here, we dropped all 128 unweighted observations with an ambiguous answer to the insurance question and got substantively similar results.
9. Personal income is not a perfect measure of unemployment because a person may not be employed the entire year and/or would receive unemployment benefits, which may be included in this variable. However, individuals who are unemployed for at least part of the previous year are likely to generally have lower incomes than individuals with jobs the entire year.
10. The observed relationship between housing eviction and health without weights is largely similar to that of the analysis with weights, with two exceptions. Eviction in wave III is only statistically significant at $p < .10$ for the unweighted binary regression with mental health as the dependent variable. Most variables related to personal income in wave III and wave IV and educational attainment were not significant in the unweighted analysis. Add Health oversampled Black adolescents with parents having education levels of more than a bachelor's degree, which might explain the observed differences between children's income and education and health when using the unweighted data (Chen & Chantala, 2014; Harris et al., 2009).
11. The weighted sample size was the same for all analyses except mental health for multinomial logistic regression, which was 16,923,611.

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Appendices

Table A1. Binary logistic regression (unweighted).

	(1) Combined poor general and mental health		(2) Poor general health		(3) Poor mental health	
	Weighted	Unweighted	Weighted	Unweighted	Weighted	Unweighted
Evicted in wave III	0.878***	0.527***	0.372***	0.462*	0.897***	0.384*
	(0.005)	(0.203)	(0.007)	(0.260)	(0.005)	(0.218)
Evicted in wave IV	1.270***	0.938***	1.100***	0.881***	1.048***	0.934***
	(0.005)	(0.215)	(0.006)	(0.245)	(0.006)	(0.225)
No health insurance in wave III	0.113***	0.137***	0.254***	0.224***	0.046***	0.080
	(0.001)	(0.052)	(0.002)	(0.074)	(0.001)	(0.058)
Poor general health in wave I	0.841***	0.721***	1.119***	1.118***	0.579***	0.347***
	(0.002)	(0.077)	(0.002)	(0.090)	(0.002)	(0.086)

Note. The unweighted sample size was 11,514.
All models include control variables and a constant term.
The reference group is non-White males with a high school degree, health insurance in wave III, good general health in wave I, and personal income less than $10,000 in each survey wave, who did not experience a housing eviction in either survey wave.
Standard errors are given in parentheses.
*$p < .1$. **$p < .05$. ***$p < .01$.

Table A2. Multinomial logistic regression of eviction on poor health (unweighted).

		(1) Combined general and mental health		(2) General health		(3) Mental health	
		Weighted	Unweighted	Weighted	Unweighted	Weighted	Unweighted
Excellent	Evicted in wave III	− 0.977***	− 0.524**	− 0.539***	− 0.542*	− 0.988***	− 0.560*
		(0.006)	(0.230)	(0.008)	(0.281)	(0.007)	(0.290)
	Evicted in wave IV	− 1.560***	− 1.249***	− 1.660***	− 1.345***	− 1.407***	− 1.115***
		(0.007)	(0.274)	(0.007)	(0.293)	(0.007)	(0.294)
	No health insurance in wave III	− 0.182***	− 0.196***	− 0.346***	− 0.315***	− 0.129***	− 0.110
		(0.001)	(0.057)	(0.002)	(0.077)	(0.002)	(0.087)
	Poor general health in wave I	− 1.160***	− 1.076***	− 1.497***	− 1.518***	− 0.631***	− 0.332***
		(0.002)	(0.094)	(0.003)	(0.103)	(0.003)	(0.127)
Good	Evicted in wave III	− 0.740***	− 0.527**	− 0.214***	− 0.376	− 0.156***	− 0.298
		(0.007)	(0.257)	(0.007)	(0.280)	(0.008)	(0.344)
	Evicted in wave IV	− 0.967***	− 0.613**	− 0.680***	− 0.505*	− 0.628***	− 0.297
		(0.006)	(0.252)	(0.006)	(0.258)	(0.008)	(0.332)
	No health insurance in wave III	− 0.005***	− 0.040	− 0.138***	− 0.107	− 0.133***	− 0.047
		(0.002)	(0.062)	(0.002)	(0.078)	(0.003)	(0.102)
	Poor general health in wave I	− 0.468***	− 0.315***	− 0.746***	− 0.734***	− 0.083***	0.025
		(0.002)	(0.089)	(0.003)	(0.097)	(0.003)	(0.146)

Note. The unweighted sample size was 11,514 for combined general and mental health and only general health, and 11,513 for only mental health.
All models include control variables and a constant term.
The reference group is non-White males with a high school degree, health insurance in wave III, good general health in wave I, and personal income less than $10,000 in each wave, who did not experience a housing eviction in either wave.
The reference dependent variable is people in poor health.
Standard errors are given in parentheses.
*$p < .1$. **$p < .05$. ***$p < .01$.

Table A3. Binary logistic regression (full results).

	(1) Combined poor general and mental health	(2) Poor general health	(3) Poor mental health
Evicted in wave III	0.878***	0.372***	0.897***
	(0.005)	(0.007)	(0.005)
Evicted in wave IV	1.270***	1.100***	1.048***
	(0.005)	(0.006)	(0.006)
No health insurance in wave III	0.113***	0.254***	0.046***
	(0.001)	(0.002)	(0.001)
Poor general health in wave I	0.841***	1.119***	0.579***
	(0.002)	(0.002)	(0.002)
Personal income in wave III			
(1) $50,000 or more	0.637***	0.798***	0.605***
	(0.005)	(0.007)	(0.005)
(2) $40,000 to $49,999	− 0.121***	− 0.431***	− 0.010***
	(0.005)	(0.009)	(0.005)
(3) $30,000 to $39,999	− 0.099***	− 0.085***	− 0.051***
	(0.003)	(0.005)	(0.003)
(4) $20,000 to $29,999	− 0.086***	− 0.024***	− 0.143***
	(0.002)	(0.003)	(0.002)
(5) $10,000 to $19,999	− 0.026***	− 0.007***	− 0.040***
	(0.001)	(0.002)	(0.002)
Personal income in wave IV			
(1) $50,000 or more	− 0.597***	− 0.615***	− 0.616***
	(0.002)	(0.003)	(0.002)
(2) $40,000 to $49,999	− 0.613***	− 0.552***	− 0.619***
	(0.002)	(0.004)	(0.002)
(3) $30,000 to $39,999	− 0.442***	− 0.463***	− 0.449***
	(0.002)	(0.003)	(0.002)
(4) $20,000 to $29,999	− 0.338***	− 0.244***	− 0.414***
	(0.002)	(0.003)	(0.002)
(5) $10,000 to $19,999	− 0.254***	− 0.229***	− 0.250***
	(0.002)	(0.003)	(0.002)
Less than high school	0.258***	0.320***	0.139***
	(0.002)	(0.003)	(0.002)
Bachelor's degree or more	− 0.337***	− 0.957***	− 0.131***
	(0.001)	(0.003)	(0.002)
White	0.505***	− 0.354***	0.954***
	(0.001)	(0.002)	(0.002)
Female	0.635***	− 0.010***	0.855***
	(0.001)	(0.002)	(0.001)
Constant	− 1.380***	− 1.761***	− 2.189***
	(0.002)	(0.003)	(0.002)

Note. The unweighted sample size was 11,514; the weighted sample size was 16,923,811.
The reference group is non-White males with a high school degree, health insurance in wave III, good general health in wave I, and personal income less than $10,000 in each survey wave, who did not experience a housing eviction in either survey wave.
Standard errors are given in parentheses.
*$p < .1$. **$p < .05$. ***$p < .01$.

Table A4. Multinomial logistic regression of eviction on poor health (full results).

		(1) Combined general and mental health	(2) General health	(3) Mental health
Excellent	Evicted in wave III	− 0.977***	− 0.539***	− 0.988***
		(0.006)	(0.008)	(0.007)
	Evicted in wave IV	− 1.560***	− 1.660***	− 1.407***
		(0.007)	(0.007)	(0.007)
	No health insurance in wave III	− 0.182***	− 0.346***	− 0.129***
		(0.001)	(0.002)	(0.002)
	Poor general health in wave I	− 1.160***	− 1.497***	− 0.631***
		(0.002)	(0.003)	(0.003)
	Personal income in wave III			
	(1) $50,000 or more	− 0.575***	− 0.773***	− 0.358***
		(0.005)	(0.007)	(0.009)
	(2) $40,000 to $49,999	0.025***	0.297***	0.342***
		(0.005)	(0.009)	(0.010)
	(3) $30,000 to $39,999	0.206***	0.220***	− 0.055***
		(0.003)	(0.005)	(0.005)
	(4) $20,000 to $29,999	0.049***	− 0.009***	0.093***
		(0.002)	(0.003)	(0.003)
	(5) $10,000 to $19,999	− 0.033***	− 0.042***	− 0.019***
		(0.002)	(0.002)	(0.002)
	Personal income in wave IV			
	(1) $50,000 or more	0.651***	0.686***	0.732***
		(0.002)	(0.003)	(0.003)
	(2) $40,000 to $49,999	0.698***	0.629***	0.708***
		(0.002)	(0.004)	(0.004)
	(3) $30,000 to $39,999	0.531***	0.561***	0.583***
		(0.002)	(0.003)	(0.003)
	(4) $20,000 to $29,999	0.375***	0.279***	0.506***
		(0.002)	(0.003)	(0.003)
	(5) $10,000 to $19,999	0.239***	0.237***	0.209***
		(0.002)	(0.003)	(0.003)
	Less than high school	− 0.423***	− 0.471***	− 0.152***
		(0.002)	(0.003)	(0.003)
	Bachelor's degree or more	0.563***	1.201***	0.203***
		(0.001)	(0.003)	(0.002)
	White	− 0.398***	0.450***	− 1.205***
		(0.002)	(0.002)	(0.003)
	Female	− 0.663***	− 0.045***	− 1.018***
		(0.001)	(0.002)	(0.002)
	Constant	0.820***	1.196***	3.501***
		(0.002)	(0.003)	(0.004)
Good	Evicted in wave III	− 0.740***	− 0.214***	− 0.156***
		(0.007)	(0.007)	(0.008)
	Evicted in wave IV	− 0.967***	− 0.680***	− 0.628***
		(0.006)	(0.006)	(0.008)
	No health insurance in wave III	− 0.005***	− 0.138***	− 0.133***
		(0.002)	(0.002)	(0.003)
	Poor general health in wave I	− 0.468***	− 0.746***	− 0.083***
		(0.002)	(0.003)	(0.003)
	Personal income in wave III			
	(1) $50,000 or more	− 0.781***	− 0.850***	0.349***
		(0.007)	(0.008)	(0.010)
	(2) $40,000 to $49,999	0.316***	0.633***	0.460***
		(0.006)	(0.009)	(0.011)
	(3) $30,000 to $39,999	− 0.139***	− 0.158***	− 0.167***
		(0.004)	(0.005)	(0.006)
	(4) $20,000 to $29,999	0.171***	0.086***	− 0.078***
		(0.002)	(0.003)	(0.004)
	(5) $10,000 to $19,999	0.132***	0.079***	− 0.093***
		(0.002)	(0.002)	(0.003)
	Personal income in wave IV			
	(1) $50,000 or more	0.502***	0.503***	0.181***

(*Continued*)

Table A4. (Continued).

	(1) Combined general and mental health	(2) General health	(3) Mental health
	(0.003)	(0.004)	(0.004)
(2) $40,000 to $49,999	0.452***	0.442***	0.142***
	(0.003)	(0.004)	(0.004)
(3) $30,000 to $39,999	0.287***	0.333***	0.212***
	(0.002)	(0.003)	(0.004)
(4) $20,000 to $29,999	0.286***	0.208***	0.148***
	(0.002)	(0.003)	(0.003)
(5) $10,000 to $19,999	0.279***	0.226***	− 0.068***
	(0.002)	(0.003)	(0.003)
Less than high school	− 0.082***	− 0.177***	− 0.020***
	(0.002)	(0.003)	(0.004)
Bachelor's degree or more	− 0.205***	0.456***	0.111***
	(0.002)	(0.003)	(0.003)
White	− 0.672***	0.231***	− 0.383***
	(0.002)	(0.002)	(0.003)
Female	− 0.588***	0.082***	− 0.253***
	(0.001)	(0.002)	(0.002)
Constant	0.517***	0.901***	1.008***
	(0.002)	(0.003)	(0.004)

Note. The unweighted sample size was 11,514 for combined general and mental health and only general health, and 11,513 for only mental health.
The weighted sample size for combined general and mental health and only general health was 16,923,811, whereas it was 16,923,611 for only mental health.
The reference group is non-White males with a high school degree, health insurance in wave III, good general health in wave I, and personal income less than $10,000 in each wave, who did not experience a housing eviction in either wave.
The reference dependent variable is people in poor health.
Standard errors are given in parentheses.
*$p < .1$. **$p < .05$. ***$p < .01$.