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Do housing and neighborhood characteristics impact an individual's risk of homelessness? Evidence from New York City

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ABSTRACT

Most existing homelessness research either connects aggregate levels of homelessness to housing market and economic characteristics, or analyzes the personal traits of chronically homeless individuals and those receiving formal institutional support. Little is known about the characteristics of individuals in the general population who become homeless, especially their housing and neighborhood contexts. This article assesses the relationship between an individual's odds of experiencing homelessness and their housing, personal, and neighborhood characteristics using data from The New York City Longitudinal Survey of Well-Being, a representative panel of New York City adults. These data are leveraged to specify a series of multilevel logistic panel regression models. Findings suggest an individual's housing conditions, particularly whether they are doubled-up or in a rent-controlled unit, and traditional risk factors such as mental health issues and drug use, help predict future homelessness. Results suggest that well-known individual characteristics common among unhoused individuals are accompanied by housing and economic factors that drive a path to experiencing homelessness.

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Introduction

In many housing markets around the world rent and home prices have increased to unprecedented levels and become unaffordable, particularly for low-income households. The lack of affordable housing supply has significant implications for access to housing and is often cited as a key contributor to substantial recent increases in homelessness (Glendening & Shinn, 2017; O'Flaherty, 2004; Quigley *et al.*, 2001). In the U.S., states like California and New York as well as the District of Columbia—each characterized by tight housing markets—have seen significant increases in homelessness rates in the past decade despite a modest decrease in homelessness nationally (National Alliance to End Homelessness, 2020). While the connection

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between housing stability—broadly defined as an individual's ability to maintain access to a quality housing arrangement[1]—and homelessness is now widely accepted, it came to prominence only recently. Most early studies investigating the causes of homelessness focused on individual-level contributors to homelessness, highlighting factors such as substance abuse, mental health, and physical health issues (e.g. Bassuk *et al.*, 1997; Koegel *et al.*, 1995). Subsequently, researchers using individual-level data to study homelessness have become more sensitive to housing characteristics (e.g. Curtis *et al.*, 2013; Marybeth Shinn *et al.*, 2007). However, few of these studies assess the relationship between an individual's neighborhood characteristics and homelessness[2] despite evidence from cross sectional data that neighborhood characteristics are sometimes associated with rates of homelessness. Another line of research is typically sensitive to both neighborhood and housing-related factors associated with homelessness, but studies in this vein use cross-sectional data and focus on aggregate rates of homelessness in cities, regions, and countries (Fargo *et al.*, 2013; Hanratty, 2017).

This study contributes to the limited body of literature exploring how an individual's housing and neighborhood contexts relate to their risk of experiencing homeless. I leverage data from The New York City Longitudinal Survey of Well-Being,[3] a representative panel of 4,000 New York City households surveyed at three-month intervals. I limit my analytical sample to the 2,326 households renting, as opposed to owning, their housing units over a three-year period spanning 2015–2018. I specify a series of multilevel logistic panel regressions with mixed effects to analyze the relationship between homelessness and time variant factors related to respondents' housing and neighborhood contexts as well as factors related to their physical and mental health and economic security while also controlling for time invariant demographic and socio-economic characteristics. In line with past literature using individual-level data, I find that personal characteristics such as drug use, material hardships, and mental health issues are associated with future instances of homelessness. Results also suggest a compelling link between an individual's housing context and future homelessness; doubling up in housing units with friends and family is positively associated with future homelessness, while occupying a rent-controlled unit is negatively associated with future instances of homelessness. An individual's neighborhood characteristics such as gentrification, high levels of unemployment, and high levels of poverty are not associated with future homelessness at statistically significant levels. Results contribute to a growing body of work emphasizing the important role housing conditions, in addition to long-cited individual factors like mental health and substance abuse, play in shaping the pathway to homelessness. Findings can inform policymakers' attempts to target scarce government resources toward reducing homelessness by strategically increasing housing security and affordability for those who are most vulnerable.

Background

Due to factors including economic crises, the emergence of HIV/AIDs, federal budget cuts for housing and urban development, and the de-institutionalization of the mentally ill, homelessness has been an increasingly visible fixture in urban areas of the United States since at least the 1980s (National Academies of Sciences *et al.*, 2018). While rates have modestly decreased nationwide since the years following the Great Recession of 2007–2009, hot coastal housing markets have experienced increased levels of homelessness, and New York City contains the largest number of homeless individuals of any American city (Coalition for the Homeless, 2020).

In response to high levels of homelessness in cities in the United States and other advanced economies, most notably the United Kingdom and Australia, researchers have conducted numerous studies focused on the characteristics of individuals and households experiencing homelessness, and the pathways leading them to become unhoused. The majority of these studies fall into one or both of two broad categories: those focusing on the common characteristics of homeless individuals or individuals at-risk of experiencing homelessness, and those focusing on structural factors such as economic fluctuations, changes in wider public health measures, and housing market strength, that are associated with increases in city or nationwide levels of homelessness.

Studies focused on the individual characteristics that are common among those experiencing homelessness often recruit survey participants in or associated with institutional settings such as homelessness prevention and rapid rehousing programs, shelters, or public housing developments, or through sampling strategies designed to identify individuals who are already experiencing chronic homelessness (Crawley *et al.*, 2013; Glendening & Shinn, 2017; Marybeth Shinn *et al.*, 2007; Shah *et al.*, 2017). While this body of work has yielded valuable insights into the mental and physical health needs and personal characteristics of those experiencing homelessness, its focus on individuals recruited from institutional or social service settings creates analytical samples that are not representative of general populations, and also likely exclude households who experience homelessness temporarily and do not seek support through formal institutions.[4] Furthermore, these studies findings related to housing, neighborhood conditions, and structural factors are limited, often because of challenges in identifying respondents' permanent addresses. Where studies in this vein do focus on housing-related factors (e.g. Diette & Ribar, 2018; He *et al.*, 2010; O'Donnell, 2019) inferences about determinants of homelessness among individuals in the general population are limited due to samples consisting of chronically homeless individuals or those participating in subsidy programs explicitly designed to prevent homelessness.

A second broad body of work is focused on the association between aggregate levels of homelessness in a country, region, or municipality and various structural factors. Unlike most studies leveraging individual-level data, this line of research is typically sensitive to the relationship between homelessness, housing markets, and neighborhood characteristics. For example, by combining community-level data with the U.S. Department of Housing and Urban Development's (HUD) point-in-time counts of homelessness, Fargo *et al.* (2013) find that several neighborhood characteristics including homicide rates, drug use, and social support were associated with single adult homelessness in American metropolitan areas. Byrne and his coauthors (Byrne *et al.*, 2013) find associations between levels of adult homelessness in metropolitan and nonmetropolitan areas and community-level rates of factors including social support, religious adherence, drug use, and alcohol consumption. Hanratty

(2017) focuses on the impact of local economic conditions on aggregate rates of homelessness, concluding that median rent level is positively and significantly associated with homelessness rates. Several studies find that areas with tight housing markets and low supplies of affordable rental housing are characterized by high rates of homelessness (e.g. Appelbaum *et al.*, 1991; Quigley *et al.*, 2001). Other analyses of aggregate rates of homelessness reinforce the relationship between housing costs and homelessness, suggesting housing subsidies weaken the link between poverty and housing deprivation while high rates of neighborhood crime can strengthen it (Bartelt *et al.*, 2017; Lee *et al.*, 2003; Stephens & Leishman, 2017). While these studies convincingly connect housing and neighborhood conditions to homelessness, they are typically unable to draw causal inferences at the individual level, and therefore say little about the mechanisms triggering an individual or household's experience of homelessness. Culhane *et al.* (1996), which studies the neighborhood characteristics of individuals admitted to shelters, is a notable exception. This study finds evidence that individuals in shelters are likely to have previously lived in areas of concentrated poverty.

Recently, scholars have forwarded theoretical arguments highlighting how both individual and structural factors play a role in contributing to homelessness (Batterham, 2019; O'Flaherty, 2004; Piat *et al.*, 2015), paving the way for empirical work assessing both types of factors in shared analytical frameworks. This work tends to utilize both individual-level data, often from panel surveys, and administrative data aggregated to represent housing and other socioeconomic factors at the neighborhood or city level. The panel data used allow researchers to make inferences about individuals who are more representative of general populations, or about broad sub-populations. They also allow researchers to use panel regression techniques that reveal how prior information on a household explains future experiences of homelessness, thereby offering empirical support for the notion that a mix of structural and individual forces shape a 'pathway' to homelessness (Clapham, 2003; Piat *et al.*, 2015). In this vein, Bramley & Fitzpatrick (2018) combine both cross-sectional and longitudinal individual-level data from the United Kingdom to conduct a multivariate analysis of factors associated with homelessness. Their findings suggest that while poverty plays a central role in causing homelessness, broader labor and housing market forces are also important factors. Alexander-Eitzman *et al.* (2013) track the addresses and sleeping locations of 400 homeless individuals in St. Louis, Missouri and conduct a spatial analysis of their neighborhood contexts. They find that homeless individuals are likely to be concentrated in areas with higher poverty, unemployment, and rent-to-income ratio levels and lower median incomes. Using Fragile Families and Child Wellbeing data, Curtis *et al.* (2013) find that the birth of a child with severe health issues substantially increases the likelihood of family homelessness, especially in high-cost cities. This study reinforces the intertwined relationship between homelessness, individual characteristics, and housing costs. Finally, Fertig & Reingold (2008) use Fragile Families and Child Wellbeing data to analyze the factors associated with homelessness for at-risk families in 20 U.S. cities. They find strong evidence that individual characteristics including mental and physical health are positively associated with homelessness. They also find a positive, although substantively small, association between community housing cost and homelessness. Collectively, this body of research advances our understanding of the association between individual and structural factors and homelessness, but still lacks robust evidence linking a household's specific housing circumstances to their chances of becoming homeless.

The present study contributes to the literature by estimating the association between individual housing, personal, and neighborhood characteristics and future experiences of homelessness. As past research has identified links between housing unaffordability and homelessness (e.g. Bartelt *et al.*, 2017; Quigley *et al.*, 2001) I hypothesize that housing characteristics associated with affordability such as housing subsidies and rent control will be linked to lower rates of homelessness, while characteristics reflecting housing cost challenges such as struggling to pay rent will be linked to higher rates of homelessness. The literature focused on pathways to homelessness also emphasizes how life events that reflect or contribute to instability in housing arrangements, such as doubling up or the presence of children in a housing unit elevate an individual's risk of homelessness (Bolger, 1996; Grant *et al.*, 2013). Extensive evidence linking individual-level economic and personal characteristics such as drug use, physical and mental health struggles, and financial hardships to homelessness is extensive and I expect the characteristics of this type included here to predict homelessness. Finally, my assessment of neighborhood factors aligns with calls to link individual-level risks and wider structures and processes that contribute to homelessness (Garside, 2009). A neighborhood's limited social capital or lack of affordable housing options might exacerbate individual level risk factors for homelessness (Batterham, 2019; Culhane *et al.*, 1996) by decreasing an individual's ability to access nearby resources in times of need and increasing financial pressure, and these factors are thus hypothesized to be associated with an individual's future risk of experiencing homelessness.

Data

I explore associations between homelessness, individual-level characteristics, and wider socioeconomic structural factors by examining data from the second panel of the New York City Longitudinal Survey of Well-Being (the Poverty Tracker), a representative panel of New York City adults surveyed at three-month intervals over a three-year period beginning in 2015. The second panel of the Poverty Tracker includes approximately 4,000 adults in New York City who were recruited in 2015 and surveyed by telephone or online by trained interviewers. The data used in this study include results from an initial intake survey through the 36-month follow-up survey conducted in 2018. I limit my analytical sample to 2,326 households renting, as opposed to owning, their housing units. I exclude homeowners from my analytical sample because renters are known to experience higher levels of housing insecurity and affordability stress than homeowners (Borrowman *et al.*, 2017). The use of data representative of the city's entire population offers an advantage over studies analyzing samples drawn from homeless or at-risk individuals who have entered various institutional support channels. For example, the data allow me to assess the predictors of homelessness for households who may experience temporary episodes of homelessness, but are not chronically homeless. They also allow me to draw inferences that inform our understanding of various housing policies' effectiveness in preventing homelessness among members of the general population.

Below, I describe my decisions regarding variable operationalization. The experience of homelessness, my dependent variable, is defined using a Poverty Tracker question included in every 3-month survey asking respondents whether they had slept in temporary housing or a group shelter, an abandoned building, automobile, or any other place not meant for regular sleeping, even for one night in the previous three months. On 'annual' surveys that were conducted 12, 24, and 36 months after the initial survey, respondents are asked a similar question, but pertaining to the previous 12-month period. If a respondent answers 'yes' to either of these questions, they are considered to have experienced homelessness during a survey year, and assigned a value equal to one in a dummy variable.

The Poverty Tracker also collects a comprehensive set of respondents' demographic characteristics, as well as information on their mental, physical and financial health and certain characteristics of their families and homes. I include information regarding respondents' housing characteristics including measures of rent insecurity, doubling up, receiving housing subsidies, living in a rent-controlled unit, and having a child living in their housing unit. These measures are tracked in each 12-month wave, and operationalized as dummy variables. A respondent is considered rent insecure if they had not paid their full rent due to a lack of money in the previous 12 months. A respondent is considered to be doubling up if they had lived with family or friends, regardless of whether the respondent paid rent to that family member or friend, due to financial problems within the previous 12 months. Receiving housing subsidies means a respondent lived in public housing or received a housing voucher in the previous 12 months. Being subject to rent control indicates a respondent resided in a rent controlled or rent stabilized unit at the time of an annual survey. Finally, having a child present in a respondent's unit is indicates a child under the age of 18 lived in the housing unit at any time in the previous 12 months.

The Poverty Tracker also collects information on respondents' personal characteristics in each survey including whether a respondent has experienced a material hardship, a severe health issue, a mental health issue or engaged in drug use in the 12-month period preceding each annual interview. Importantly, these characteristics all likely reflect structural forces such as economic fluctuations and inequality in access to health care and social services. For ease of interpretation, I classify them as personal characteristics, as they are distinct from the housing metrics described above, but still measured at the individual level. A material hardship indicates a respondent ran out of money or failed to pay bills and utilities, go to the doctor, or buy food due to the cost. A severe health issue occurs when a respondent claims a health problem or disability prevented from working or limited the kind or amount of work they could do. Following past research (e.g. Fertig & Reingold, 2008) that leverages language from the Composite International Diagnostic Interview Short-Form (Kessler *et al.*, 1998), mental health issues are considered present when respondents indicate they had, in the past 12 months, felt sad, blue, depressed for two or more weeks in a row or felt worried, tense, or anxious for most of the time in a period lasting one month or longer. Drug use is noted if a respondent answers affirmatively either to using any prescription drugs on their own without a doctor's prescription or more than recommended by a doctor, or to using any other drugs on their own, such as inhalants, marijuana, cocaine or crack, LSD, heroin and ecstasy. Poverty Tracker data are also used to control for respondent age, race and ethnicity, income at the baseline survey, rent burden—or the expenditure of more than 30% of income on rent—at the baseline survey, and whether or not the respondent had received at least a high school degree.

To supplement the individual-level data provided by the Poverty Tracker, neighborhood-level data are also collected at the zip code level in the years corresponding to each Poverty Tracker survey wave from the United States Census Bureau's American Community Survey and the Furman Center for Real Estate and Urban Policy's at NYU.[5] I use the Social Explorer (Social Explorer, 2018) to access American Community Survey data including a zip code's unemployment rate, median household rent, and the percentage of respondents living below the Census-defined poverty threshold, which varies depending on family size. I include a measure of gentrification in 2015 at the New York City Sub-Borough Level provided by the NYU Furman Center (Furman Center, 2016). I include whether a neighborhood is gentrifying due to gentrification's association with increased housing costs in low-income neighborhoods (see Freeman, 2005). By pairing Poverty Tracker data with this information on neighborhoods, the salience of personal characteristics, neighborhood context, and housing can be assessed simultaneously. This design informs a set of policy recommendations, to be discussed below, related to homelessness prevention and tenuous housing arrangements rather than to drivers of long-term homelessness.

Table 1 presents the individual and neighborhood characteristics of respondents who experienced homelessness in any wave of the Poverty Tracker alongside the full sample's descriptive statistics.

Out of 5,218 person-years 295 instances, or 5.65% of total observations, of homelessness were recorded.[6] Of the survey respondents who reported experiencing homelessness, nearly two thirds (65.2%) reported one instance of homelessness, while 18.9% reported two instances, and 15.9% reported three or four instances. In line with expectations, those experiencing homelessness were more likely to have experienced rent insecurity and doubling up in the 12 months preceding their experience of homelessness and less likely to be in a rent-controlled unit. Given that past research has indicated housing subsidy as a potential protection against homelessness (Shinn *et al.*, 1998), it runs counter to expectations that those experiencing homelessness lived in subsidized housing at a nearly identical rate to the sample as a whole. This may be partially explained by the elevated number of individuals experiencing homelessness who had doubled up, and were thus ineligible for or unable to use subsides. Personal and neighborhood characteristics associated with individuals experiencing homelessness all align with expectations. Of note are the percentages of material hardship and mental health issues among respondents experiencing homelessness, which are both

Table 1. Full analytical sample descriptive statistics.

	Experienced homelessness*		Full sample**	
	Mean	Std. dev.	Mean	Std. dev.
Housing characteristics				
% Rent insecure	42.37	49.49	22.53	41.79
% Doubled up	31.53	46.54	6.69	24.98
% Subsidized housing	14.23	35.00	14.47	35.18
% Rent controlled unit	34.57	47.64	45.86	49.83
% Child living in housing unit	28.22	45.09	28.38	45.08
Personal characteristics				
% Material hardship	69.49	46.12	39.86	48.97
% Severe health issue	34.57	47.64	28.89	45.33
% Mental health issue	22.53	41.89	10.11	30.15
% Drug use	26.10	43.99	14.55	35.26
Neighborhood characteristics				
% Neighborhood unemployment	10.47	3.64	9.81	3.71
Neighborhood median rent	1,235.17	358.84	1,295.61	373.52
% Neighborhood poverty	21.63	9.42	20.75	9.02
% Neighborhood gentrification	41.02	49.27	36.77	48.22
Demographic controls				
% Rent burdened at baseline survey	42.71	49.55	38.42	48.64
Age	42.21	15.72	47.45	17.42
% Male	50.51	50.08	37.13	48.29
% Female	49.49	50.08	62.87	48.31
% White Non-Hispanic	11.52	31.99	23.71	42.53
% Black Non-Hispanic	38.31	48.70	29.14	45.45
% Asian Non-Hispanic	1.36	11.58	3.83	19.20
% Other Race	13.90	34.65	5.94	23.64
% Hispanic	34.92	47.75	37.37	48.38
Income at baseline survey	$17,277.91	$40,558.08	$40,906.7	$80,247.58
% Less than high school education	53.90	49.93	40.28	49.05

Notes: *n = 295 person years. **n = 5,218 person years.

approximately twice the rate of the full sample. Respondents experiencing homelessness are also substantially younger than the sample mean and more likely to be male, identify as Black or 'other' race, low income, and hold less than a high school degree. These characteristics generally align with past literature using panel data to study homelessness in the U.S. (Curtis *et al.*, 2013; Fertig & Reingold, 2008). However, one previous study analyzed a sample in which the homeless population was better educated than the housed portion of the sample (Shinn *et al.*, 2007), which runs counter to the higher percentage of those experiencing homelessness in this sample lacking a high school education.

Methods

I conduct a series of multivariate regression analyses. I choose a multilevel mixed-effects logistic panel regression approach to control for individual and neighborhood-level effects while also accounting for unobserved variation at the neighborhood level. First, in Model 1, I estimate the relationship between future homelessness and a series of time-invariant control variables. Next, in Model 2, I add a series of time-variant, individual housing-related factors. In Model 3, I add personal characteristics to determine how the inclusion of these more traditional contributors to homelessness impact the housing variables. Finally, in Model 4, I add neighborhood-level covariates to construct this study's final model. Each of these models also estimates random effects at the neighborhood—here, zip code—level. To take advantage of the data's panel structure, each variable related to housing, personal, and neighborhood characteristics, as described above, is lagged by one survey wave,[7] whereas homelessness is measured at each wave and control variables are measured only at the baseline survey. The basic formula for this model is as follows:

$$\mathrm{Ln}\ (\mathrm{P}(\mathrm{Yi} = 1|\mathrm{xi,u}) / \mathrm{P}(\mathrm{Yi} = 0|\mathrm{xi,u})) = \beta_0 \sum\_(k=1) \wedge n \beta_k \mathrm{x}_{\mathrm{ki}} + \mathrm{u}_{\mathrm{j}}$$

where P is the probability that a respondent experiences homelessness, Yi represents the binary variable homelessness, with $Yi = 1$ in the case of homelessness and $Yi = 0$ when the respondent remains housed. β_0 represents the intercept, βk represents the coefficient, and x_{1i}, …, x_{ki} represent the independent variables estimated with fixed effects. βk measures the effect on the log odds ratio of a one-unit increase in x_{ki}. u_j represents the random effect of the second level control for neighborhood. For ease of interpretation, panel regression coefficients are provided as odds ratios in Table 2 below. An odds ratio above 1 suggests an independent variable is positively associated with future homelessness, whereas an odds ratio below one suggests a negative association between a variable and future homelessness. Put another way, a one-unit change in an independent variable can either increase or decrease the odds of a respondent experiencing homelessness in the subsequent survey wave. For example, an odds ratio of 2 for a given independent variable would indicate a one unit increase in that variable results in a respondent's odds of experiencing homelessness in the subsequent survey wave being multiplied by 2. An odds ratio of .5 for a given independent variable would indicate a one unit increase in that variable results in a respondents' odds of experiencing homelessness in the subsequent survey wave being multiplied by .5.

Results

Results from the logistic regression models estimating the relationship between a respondent experiencing homelessness and past information on their housing, personal, and neighborhood characteristics are displayed in Table 2. Collectively, results suggest that housing-related and personal characteristics play an important role in shaping outcomes related to homelessness, while neighborhood context does not.

Estimates from Model 1, which estimates the unconditional association between homelessness and a series of control variables, largely aligns with expectations. Homelessness is positively and statistically significantly associated with being non-Hispanic Black or other race and having less than a high school education. Being older, female, and higher income are negatively associated with homelessness at statistically significant levels. Counter to expectations, being rent burdened at the baseline survey is associated with slightly below even odds of future homelessness. This might be explained by New York City's overall cost of living, which causes a high percentage of households to spend relatively high proportions of their income on rent (Desmond, 2018), thereby obscuring any expected relationship between rent

Table 2. Odds ratios from multilevel logistic regression estimates of homelessness.

	Model 1	Model 2	Model 3	Model 4
Control variables				
Rent burden at baseline survey	0.828*	0.994	0.926	0.941
	(0.0901)	(0.132)	(0.127)	(0.130)
Age	0.984***	0.985***	0.986***	0.986***
	(0.00307)	(0.00406)	(0.00470)	(0.00474)
Female	0.533***	0.503***	0.504***	0.515***
	(0.0561)	(0.0663)	(0.0696)	(0.0714)
Black Non-Hispanic[a]	1.506**	1.577**	1.614**	1.608**
	(0.273)	(0.353)	(0.376)	(0.388)
Asian Non-Hispanic	0.335**	0.445	0.544	0.580
	(0.162)	(0.247)	(0.305)	(0.325)
Other	2.867***	3.065***	2.957***	2.976***
	(0.623)	(0.821)	(0.821)	(0.844)
Hispanic	1.058	1.150	1.079	1.092
	(0.195)	(0.261)	(0.256)	(0.269)
Income at baseline survey (000 s)	0.988***	0.988***	0.988***	0.988***
	(0.00192)	(0.00245)	(0.00253)	(0.00252)
< High School Education	1.507***	1.424***	1.379**	1.366**
	(0.169)	(0.194)	(0.196)	(0.195)
Housing characteristics				
Rent Insecure		1.702***	1.117	1.118
		(0.237)	(0.168)	(0.169)
Doubled up		5.143***	3.862***	3.751***
		(0.805)	(0.633)	(0.621)
Subsidized housing		1.023	0.895	0.888
		(0.196)	(0.178)	(0.178)
Rent controlled unit		0.608***	0.605***	0.608***
		(0.0836)	(0.0855)	(0.0864)
Child living in housing unit		0.924	0.971	0.964
		(0.137)	(0.149)	(0.149)
Personal characteristics				
Material hardship			2.488***	2.477***
			(0.391)	(0.390)
Severe health issue			1.210	1.218
			(0.194)	(0.196)
Mental health issue			1.927***	1.935***
			(0.328)	(0.331)
Drug use			1.669***	1.691***
			(0.274)	(0.278)
Neighborhood characteristics				
% Neighborhood unemployment				1.034
				(0.0309)
Neighborhood median rent				1.033
				(0.0391)
% Neighborhood poverty				0.994
				(0.0145)
Neighborhood gentrification				1.077
				(0.230)
Random effect intercept	1.291**	0.517***	0.581***	0.576***
	(0.129)	(0.110)	(0.117)	(0.117)
Constant	0.132***	0.108***	0.0594***	0.0297***
	(0.0307)	(0.0322)	(0.0198)	(0.0247)
Observations	5.218	5.218	5.218	5.218
Wald chi2	177.92***	305.35***	331.17***	335.26***

Note: Standard errors in parentheses.
[a]White is reference category for race.
***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

expenditures and homelessness. Additionally, other research, albeit focused on community, not individual homelessness, links rent burden to homelessness only when the median burden in a community is slightly above the 30% threshold utilized in this study (Glynn *et al.*, 2021).

Model 2, which includes potential housing-related predictors of homelessness and a series of demographic and socioeconomic control variables, suggest a strong nexus exists between a respondent's housing circumstances and their likelihood of experiencing homelessness. Experiencing rent insecurity or doubling up with friends and family were both positively associated with future homelessness, whereas living in a rent control unit was negatively associated with future homelessness. While receiving a housing subsidy was associated with lower-than-even odds of experiencing homelessness, which aligns with past research (Shinn *et al.*, 1998), this relationship was not statistically significant. Even so, while subsidies are not significantly associated with lower rates of future homelessness here, the potential cost savings associated with offering housing subsidies to those who are already homeless can be considerable (Culhane *et al.*, 2011) and are not called into question by my findings. Finally, respondents who report children living in their units have statistically equal odds of experiencing homelessness relative to those without children.

The addition of housing-related variables leaves the coefficients of the control variables largely unchanged. One exception is that the variable representing rent burden at the baseline survey becomes insignificant. The inclusion of the variable representing rent insecurity, which is both time-varying and more indicative than rent burden of a respondent's struggle to pay rent, is likely responsible for the loss of rent burden's significance in the model. Additionally, the demographic control for being Asian loses its significance, suggesting that relatively advantageous housing characteristics among Asian respondents may have been the cause of the significant, negative association between identifying as Asian and homelessness in Model 1.

Model 3 introduces a set of variables representing personal characteristics to the housing-related variables included in Model 2, resulting in an increase in the model's overall statistical significance. Variables indicating whether an individual has suffered a material hardship, mental health issue, or has engaged in drug use, are all positively associated with future homelessness at statistically significant levels. These findings align with findings from research focusing on how personal risk factors can serve as predictors of homelessness (Bassuk *et al.*, 1997; Glendening & Shinn, 2017; Koegel *et al.*, 1995). The relationship between a respondent having a severe health issue and experiencing homelessness is positive, but not statistically significant. While the introduction of these variables does not change the direction of the odds of any of the control variables, the housing variable related to rent insecurity loses its statistical significance relative to Model 2. This suggests the previously observed significant relationship between rent insecurity and homelessness was a proxy for the more meaningful association between respondents' personal characteristics—likely the variable reflecting material hardships, which, like rent insecurity, reflects financial struggles—and their odds of becoming homeless.

Model 4, which adds a series of neighborhood-level covariates to Model 3, represents the final results of my analysis. Figure 1 provides a visual representation of the odds ratios associated with each variable in this final model.[8]

In this model, the housing-related characteristics of doubling up and living in rent-controlled units maintain their direction and statistical significance. Of all time-variant variables included in this study, doubling up has the largest substantive impact on future homelessness, as doubling up in one time period multiplies a respondent's odds of experiencing homelessness in the subsequent period by 3.751. This finding suggests that despite doubling-up's potential to offer a household substantial savings on rent payments (Pilkauskas *et al.*, 2014), living with friends and family is likely better understood as part of the pathway to homelessness than as a voluntary cost-saving measure. The directions and significance levels of all variables related to personal characteristics are also unchanged after the inclusion of neighborhood variables. Here, we observe a respondent's odds of experiencing homelessness multiplied by 2.477 and 1.935 when they experience material hardships or mental health issues, respectively. The elevated importance of material hardships and doubling-up over all other variables reinforces findings of a strong relationship between these two factors, as past research finds doubling up to be three times more likely among those who had experienced job loss relative to those who were employed (Wiemers, 2014).

Despite the strong connection previous scholarship has identified between neighborhood-related characteristics and homelessness (e.g. Lee *et al.*, 2003; Quigley *et al.*, 2001), none of the neighborhood variables included here were predictive of

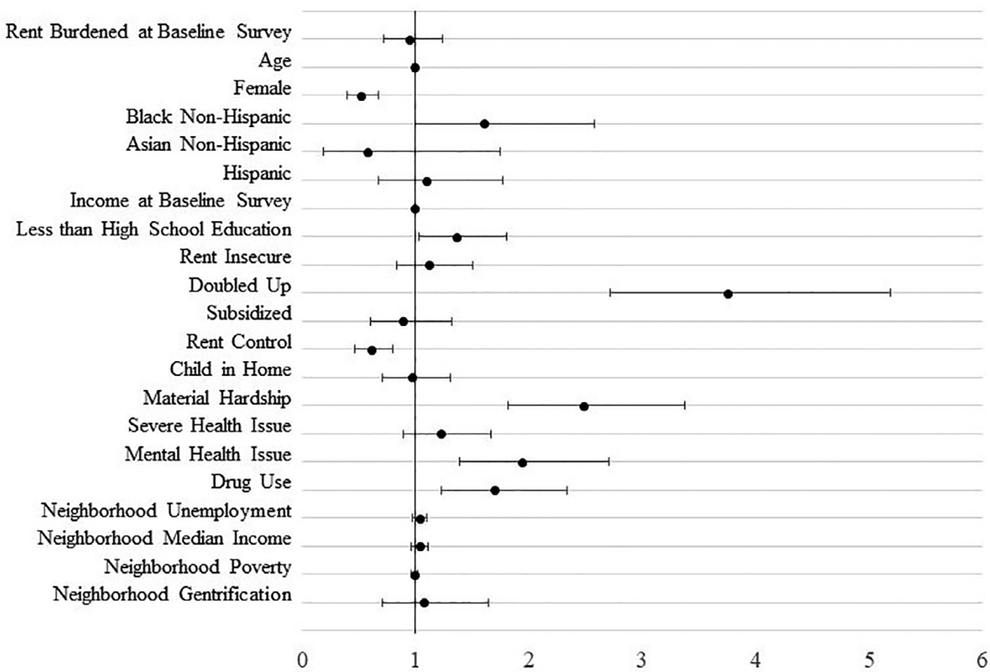

Figure 1. Odds ratios from logistic regression with 95% confidence intervals.

future experiences of homelessness at statistically significant levels, and their inclusion results in a minimal increase in the overall significance of the model. Several explanations exist for the lack of neighborhood significance in this study. First, prior research identifying a relationship between neighborhood characteristics and rates of homelessness tend to rely on cross-sectional rather than longitudinal data. Thus, these studies may detect associations between the areas in which already-homeless individuals are concentrated rather than the neighborhoods from which these individuals came. These studies also reflect the locations of shelters where concentrations of homeless individuals often exist, whereas the sample used here reflects a more uniform geographic distribution of participants recruited from the general public. Additionally, data limitations partially related to protecting Poverty Tracker respondent anonymity prevent researchers from analyzing neighborhood factors at scales more granular than the zip code level. According to the U.S. Census, zip codes in New York City are extremely populous, sometimes exceeding 100,000 residents. This scale prevents the identification of potential relationships between neighborhood characteristics at the Census block or block group level and homelessness, which may be more meaningful. Likewise, the zip code level may be too small to capture housing and economic trends that operate at the city or regional level. However, the lack of significance of neighborhood characteristics in this article are not completely counter to expectations, as these results align with past studies finding that individual-level socioeconomic circumstances and networks play a greater role in increasing housing stability than neighborhood conditions (Turney & Harknett, 2010). Finally, the lack of a significant association between homelessness and neighborhood gentrification aligns with several studies concluding that gentrifying neighborhoods, relative to non-gentrifying neighborhoods, do not increase displacement among low-income renters (Ding *et al.*, 2016; Freeman, 2005). However, it is possible that measuring the association between longitudinal changes in gentrification, rather than whether or not a neighborhood is already gentrifying, would present a better opportunity to measure whether neighborhood change and homelessness were related.

Importantly, the results described here are subject to several limitations. First, given the Poverty Tracker's somewhat recent inception and the specific questions asked in each wave, only a baseline survey and three subsequent waves could be incorporated into this study. As additional survey waves emerge, additional covariates will become viable for inclusion, enabling the specification of a more robust regression model. Second, as described above, the lack of granularity in neighborhood covariates calls their accuracy into question. This study suggests the broader zip code-level context in which an individual lives may not significantly impact their odds of experiencing homelessness, but the demographic and socioeconomic characteristics of smaller geographies may play a more meaningful role in preventing or contributing to homelessness. Third, New York City's policy context related to homelessness, which guarantees all individuals the right to shelter, may have a varied effect on different populations depending on how close they are to a shelter, how able they are to travel within the city, and how willing they are to enter a shelter, especially depending on household size and structure. This limitation suggests future research should seek to directly study the spatial relationship between the risk of homelessness and shelters. In a similar vein, the sample's location in New York City calls the generalizability of findings into question. For example, the average home size in the Northeastern United States and in U.S. metropolitan areas' urban centers are smaller than in other regions and areas of the country (Dietz & Siniavskaia, 2011), which may make doubling up in a city like New York more strenuous. On the other hand, the high cost of housing in New York city's real estate market is similar to other major global cities, and offers insights that can inform policy responses across the North American context and in advanced economies worldwide. A final limitation of note is that Poverty Tracker survey is focused on individuals with physical addresses, which, by definition, leads to underrepresentation of those experiencing homelessness at the time of survey recruitment. Despite these limitations, results offer compelling evidence that housing characteristics and individuals' mental and physical health are meaningfully associated with the possibility of experiencing homelessness.

Discussion

This study utilizes the Poverty Tracker survey's longitudinal data to gain insights into the predictors of homelessness in New York City. It joins a small group of similar studies (Bramley & Fitzpatrick, 2018; Curtis *et al.*, 2013; Fertig & Reingold, 2008) that are able to associate past individual information with future experiences of homelessness, thereby allowing researchers to identify the factors that predict homelessness for the general population. Given that even temporary periods of homelessness can cause deleterious impacts on well-being (Johnstone *et al.*, 2016), research focused on households in unstable housing situations who may only suffer from intermittent, or even one off, experiences of homelessness offers policymakers, planners, and social service workers valuable information related to a vulnerable but difficult-to-monitor group. My research also aligns with a growing body of work emphasizing the potential association between an individual's neighborhood characteristics and homelessness (e.g. Alexander-Eitzman *et al.*, 2013). The fact that I find no evidence that an individual's geographical context at the zip code level impacts their odds of becoming homeless can be interpreted as evidence that variations in local conditions, and their theoretical link to different levels of social and economic resources for those struggling to maintain consistent shelter, are less important than the challenges associated with struggling to afford rent, doubling up, and suffering from physical or mental health issues.

Results suggest that multiple drivers related to housing and personal characteristics likely simultaneously interact to create the conditions leading to homelessness. The prominence of doubling up in this complicated set of factors aligns with past findings that doubling up is often a key response to economic hardship (Seltzer *et al.*, 2012), and that it can erode social capital and be accompanied by expectations of financial contributions and household labor (Skobba & Goetz, 2015). These findings suggest, in line with recommendations from other studies of homelessness using data on individual-level housing and personal characteristics (e.g. Corman *et al.*, 2016), that policy efforts to prevent homelessness should not occur in silos related to housing, financial health, mental health, or substance abuse, but should instead seek opportunities to identify how these conditions might interrelate. Identifying a household suffering from one of these issues likely presents an opportunity to inquire about and address others. This is no small task, as individuals often hold private information that helps them understand when they might be at risk of homelessness, but this information is difficult or impossible for program administrators to gather. Indeed, the survey data used here is also likely subject to respondents' withholding of information—especially around sensitive topics such as mental health or drug use—which might mask associations between certain characteristics and homelessness. However, better advertising of prevention programs that are based on an understanding of which conditions are most likely to precede homelessness would be helpful in increasing the likelihood that individuals seek assistance before losing their shelter (O'Flaherty *et al.*, 2018). Measures aimed at homelessness prevention, rather than response, especially where prevention efforts take place outside of the traditional shelter system, have been identified as resource-efficient and capable of yielding large reductions in homelessness (Culhane *et al.*, 2011; Culhane & Metraux, 2008; Fowler *et al.*, 2019). For example, in New York City, researchers found that shelter entries decreased in neighborhoods in which Homebase, a homelessness prevention program, operated (Goodman *et al.*, 2016).

My findings related to the importance of housing instability on the pathway to homelessness also highlight the need for permanent, stable housing situations for households struggling with financial, physical, or mental health issues. Permanent supportive housing is an appealing solution, as it offers both housing and on-site services to households that might otherwise experience chronic homelessness. Although some have called into question the efficacy of this model on reducing levels of homelessness in communities (Corinth, 2017), the wider body of evidence on permanent supportive housing's effectiveness indicates that households receiving a combination of housing support and social services experience positive outcomes related to length of tenure and hospital visits, and such programs are generally viewed positively by consumers (Rog *et al.*, 2014).

Finally, results underscore the power of individual-level longitudinal data in identifying predictors of homelessness. Designers of future longitudinal surveys or supplements to existing surveys are encouraged to include questions related to respondents' housing situations, as housing has repeatedly been identified as a site of central importance in a household's financial, mental, physical, and social health. Survey responses related to an individual's assessment of his or her own neighborhood conditions would also be valuable. Additional sources of survey data would offer a much-needed compliment to existing forms of homelessness data. Perhaps the most common source, point-in-time counts, are unreliable (Agans *et al.*, 2014), often lead to severe undercounts, cannot trace transitions into and out of homelessness (National Law Center on Homelessness & Poverty, 2017) and are, by nature, unable to identify households on the precipice of homelessness who might receive support before losing their shelter. Researchers, policymakers, and vulnerable communities alike would benefit from the availability of additional individual-level data sources that can be used to study and address the factors leading to homelessness.

Overall, findings from this study add to the emerging body of evidence that a household's experience with housing-related factors can meaningfully add to or detract from their odds of becoming homeless. Rent control's association with lower rates of homelessness suggests policies promoting long-term stability in rental costs might be effective in stemming homelessness—especially in high-cost areas. Doubling up can be viewed as a clear warning sign that a household may be on the path to experiencing homelessness. These results point to the need for homelessness-related policies to include preventative measures aimed at keeping families housed, and for investments in housing to be seen as a broader contributor to public health, aligning with healthcare providers across the country (Evans, 2012) that now include providing housing for the unhoused in their suites of health interventions.

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Notes

1. As noted by Frederick et al.,(2014) a widely accepted definition of housing stability does not exist among housing researchers. The authors suggest the possibility that the term should be understood as multidimensional, and should be assessed based on traditional metrics of housing access and related factors such as educational status, financial status, the use of harmful substances.
2. See Linton et al., 2017 for an exception.
3. The New York City Longitudinal Survey of Wellbeing, also known as Poverty Tracker, was developed by the Columbia Population Research Center with funding from Robin Hood and in collaboration with the Center on Poverty and Social Policy. Access to the data, as well as codebooks and additional information, can be found at https://cprc.columbia.edu/content/new-york-city-longitudinal-survey-wellbeing
4. Importantly, studies relying on samples drawn from institutional settings yield insights about the non-private household population, which is a subgroup traditionally challenging for general population surveys like the one used in the present study to capture.
5. Poverty Tracker data are geocoded at the zip code level based on the mailing address of each respondent. This level of granularity is not ideal for analysis of neighborhood context, especially in a densely populated urban area such as New York City. However, it is required to maintain respondent anonymity.
6. This rate of homelessness is challenging to situate among benchmarks, as it spans across four years, includes a portion of households who have multiple experiences of homelessness, and only tabulates respondents (as opposed to all those living in a household) as homeless. U.S. Department of Housing and Urban Development-led point-in-time counts during the study period typically report around 1% of New York's population as homeless (see https://files.hudexchange.info/reports/published/CoC_PopSub_CoC_NY-600-2015_NY_2015.pdf).
7. Sensitivity analyses were conducted using lags of two time periods for variables that might be suspected of having more delayed impacts on future homelessness such as material hardships and levels of neighborhood gentrification. In each instance, the model strength was not improved over the final model selected, and the direction and significance of covariates did not change.
8. Other race omitted due to chart size limitations

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