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Who gets evicted? Assessing individual, neighborhood, and network factors

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ABSTRACT

The prevalence and consequences of eviction have transformed the lived experience of urban poverty in America, yet little is known about why some families avoid eviction while others do not. Applying discrete hazard models to a unique dataset of renters, this study empirically evaluates individual, neighborhood, and social network characteristics that explain disparities in displacement from housing. Family size, job loss, neighborhood crime and eviction rates, and network disadvantage are identified as significant and robust predictors of eviction, net of missed rental payments and other relevant factors. This study advances urban sociology and inequality research and informs policy interventions designed to prevent eviction and stem its consequences.

1. Introduction

Most low-income families receive no government housing assistance and reside in the private rental market. In recent years, these families have watched their incomes fall or flat line as their housing costs have soared (Collinson, 2011). Today, over half of poor renting families spend at least half of their income on housing costs, with a quarter dedicating over 70 percent to it (Eggers and Moumen, 2010). As a result, eviction has become commonplace in low-income communities (Desmond and Shollenberger, 2015). In 2013, renters in over 2.8 million homes thought they would be evicted soon (Desmond, 2015).

The consequences of eviction are many and severe. Beyond being a leading cause of family homelessness and residential instability (Burt, 2001; Phinney et al., 2007), an eviction record can prevent families from benefitting from public housing and can tarnish a leaseholder's credit rating (Greiner et al., 2013). When families do find subsequent housing after involuntary displacement, they often accept substandard conditions and relocate to disadvantaged neighborhoods (Desmond et al., 2015; Desmond and Shollenberger, 2015). These ramifications help explain why families who experienced forced removal from housing report significantly higher levels of material hardship and depressive symptoms years after the event (Desmond and Kimbro, 2015; Osypuk et al., 2012).

Despite the fact that the prevalence and consequences of eviction have transformed the lived experience of urban poverty in America, very little is known about who gets evicted. Nonpayment of rent is a leading cause of eviction, but not every tenant in arrears is forced out (Desmond, 2012a). Some families who fall behind—owing to a reduction in work hours,

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public benefits sanction, job loss, or any number of reasons—avoid eviction while others do not. What explains the difference?

Drawing on a unique dataset of Milwaukee renters, this study empirically evaluates several potential mechanisms for understanding disparities in eviction among renting families: *discrimination* (individual demographics); *life shocks* such as job loss or relationship dissolution (individual misfortunes); *gentrification* and *concentrated disadvantage* (neighborhood characteristics); and *social isolation* (network composition). Doing so not only contributes to identifying the subpopulations of low-income families at heightened risk of displacement; it also holds theoretical implications for understanding the nature of inequality as well as for unsettled debates about housing discrimination, gentrification, and the material consequences of network disadvantage.

This study also can also inform policymakers searching for the most effective way to prevent eviction and stem its consequences. If we find demographic factors, such as race or gender, to be most consequential for predicting eviction, that would suggest enforcing anti-discrimination legislation. Should life shocks be identified as powerful predictors of eviction, on the other hand, that would support the need for targeted interventions to soften the blow of job loss or other misfortunes. Finding that renters living in gentrifying neighborhoods are more likely to be evicted would imply that neighborhood-level interventions, such as “anti-eviction zones,” could make a difference. Finally, if we find the composition and character of a tenant's social network to be decisive, that would suggest social policies designed to strengthen or alter renters' family- or friend-based safety net.

1.1. Individual-level explanations 1: discrimination

Despite researchers' and policymakers’ longstanding interest in housing discrimination, very few studies have investigated the relationship between individual characteristics (e.g., race, gender) and forced displacement from housing. Most studies on housing discrimination focus on buying or renting housing and the aggregate consequences of unfair treatment on racial residential segregation (Massey and Denton, 1993). Owing to data limitations—e.g., audit studies, a powerful tool used to document discrimination in housing access, cannot be used to evaluate displacement—much less is known about discrimination in the eviction process.

The only study to date that has examined discrimination in the eviction decision has focused on the role of children. Analyzing survey and administrative data of tenants appearing in housing court, it found that families with children were far more likely to receive an eviction judgment, controlling for arrears, a discrepancy that reflected landlord discretion (Desmond et al., 2013). Relatedly, studies have shown that low-income women, especially those who live in black and Latino neighborhoods, are at heightened risk of eviction and foreclosure because (in the case of eviction) they are disadvantaged when it comes to making payments and repaying their debts (Desmond, 2012a) or (in the case of foreclosure) they are disproportionately targeted by the subprime lending industry (Baker 2014). These findings lead to the following hypotheses:

Hyp. 1a. All else equal, families with more children will be more likely to be evicted than households with fewer children.

Hyp. 1b. All else equal, women will be more likely to be evicted than men.

There is considerable evidence of the prevalence of racial discrimination in the housing market. Although discrimination at the point of housing access has declined in recent years, several studies have documented its persistence (Pager and Shepherd, 2008; Ross and Turner, 2005). Emphasizing the role of racial segregation, recent work has shown that black and Hispanic communities were disproportionately affected by the foreclosure crisis (Rugh, 2015; Rugh and Massey, 2010). While no study to date examines if racial minorities who fall behind in rent are more likely to be evicted, compared with whites who also fall behind, the weight of the evidence on housing discrimination suggests the following hypothesis:

Hyp. 1c. All else equal, black and Latino tenants will be more likely to be evicted than white tenants.

On the other hand, because of widespread racial discrimination in the front end of the housing process, with respect to access—or more precisely, because of the aggregate consequences of that discrimination: entrenched racial residential segregation—there may be little racial discrimination in the back end, with respect to eviction. Because high levels of racial segregation characterize many American cities, landlords operating in racially homogenous neighborhoods have good reason to assume that replacement renters will share the racial identity of evicted renters. If this is the case, then race, which drives so many other urban processes, may do little to predict why some renters are evicted and others are not—precisely because race already does so much to predict where renters live.

1.2. Individual-level explanations 2: linked misfortunes

Whereas the preceding hypotheses predict that certain protected groups disproportionately experience eviction, investigating the relationship between critical life shocks and eviction may also help illuminate the degree to which forced displacement is explained as the outcome of a sequence of misfortunes. Job loss is an obvious potential precursor to eviction. The last several decades have witnessed a precipitous decline in union strength alongside the rise of precarious work, characterized by the proliferation of jobs offering little security (Herzenberg et al., 1998). Under these conditions, terminations have become "a basic component of employers' restructuring strategies" (Kalleberg, 2008: 5). Renters who lose their jobs may soon thereafter lose their homes, especially if they have high rent-to-income ratios and no savings to cover a sudden income loss. Accordingly, we hypothesize that:

Hyp. 2a. All else equal, tenants who lose their job will be more likely to experience eviction the following year.

We also consider the association between relationship dissolution and eviction. The termination of a serious romantic relationship often results is a sudden drop in household income. Relationship dissolution can lead some individuals to experience temporary or long-term setbacks in material wellbeing (Amato, 2000; Osborne et al., 2012) and psychological distress (Rhoades et al., 2011). These considerations lead to the expectation that:

Hyp. 2b. All else equal, tenants who experience the dissolution of a serious romantic relationship will be more likely to experience eviction the following year.

The final misfortune we consider is eviction itself, as past evictions might be a suitable predictor of subsequent ones. For one, some renters may be serial evictees for whom eviction has become routine. These renters may be extremely poor or may behave in a certain way—owing to mental health conditions, participation in illicit activities, or a chronic abusive relationship, for example—that leads them to be regularly evicted. And irrespective of renters' behavior, landlords may be more prone to evict tenants with past evictions than those with no eviction history. Just as employers infer that laid-off workers are of low ability (Gibbons and Katz, 1991), landlords may make a similar inference about evicted renters and be less willing to work with them should they miss a rent payment. Accordingly, we hypothesize that:

Hyp. 2c. All else equal, the risk of eviction decreases with time since last eviction.

1.3. Neighborhood-level explanations: gentrification and concentrated disadvantage

Besides individual characteristics, the composition of a renter's neighborhood may also affect his or her likelihood of eviction. To begin, we analyze the relationship between eviction and living in a gentrifying area. American cities are experiencing a "resurgence of gentrification" marked by increased capital and population flows to urban areas (Smith, 1996). Social scientists have long believed that gentrification—in the form of neighborhood revitalization and concomitant population shifts to more affluent households—leads to the systematic displacement of low-income residents. Landlords operating in gentrifying neighborhoods may provoke evictions by raising rents or may clear their buildings through "no cause" evictions in hopes of attracting a better-off clientele (Marcuse, 1986; Newman and Wyly, 2006).

However, studies also have found no evidence that gentrification displaces poor families (Vigdor, 2002). Freeman and Braconi (2004) even found gentrification to be associated with lower rates of residential turnover among low-income families, speculating that the benefits of neighborhood revitalization lead poor renters to make "greater efforts to remain in their dwelling units, even if the proportion of their income devoted to rent rises" (p. 51). The question of forced displacement has long been at the center of the gentrification debate. Our study investigates if living in a gentrifying neighborhood is a significant predictor of forced displacement by addressing the following hypothesis:

Hyp. 3a. All else equal, tenants who live in gentrifying neighborhoods will be more likely to be evicted.

If families fight to stay in gentrifying neighborhoods, do they (by the same logic) exert little resistance when facing eviction from disadvantaged areas? Ethnographic research has shown that poor renters seeking to move from undesirable neighborhoods sometimes actively initiate an eviction to save enough money to relocate (Desmond, 2012a). Because securing an apartment entails paying first (and sometime last) month's rent in addition to a security deposit, some rent-burdened families are able to execute a move only if they withhold payments from their current landlord. If this strategy is more common in disadvantaged neighborhoods, then we might expect that:

Hyp. 3b. All else equal, tenants who live in high-crime neighborhoods will be more likely to be evicted.

A final consideration about the relationship between ecological characteristics and renters' likelihood of eviction extends beyond conventional accounts about gentrification and concentrated disadvantage to recognize that urban neighborhoods are *markets* or "social action fields" (Fligstein and McAdam, 2012). Housing stock is owned and managed by a limited number of landlords who often spatially cluster their properties, owing to geographic familiarity and ease of property management, and interact with each other at community events, professional gatherings, or on the street (Logan and Molotch, 1987). Landlords therefore have the ability to monitor one another's actions and orient their own behavior accordingly (Fligstein, 1996). Property management strategies may diffuse from landlord to landlord, block to block, resulting in an urban landscape in which eviction is spatially concentrated in a way that resembles the concentration of business practices within industries owing to transmission across firms (Simmons et al., 2007). Owing to landlord practices, similar neighborhoods could have qualitatively different eviction rates, resulting in a renter's likelihood of eviction being influenced in part by how routine eviction has become in her or his neighborhood. We thus hypothesize:

Hyp. 3c. All else equal, a tenant's likelihood of eviction will be positively associated with his or her neighborhood's eviction rate.

1.4. Network-level explanations: upward and downward ties

Last, we examine the association between social networks and eviction. Sociologists long have thought the urban poor "live within a very circumscribed and limited social world," with few strong ties to the middle class (Massey and Denton, 1993: 161). Wilson (1987) argued that this aspect of urban poverty, "social isolation," was at the root of many problems besetting the inner city, from joblessness to family complexity. These ideas have informed large-scale policy initiatives, from mixed-income housing to neighborhood relocation programs, designed to connect low-income families to more "prosocial and affluent social networks" (U.S. Department of Housing and Urban Development, 2011: 1, 23).

Empirical research analyzing the benefits of low-income families' ties to the middle class has been mixed. Some studies have linked social capital to getting a job (Granovetter, 1995; Fernandez and Fernandez-Mateo, 2006), status attainment (Lin, 1999), and home ownership (Heflin and Pattillo, 2002). Other studies, however, have found that low-income families face considerable barriers when seeking help from better-off ties. As a result, poor families tend to rely more on each other to make daily ends meet (Stack, 1974). Researchers also have found that the composition of a family's social network has limited effects on employment opportunities (Henly et al., 2005; Mouw, 2003). Smith (2005), for example, found that employed blacks were often disinclined to help their out-of-work friends and relatives, owing to potential reputational costs job referrals could bring.

The moment of eviction offers a unique opportunity to evaluate if the composition of one's social networks is associated with material benefits. Helping a relative or friend avoid eviction is not accompanied by the reputational risks that come with referring someone for a job in one's workplace. The costs are typically only financial. Moreover, although middle-class relatives or friends might play a limited role in low-income families' daily exchanges to obtain necessary resources, they may play a larger role in times of emergency (Briggs 1998; Desmond, 2012b). When poor renters face unexpected setbacks, they may ask their middle-class ties to provide cash contributions that could prevent one problem from turning into several. This leads to the following hypothesis:

Hyp. 4a. All else equal, renters embedded in advantaged social networks will have a lower prevalence of eviction.

If ties to homeowners or the gainfully employed are potentially helpful for low-income families in critical times of need, could ties to the truly disadvantaged be potentially harmful? This question is not concerned with the unhelpfulness of certain ties (e.g., a null relationship between network advantage and eviction) but with the potential of a renter's degree of *network disadvantage*—the proportion of one's strong ties to people who are unemployed, addicted to drugs, in abusive relationships, or who have experienced major, poverty-inducing events (e.g., incarceration, teenage pregnancy)—to increase his or her propensity for eviction. Families embedded in disadvantaged networks could experience a kind of normalization of suffering whereby consequential events (like eviction) come to be seen as a regular part of life, as hardships to be endured rather than resisted (Bourdieu et al., 1999; Hirschfield and Piquero, 2010). Alternatively, people embedded in disadvantaged networks may be more likely to commit eviction-warranting behavior—or to have close ties bring such behavior into their homes—involving poverty, crime, or disruptive activity (Desmond and Valdez, 2012). These considerations suggest the following hypothesis:

Hyp. 4b. All else equal, renters embedded in disadvantaged social networks will have a higher prevalence of eviction.

2. Data

To address these hypotheses, this study draws on the *Milwaukee Area Renters Study* (MARS). Designed to collect new data related to housing, poverty, and urban life, MARS is an in-person survey of 1,086 rental households in Milwaukee. The University of Wisconsin Survey Center supervised data collection, which took place between 2009 and 2011.[1] One person per household, usually an adult leaseholder, was interviewed. Comprised of more than 250 unique items, the MARS instrument was administered in English and Spanish. According to the most conservative calculation (AAPOR Rate 1), MARS has a response rate of 83.4%.

Households were selected through multi-stage stratified sampling. Drawing on Census data, Milwaukee block groups were sorted into three strata based on racial composition. Block groups were placed in white, black, or Hispanic strata if these respective groups made up the largest proportion of the population. Then, each of these strata was subdivided into high- and low-poverty neighborhoods based on the overall income distribution of each racial or ethnic group in the city. Blocks from within each of these six strata were randomly selected. When a block was selected into the sample, interviewers visited every household in the selected block, saturating the targeted areas. This sampling strategy resulted in renting households from

[1] The MARS survey took place in the wake of the foreclosure crisis. Although foreclosures of rental property increased during the crisis (Been and Glashausser, 2009), evictions in Milwaukee actually declined (Desmond, 2012a). These opposing trends may somewhat cancel out one another.

across the city being included in the study. The MARS study drew from 168 of 591 unique block groups, representing 28% of Milwaukee neighborhoods. To focus on renting households, interviewers screened out owner-occupied dwellings. MARS also includes an oversample of 100 recently evicted tenants, who were randomly selected from closed Milwaukee eviction cases that occurred 12–24 months prior to the final fielding of the survey.

After data collection, custom design weights for the regular sample and oversample were calculated to reflect the inverse of selection probability, facilitated by the Lahiri (1951) procedure, based on the demographic characteristics of Milwaukee's rental population and adjusted to MARS's sample size. The Lahiri procedure allows the sampler to select probability samples (with a probability proportional to size) and to compute the selection probabilities for the resulting sample. Selection probabilities are then used to calculate the design weights for the overall sample. We use these custom weights to facilitate descriptive statistics generalizable to Milwaukee's rental population.

Because MARS focused on renters, everyone in the sample was at risk of eviction. Milwaukee is a strategic setting in which to investigate the experiences of urban renters for at least three reasons. First, the characteristics of Milwaukee's residents (Pager, 2007) and rental market (U.S. Department of Housing and Urban Development, 2009) are comparable to those of many U.S. cities. Second, renter protections in Milwaukee also are fairly typical, especially compared to wealthy cities with an economically-diverse rental population (Manheim, 1989), and available data suggest that neither Milwaukee nor Wisconsin have an unusual eviction rate (Desmond, 2015). Third, studying Milwaukee not only expands sociological data on and knowledge of different urban environments; it also may produce findings more applicable to cities distinct from America's exceptional global hubs (Small, 2007). That said, future research is needed to evaluate the extent to which these findings are generalizable to settings beyond Milwaukee. Table A1 compares the weighted MARS sample with renters represented in the 2010 American Community Survey (ACS). Milwaukee renters have similar levels of education as those represented in the ACS, if smaller household incomes. The share of white renters is slightly larger in MARS, and the share of black and Hispanic renters is slightly higher in the ACS.

2.1. *Measuring eviction*

The centerpiece of the MARS questionnaire is a housing roster used to obtain a two-year residential history from each respondent. Respondents were asked to list all the places they "lived or stayed for at least a month." They also were asked to provide the addresses or crossroads of each residence. This information was geo-coded using ArcGIS and an associated road network database. Then each current and past residence was assigned to a census block group—our neighborhood metric—and linked to aggregate population estimates. Carefully collected retrospective data have been shown to be considerably accurate (Haas, 2007). Retrospective data are most reliable when they involve salient life events (Mathiowetz and Duncan, 1988); are limited to a recent recall period (Beckett et al., 2001); and are collected with the aid of a memory prop (Sayles et al., 2010). The retrospective data in our study meet all three criteria. They focus on the memorable shock of eviction; are restricted to a two-year recall period; and were collected with a recent history calendar to prime memory.

Measuring people's reasons for moving is not simple. When asked why they moved, tenants may respond in a way that maximizes their own volition or social desirability. As Desmond (2012a,b) learned while conducting fieldwork among low-income tenants, someone who was, say, evicted from a run-down apartment is more likely to explain that she moved "because the landlord wouldn't fix anything" than because she was forced out. Accordingly, to collect reliable data about the motivations for moving, MARS interviewers asked each respondent a series of ordered yes/no questions, beginning with involuntary removals and ending with voluntary moves:

1) An eviction is when your landlord forces you to move when you don't want to. Were you, or a person you were staying with, evicted?
2) Did you, or a person you were staying with, [leave after receiving] an eviction notice?
3) Did you move away from this place because your landlord told you, or a person you were staying with, to leave?
4) Did you move away from this place because you, or a person you were staying with, missed a rent payment and thought that if you didn't move you would be evicted?
5) Did you move away from this place because the city condemned the property and forced you to leave?
6) Did you move away from this place because:
   (a) The landlord raised the rent?
   (b) The neighborhood was dangerous?
   (c) The landlord wouldn't fix anything and your place was getting run down?
   (d) The landlord went into foreclosure?

Respondents who answered no to question 1 were asked question 2, and so on. If a respondent answered no to all of these questions, she or he finally was asked, "I see that none of these reasons fit your case. Why did you move away from this place?" We believe this approach minimized recall bias and allowed us to collect accurate data on the motivations for moves. MARS offers the most comprehensive data to date on involuntary displacement in a representative sample of urban renters in a major American city.

For this paper, we record all residential moves renters undertook two years prior to being surveyed. A move is considered to be an "eviction" if it was initiated by a landlord and involved situations in which a tenant had no choice other than to relocate (or thought as much) (items 1–3 above). This includes formal evictions (which are processed through the court) and informal evictions (which are not).[2] Landlord foreclosures and building condemnations are not included in this definition.

3. Methods

To investigate multiple factors associated with experiencing eviction, we estimate a series of discrete hazard models. These models allow for multiple "failures" (evictions) per respondent. The unit of observation is person-months, clustered within respondents. Discrete hazard models are ideal because they allow us to estimate the association of time-variant and time-invariant variables with eviction. Discrete hazard models also allow us to account for the "right-censoring" of observations: the fact that some renters who do not experience evictions during the 24-month observation period will experience eviction in the future. This is done by conditioning on the cumulative exposure of renters to the hazard of eviction, here measured by a variable that accounts for the number of months since the respondent last experienced an eviction. For renters with no previous evictions, this variable measures the number of months since the respondent began living in the first residence reported to the interviewer within the observation period.

3.1. Individual-level characteristics

To assess Hypotheses 1a-c, we include variables recording each respondent's sex (1 = female) and the number of children in the household. To measure a respondent's race and ethnicity, we include indicator variables for *African-American Tenants* and *Hispanic Tenants*, leaving white and "other race" tenants as the reference group.

To address Hypotheses 2a-b, we include indicator variables that measure two "shocks" that could lead to eviction: job loss and relationship dissolution. These variables take the value of 1 if a respondent reported losing a job or exiting a self-defined "serious" relationship in the year before eviction.[3] As noted above, we also include a variable that measures "time since eviction." A measure of cumulative risk is a standard component of discrete hazard models, but the association of "time since eviction" with subsequent evictions is also of empirical interest as it can be used to estimate potential downstream consequences of previous evictions (Hyp. 2c).

3.2. Neighborhood characteristics

With respect to Hypotheses 3a-c, which assess the influence of neighborhood characteristics on the likelihood of eviction, all households in our sample were assigned to a census block group, our neighborhood metric.[4] Each block group was then linked to aggregate data from the 2010 U.S. Census, crime records from the Milwaukee Police Department, and eviction records from Milwaukee County courts.

We created a neighborhood disadvantage scale via factor analysis to measure neighborhood quality. In line with prior research (Sampson, Morenoff, and Gannon-Rowley, 2002), we loaded seven neighborhood characteristics onto a single scale, including: median household income, violent crime rate, and the percentages of families below the poverty line, of the population under 18, of residents with less than a high school education, of residents receiving public assistance, and of vacant housing units. The scale is standardized with a zero mean and a unit standard deviation. It ranges from −1.57 to 2.92, showing considerable variation within our sample.

To investigate the relationship between gentrification and eviction, we include three potential measures of gentrification in successive models. First, we include dummy variables indicating whether a Census tract is "gentrified" or "ungentrified," drawing on the American Community Survey (Ruggles et al., 2015).[5] We classify tracts as *gentrified, ungentrified,* or *ineligible for gentrification* following definitions developed by Maciag (2015), which in turn is based on Freeman (2005). To begin, we categorize as "eligible" for gentrification tracts with 2000 median household incomes and median home values in the bottom 40th percentile of Milwaukee's metropolitan area. We consider tracts "gentrified" if (1) between 2000 and 2010 they were among the top-third of eligible tracts in terms of increased median home values and increased percentage of adults with bachelors' degrees and (2) median home values increased after adjusting for inflation.

We analyze two other variables that may be correlated with gentrification processes: *percentage black* and *concentrated disadvantage*. If evictions are more commonly experienced in neighborhoods undergoing demographic transformations (as opposed to segregated areas), then we would expect to find a significant squared term. That is, we would expect the likelihood

[2] Informal evictions are landlord-initiated forced moves carried out beyond the purview of the legal system, as when a landlord tells a family to leave or changes their locks (Desmond and Shollenberger, 2015; Hartman and Robinson, 2003).

[3] In the event that these shocks co-occurred in the same month as an eviction (and thus the precedence of the shock to the eviction cannot be established), we have chosen not to code the job loss or relationship dissolution variables with the value of 1. To ensure robustness of our findings, we also considered a version of the shock variables wherein co-occurrences are coded with the value of 1; all findings were substantively identical.

[4] In Milwaukee, the population of the average block group was 1135 in 2010.

[5] Because block-group units proved too small to facilitate precise estimates of neighborhood change over time, we used Census tracts when assessing the relationship between gentrification and eviction.

of eviction to increase as neighborhoods approach some “tipping point” in terms of racial composition or concentrated disadvantage before decreasing as neighborhoods become more homogeneous.

Our measure of neighborhood crime rate (Hyp. 3b), based on Milwaukee Police Department data, is the sum of all counts of all National Incident-Based Reporting System (NIBRS) Group A and B offenses per 100 people.[6] Last, to explore a potential relationship between a neighborhood's eviction rate and a renter's propensity for eviction (Hyp. 3c), we draw on all court-ordered evictions that took place in Milwaukee over the study period. These records were pulled, pruned of all court outcomes other than eviction judgments, geocoded by address, and aggregated to block groups. Because our observations are people-months, all neighborhood indicators refer to the neighborhood in which a respondent lived in a given month. However, to adjust for seasonal variation, these indicators refer to annual rates that correspond to the focal neighborhood and people-month.[7]

3.3. Network disadvantage scale

To being investigating Hypotheses 4a-b, we collected egocentric social network data through a name-generator. Respondents were handed a half sheet of paper and asked to write down their close friends and family members who were adults. After listing their closest kin and friends, respondents were asked how many of their listed ties: (1) own their home; (2) graduated from college; (3) have a full-time job; and (4) have a part-time job. Responses were summed and divided by four to create a global measure of “upward connections,” or the percentage of close ties that are advantaged.

Previous studies typically stop there (e.g., Tigges et al., 1998). However, tenants who participated in MARS were also asked how many of their listed ties: (1) had a child before they were 18; (2) receive public assistance; (3) have a criminal record; (4) have had a child removed from their custody; (5) have been evicted; (6) have been to jail or prison; (7) are currently in an abusive relationship; and (8) are currently addicted to drugs. Responses to these questions were summed and divided by eight to create a global measure of “downward connections.” Here, a score of 1 would indicate that all of the respondent's close family members and friends experienced each of the eight conditions, while a score of 0 would indicate that none did.

We also asked each of our respondents how many of their ties lived in Milwaukee and how many lived in their neighborhood. Table A2 displays the summary statistics of the variables used to measure network advantage and disadvantage; Table A3 displays their covariance matrix.[8] Like most network data, ours is static, measured only at one point in time. This requires us to accept the assumption that respondents' strong ties were stable over our two-year study period. This assumption is reasonable, since the composition of one's close friends and family members tends not to shift significantly over short time frames (Ruef et al., 2003). However, this data limitation is worth bearing in mind.

3.4. Controls

All our models control for a number of factors potentially related to eviction. Because family structure is an important predictor of eviction (Desmond et al., 2013), we control for marital status and the number of other adults in the household. We also observe if respondents have a criminal record in general and a felony conviction in particular, because these marks can influence one's housing prospects. To account for socioeconomic status, we control for variables indicating whether the respondent has less than a high school degree, a high school degree, or some college education. We also control for each renter's income, roommates' total income, and the cost of rent (net of assistance). As a final demographic control, we include a measure for age.

Because evictions are often due to missed rental payments, all of our models control for *payment history*. This variable is based on a question asking whether a renter was never, rarely, sometimes, often, or always late with rent when living at a given residence. We consider someone to be a “late payer” if they were sometimes, often, or always late with payments. We consider a renter to have a “history of late payment” if she or he was a “late payer” at their focal apartment (at the time of observation) or at the apartment that preceded their focal apartment. We do this because the stigma of a “late payer” can follow a renter, whether through informal communication among landlords or through publicly accessible eviction records. We reason that landlords keep tenants with recent histories of late payments on a shorter leash than those with clean records. See Table A4 for a descriptive summary of all variables used in the analyses.

[6] The NIBRS includes 21 Group A and 11 Group B offenses. Group A offenses include arson, assault, bribery, burglary, forgery, destruction of property, drug offenses, embezzlement, extortion, fraud, gambling, homicide, kidnapping, theft, motor vehicle theft, obscenity, robbery, forcible and nonforcible sex offenses, stolen property, and weapons violations. Group B offenses include bad checks, curfew violations, disorderly conduct, driving under the influence, drunkenness, nonviolent family offenses, liquor law violations, peeping Toms, runaways, trespassing, and all other offenses.

[7] Landlords who utilize professional management services may have a different approach to eviction than those who manage property themselves; however, the utilization of professional management services does not vary significantly across neighborhood contexts (Desmond and Wilmers 2016).

[8] To assess how well the MARS survey encouraged respondents to recall their close friends and family members, we compared our data to social network data collected through the General Social Survey's (GSS) name generator (McPherson et al., 2006). On average, MARS respondents reported significantly more ties than GSS respondents, and there is more variation in network size in MARS. That the MARS name generator collected information about more ties than the GSS—the standard-bearer for nationally representative data on social networks (Marsden 2005)—increases our confidence in the effectiveness of our survey instrument to encourage the reporting of strong ties.

4. Findings

4.1. Individual characteristics

We fit a progression of discrete hazard models to examine how individual, neighborhood, and network characteristics are associated with renters' odds of eviction. We begin with two models that contain only individual-level predictors. The first contains demographic factors motivated by Hypotheses 1a-c. The second model includes life shocks motivated by Hypotheses 2a-c.

The estimated coefficients in the first model support Hypothesis 1a*:* children increase the risk of eviction. For ease of interpretation, we calculate the marginal effect of each additional child on a renter's probability of eviction (Long and Freese, 2014). The marginal effect is estimated by averaging "individual marginal effects" across all observations. The individual marginal effect is ($p_{x+1}-p_x$), where p_x is the estimated probability that this observation results in an eviction, and p_{x+1} is the estimated probability of eviction if that renter has one more child. The individual marginal effect is interpreted as the change in eviction probabilities associated with an additional child. By averaging individual marginal effects across all respondents, we arrive at the average change in eviction probabilities associated with an additional child.

The marginal effect of an additional child on a renter's *monthly* probability of eviction is 0.002, compared to a base (monthly) eviction probability of 0.006. Note that these small probabilities scale to higher rates of eviction over greater time periods. A 0.005 monthly probability of eviction implies a 0.058 probability of eviction in a given year, while a 0.007 monthly probability of eviction implies a 0.081 annual probability. Extrapolating to *annual* eviction rates, we predict that a renter with two children has an 11.7% chance of being evicted in a given year, compared to a 9.5% chance for a renter with one child and a 7.3% chance for a childless renter.[9] This finding suggests that family discrimination colors the eviction decision, with each successive child further increasing a renter's odds of eviction. We did not find that women or racial minorities were at greater risk of eviction (all else equal).

Model 2 of Table 1 displays evidence showing that renters who lose their job are at higher risk of eviction. An analysis of marginal effects shows that renters who have lost their jobs are approximately twice as likely to be evicted than the average Milwaukee renter. Renters with long and unblemished rental histories are at lower risk of eviction than renters with shorter rental histories or evictions in their recent past. Relationship dissolution, however, was not associated with eviction rates after conditioning on other factors. Notably, the coefficient *Number of Children* remains highly significant and predictive of eviction even after we control for life shocks and habitual late payments, which unsurprisingly are predictive of eviction.

Table 1
Discrete hazard models with individual-level covariates.

	I		II	
	Coef.	S.E.	Coef.	S.E.
Lost job prev. year			0.946**	(0.289)
Breakup prev. year			−0.629	(0.751)
Hispanic tenant	0.130	(0.375)	0.175	(0.372)
Black tenant	0.075	(0.305)	0.119	(0.312)
Married	−0.103	(0.375)	−0.094	(0.368)
Number of kids	0.257***	(0.070)	0.237***	(0.069)
Number of adults	−0.375	(0.280)	−0.381	(0.285)
Female tenant	0.189	(0.291)	0.211	(0.279)
Payment history	0.526*	(0.238)	0.472*	(0.238)
Current income	−0.196	(0.176)	−0.134	(0.174)
Roommate income	−0.000	(0.000)	−0.000	(0.000)
Monthly rent	0.237	(0.261)	0.129	(0.272)
Criminal record	0.199	(0.331)	0.125	(0.320)
Felony record	0.184	(0.395)	0.251	(0.383)
Less than HS education	−0.010	(0.579)	0.034	(0.573)
High school education	0.536	(0.521)	0.581	(0.514)
Some college education	0.344	(0.508)	0.364	(0.501)
Age	0.000	(0.010)	−0.000	(0.010)
Time since eviction	−0.007**	(0.002)	−0.007**	(0.002)
Constant	−5.507***	(0.697)	−5.626***	(0.702)
N (observations)	12,707		12,707	
N (groups)	653		653	
Pseudo R^2	0.051		0.061	

Notes. Clustered standard errors in parentheses.
* $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$ (two-tailed).

9 Yearly probabilities are derived using the formula $p_y = 1\text{-}(1\text{-}p_m)^{12}$, where p_y is the annual probability and p_m is the monthly probability.

4.2. Neighborhood factors

We now examine neighborhood-level determinants of eviction. The first three models of Table 2 are simple models meant to investigate whether residents of gentrifying neighborhoods experience higher rates of eviction. We examine whether gentrified or ungentrified neighborhoods experience higher rates of eviction than wealthier neighborhoods that are considered ineligible for gentrification. We also estimate a possible curvilinear relationship between concentrated disadvantage scores as well as the percentage of households in each neighborhood that are African-American. We find no significant effect for any of our indicators of gentrification, suggesting that renters living in racially or economically transitioning neighborhoods do not have a higher likelihood of eviction than renters living in racially and economically homogeneous areas (conditional on other covariates).[10]

Because we did not find evidence of a curvilinear relationship between eviction and concentrated disadvantage or between eviction and *Percent Black*, we omit the corresponding squared terms in further models.

Digging deeper into this finding, in Model 4 of Table 2 we account for each neighborhood's crime and eviction rate, as well as its level of concentrated disadvantage. Supporting Hypotheses 3b and 3c, we find that a neighborhood's crime and eviction rates are significant predictors of eviction.[11] Net of payment history, a standard-deviation increase in crime rate is associated with a 0.003 increase in the *monthly* probability of eviction, while a standard-deviation increase in the eviction rate is associated with a 0.002 increase. Note that concentrated disadvantage is no longer significant in this model. This suggests that an area's crime and eviction rate likely mediates the relationship between neighborhood disadvantage and the probability that a renter will be evicted.

4.3. Network composition

Next we show a series of models that assess how the likelihood of eviction may be associated with network advantage and disadvantage. Model 1 of Table 3 shows a large, statistically significant association between network *disadvantage* and eviction, while Model 2 shows a null relationship between network *advantage* and eviction.[12] These models control only for cumulative hazard (time since previous eviction) as well as late payment history. In Model 1, we find that a standard-deviation increase in network disadvantage is associated with a 0.002 increase in the monthly probability of eviction, or an annual probability increase of 0.024.

Model 3 shows that the significant association of network disadvantage with eviction changes little when we control for network advantage, network size, or the location of network ties (e.g., if close kin and friends live within the city). This model implies that network disadvantage may have an adverse effect on housing stability rather than simply reflecting a lack of

Table 2
Discrete hazard model of evictions with neighborhood covariates.

	I		II		III		IV	
	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.
Ungentrified tract	0.444	(0.314)					0.318	(0.484)
Gentrified tract	0.301	(0.436)					0.449	(0.499)
Pct. black			0.004	(0.004)			−0.005	(0.004)
Pct. black squared			−0.000	(0.000)				
Concentrated disadvantage					0.210	(0.104)	0.134	(0.179)
Con. disadv. squared					0.045	(0.745)		
Crime rate							0.588***	(0.165)
Eviction rate							4.597*	(1.882)
Payment history	0.794***	(0.240)	0.883***	(0.203)	0.878***	(0.201)	0.776**	(0.246)
Time since eviction	−0.008***	(0.002)	−0.007***	(0.002)	−0.007***	(0.002)	−0.007**	(0.002)
Constant	−5.399	(0.286)	−4.962***	(0.235)	−5.113***	(0.145)	−6.460***	(0.451)
N (observations)	12,185		15,048		13,682		11,668	
N (groups)	661		735		708		640	
Pseudo R^2	0.020		0.021		0.026		0.0468	

Notes. Clustered standard errors in parentheses. Reference category for gentrification variables is "Tract Ineligible for Gentrification."
* $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$ (two-tailed).

[10] A closer look at the data reveals that on average poor ungentrified neighborhoods have higher crime and eviction rates than both gentrified neighborhoods and those ineligible for gentrification. Gentrified neighborhoods have lower crime and eviction rates than ungentrified neighborhoods and higher rates than (relatively affluent) ineligible neighborhoods.

[11] The bivariate correlation between crime and eviction rates is.163 among in-sample block groups (n = 778).

[12] Several alternative and disaggregated measures of network advantage, such as the number of family members with college degrees and the number who have had helped respondents pay the rent, were also not found to be significantly associated with eviction.

Table 3
Discrete hazard models of evictions with network and neighborhood covariates.

	I	II	III	IV
	Coef.	Coef.	Coef.	Coef.
Network disadvantage	3.613***		3.750***	3.541***
	(0.734)		(0.806)	(0.850)
Network advantage		0.235	1.088	1.257
		(0.576)	(0.677)	(0.789)
Milwaukee ties			0.058	0.060
			(0.037)	(0.041)
Total ties			−0.043	−0.022
			(0.034)	(0.037)
Concentrated disadvantage				0.101
				(0.144)
Crime rate				0.542***
				(0.131)
Eviction rate				4.786**
				(1.748)
Percent black				−0.006
				(0.003)
Payment history	0.783***	0.903***	0.788***	0.776***
	(0.207)	(0.198)	(0.204)	(0.227)
Time since eviction	−0.005**	−0.007***	−0.005**	−0.006**
	(0.002)	(0.002)	(0.002)	(0.002)
Constant	−5.442***	−5.163***	−5.815***	−7.123***
	(0.148)	(0.233)	(0.339)	(0.454)
N (observations)	14,947	14,947	14,923	13,196
N (groups)	722	722	721	688
Pseudo R^2	0.031	0.019	0.034	0.061

Notes. Clustered standard errors in parentheses.
* p < 0.05; ** p < 0.01; *** p < 0.001 (two-tailed).

network resources. As Model 3 shows, network disadvantage's positive association with eviction is not mediated by network resources.

In Model 4, we control for all neighborhood and network measures. The coefficients for network disadvantage, crime rate, and eviction rate are robust, remaining significant and maintaining their size. Network and neighborhood disadvantage may operate independently of one another when it comes to influencing eviction.

5. Discussion

Although the rise of housing burden among low-income families has increased the prevalence of eviction in poor communities, social scientists know very little about who gets evicted. This is the first study to rigorously investigate the determinants of eviction. To do so, we applied discrete hazard models to a novel dataset of renters in Milwaukee to identify which characteristics are associated with forced displacement. The results of this study can be summarized in a comprehensive model predicting eviction, one that incorporates individual, neighborhood, and network characteristics (see Table 4). In Model 1 of Table 4, we see that network disadvantage as well as neighborhood crime and eviction rates have maintained their significance and coefficient size. We also find that the coefficient for number of children in the household remains significantly associated with an increased likelihood of eviction. The coefficient for previous job loss remains positive but has lost significance. A history of late payments is not significant in the models in Table 4, despite having been significant in all of the preceding models. This suggests that landlords consider several factors, such as the desirability of the tenant and the rental unit, when deciding whether to evict a tenant who has fallen behind in rent.

In Model 2 of Table 4, we account for a possible objection to our measure of network disadvantage: that the association between network disadvantage and eviction is spurious because some respondents' close kin and friends have been evicted.[13] Perhaps we are merely finding that respondents lived with close ties who had been evicted, which would increase both their network disadvantage and likelihood of eviction. Accordingly, in Model 2, we include the percentage of friend and family ties with evictions as independent controls. Despite this disaggregation, our network disadvantage measure maintains its size and significance.

Estimating marginal effects from Model 1, we now find that each child in the household is associated with a 0.002 increase in the monthly probability of eviction, while a history of late rent payments is associated a 0.002 increase. With respect to neighborhood factors, the average marginal effect of a standard-deviation increase in crime rates on the monthly probability of eviction is about 0.002, while the association for a standard-deviation increase in neighborhood eviction rates is around

[13] The mean percentage of strong ties that have experienced eviction is 5% (see Table A2).

Table 4
Discrete hazard models of evictions with full set of covariates.

	I		II	
	Coef.	S.E.	Coef.	S.E.
Network characteristics				
Network disadvantage	4.111***	(1.159)	3.842**	(1.227)
Family evictions			1.026	(0.641)
Friend evictions			−0.495	(0.622)
Neighborhood characteristics				
Concentrated disadvantage	−0.022	(0.243)	−0.030	(0.246)
Crime rate	0.575*	(0.251)	0.595*	(0.260)
Eviction rate	3.913*	(1.592)	3.763*	(1.644)
Percentage black	−0.007	(0.006)	−0.007	(0.006)
Ungentrified	−0.133	(0.655)	−0.131	(0.656)
Gentrified	0.140	(0.597)	0.067	(0.582)
Individual characteristics				
Payment history	0.346	(0.299)	0.326	(0.310)
Lost job prev. year	0.539	(0.388)	0.565	(0.397)
Breakup prev. year	−0.338	(0.756)	−0.286	(0.757)
Hispanic tenant	0.000	(0.625)	0.332	(0.629)
Black tenant	0.135	(0.566)	0.187	(0.563)
Married	0.058	(0.445)	0.090	(0.451)
Number of kids	0.248**	(0.093)	0.240**	(0.092)
Number of adults	−0.803	(0.455)	−0.797	(0.452)
Female tenant	−0.053	(0.359)	−0.034	(0.362)
Current income	−0.186	(0.217)	−0.207	(0.212)
Roommate income	0.000	(0.000)	0.000	(0.000)
Monthly rent	−0.001	(0.546)	0.026	(0.514)
Criminal record	0.114	(0.434)	0.121	(0.443)
Felony record	0.369	(0.482)	0.384	(0.488)
Less than HS education	−0.281	(0.631)	−0.339	(0.639)
High school education	0.617	(0.527)	0.532	(0.525)
Some college education	−0.139	(0.593)	−0.200	(0.591)
Age	0.003	(0.013)	0.005	(0.014)
Time since eviction	−0.005	(0.003)	−0.005	(0.003)
Constant	−6.611***	(0.894)	−6.669***	(0.909)
N (observations)	9689		9689	
N (groups)	553		553	
Pseudo R^2	0.104		0.107	

Notes. Clustered standard errors in parentheses.
* $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$ (two-tailed).

0.001. The average marginal effect of a standard-deviation increase in network disadvantage remains approximately 0.002. Notably, the observed range of network disadvantage in our sample is roughly seven standard deviations large. This means that network disadvantage can result in extreme residential instability for a substantial minority of renters. In Model 1, the average renter is associated with a 7% chance of eviction in a given year. A two standard-deviation increase in network disadvantage would raise that renter's odds of eviction to 11.3%, while a three standard-deviation increase raises them to nearly 13.5%. Additional sources of disadvantage—e.g., job loss, multiple children, residence in a high-crime neighborhood—only send this rate higher.

We stress that each factor we have identified as being significantly associated with eviction is *net of* missed rent payments. Because we account for this eviction-warranting behavior, our findings cannot be reduced to straightforward economic conditions. How, then, should we make sense of our results?

Individual Characteristics. Starting with individual-level factors, this study found that a renter's likelihood of eviction increased with her or his number of children, net of socioeconomic factors, race, and rental payment history. We found no evidence that black, Latino, or female tenants were more likely to be evicted. Because of the economic and racial segregation of cities like Milwaukee, a biased landlord with property in, say, a poor black neighborhood has little chance of replacing black tenants with white ones or low-income tenants with a more financially-secure family. Neighborhood segregation produces housing market segmentation. Accordingly, operating in certain neighborhoods largely entails renting exclusively to certain demographic groups. If the racial and economic composition of a landlord's tenant base remains stable, then what fluctuates is family composition and size. Accordingly, while landlords may have no interest in disproportionately exposing women or racial minorities to eviction—*net of* economic and eviction-warranting factors—they do have an interest in replacing large households with smaller ones, or families with childless tenants. Because children can cause added stress on property, disturb neighbors, and attract unwanted state scrutiny by child welfare agents or law enforcement officers, landlords may be more likely to evict large families who fall behind in rent than smaller families or adult-only households. This finding remained significant and stable across all models. The sociology of discrimination is vibrant and established, but it centers primarily on racial and gender discrepancies (Pager and Shepherd, 2008). Our study contributes to elevating the importance of family discrimination in the housing market in general and the eviction decision in particular.

Although the findings were mixed, this study also identified job loss as a possible predictor of eviction. Renters who lose their jobs experience not only a sudden loss of income but also the loss of predictable *future* income. From a landlord's perspective, this makes job loss qualitatively different from other unexpected negative events that might cause a tenant to fall behind in rent (e.g., robbery, unusual medical expenses) because it becomes unclear how the tenant, now lacking an income stream, will be able to catch up or pay next month's rent. This consideration likely leads landlords to evict laid off renters at higher rates than similar tenants who fall behind for other reasons. The same logic would apply to relationship dissolution only if that dissolution altered the composition of a household (e.g., a live-in boyfriend moves out). Our null finding regarding the link between relationship dissolution and eviction suggests that, unlike job loss, a sizeable proportion of breakups in our sample likely did not have a drastic effect on tenants' household income.

If job loss is linked to eviction, then anti-eviction policies could be developed to help temporarily unemployed renters remain in their homes and neighborhoods. But there is a deeper policy implication to this finding. Most research on job loss focuses on outcomes specific to the labor market (e.g., length of unemployment, earnings losses) (Gibbons and Katz, 1991; Couch and Placzek, 2010). However, the findings of this study suggest that the effects of job loss are wide-reaching and can be found beyond the economic sector. Labor market instability begets housing and neighborhood instability. Beyond this empirical contribution, this finding speaks to a broader implication for research on inequality: namely, the need to understand poverty, not simply as the result of low incomes, but as hardship too often experienced as *correlated adversity*, the linked ecology of maladies across multiple dimensions and institutions (Alkire and Foster, 2011).

Neighborhood Factors. With respect to neighborhood-level factors, this study found no evidence that renters residing in gentrifying or in racially- and economically-integrated neighborhoods had a higher likelihood of eviction. Most studies begin with a focus on gentrification and inquire about eviction (e.g., Freeman and Braconi, 2004; Newman and Wyly, 2006). Our study proceeded in the opposite direction, beginning with eviction and inquiring about gentrification. This approach led us to document a higher likelihood of eviction among renting families in disadvantaged neighborhoods, compared to their counterparts in transitioning areas of the city. This finding neither confirms nor challenges claims about the extent to which gentrification results in the displacement of low-income tenants. What it does imply, however, is that researchers interested in forced moves and housing instability should expand their focus beyond gentrification to include *ungentrifying*, disadvantaged neighborhoods where most evictions take place.

More specifically, we found that renters' chances of eviction increase with their neighborhood's crime and eviction rates. What might explain this pattern? We speculate that tenants living in high crime areas might put up less of a fight when facing eviction—e.g., approaching family members for help, attending court hearings, negotiating with their landlord—than similar tenants in more desirable neighborhoods.[14] These tenants may view eviction as an opportunity to relocate to a better neighborhood or even execute a strategic eviction by purposefully withholding rent to save money for a move. This strategy may prove ineffective, however, as previous studies have shown that evicted tenants often relocate to neighborhoods with higher crime rates (Desmond and Shollenberger, 2015).

This study also documented an association between the likelihood of eviction and a neighborhood's eviction rate. If tenants in high-eviction areas are themselves more likely to be evicted, net of eviction-warranting behavior, it may be because eviction has come to be viewed by landlords in that neighborhood as a routine aspect of doing business. Landlords operating in the same neighborhood may share business practices and perspectives (Fligstein, 1996), resulting in a kind of localized calibration of property management styles and techniques. After all, landlords exert a great deal of discretion over the eviction decision, with some relying on displacement more frequently than others with similar tenant bases (Desmond, 2012a; Lempert and Monsma, 1994). This finding reinforces the importance of incorporating landlords into our models of neighborhood selection and urban dynamics.

Network Composition. Finally, with respect to network factors, we found that tenants with strong "downward" ties—those to people who had either experienced significant "poverty shocks" (e.g., eviction, incarceration, teenage pregnancy) or who were presently disadvantaged (e.g., jobless, addicted to drugs, in an abusive relationship)—had a higher likelihood of eviction, all else equal. Yet we found no evidence that tenants with strong "upward" ties—to homeowners, the gainfully employed, or the college educated—were less likely to be evicted.[15] The latter finding supports an observation made repeatedly in the ethnographic literature: that ties to the middle-class often are ineffective at helping low-income families meet daily needs or avoid common yet critical setbacks (Desmond, 2012b; Stack, 1974).

[14] Among our sample, renters' perceptions of neighborhood safety was strongly influenced by the crime rate of their environment. All renters were asked, "How safe do you feel in this neighborhood?" The likelihood that a renter who answered "not at all" or "a little bit" was significantly associated with the crime rate in her or his neighborhood ($b = 0.005$, $p < 0.001$).

[15] Table A5 displays the percentage of respondents whose strong ties had certain advantages and disadvantages. Around one-third of respondents had a strong tie who owned their own home. A similar proportion had a strong tie with a college degree. Almost two-thirds of respondents had a strong tie with someone who has a full-time job. A considerable subsample of renters, then, had "advantaged" strong ties.

If upward ties do not help tenants avoid eviction, why might downward ties actually *increase* a tenant's odds of displacement? We speculate that two mechanisms may be at work. First, from a landlord's perspective, tenants embedded in disadvantaged networks may come to be viewed as undesirable. Inviting one's closest friends and family over may draw the ire of landlords if those ties are themselves involved in violent relationships or criminal behavior. Second, from a tenant's perspective, one's network might influence the degree of urgency one assigns to an eviction as well as critical information regarding rights, procedures, and ways of responding to an eviction notice. Tenants with strong downward ties may come to normalize eviction, thinking of it as a hardship to endure rather than resist (e.g., by going to court), if their close kin and friends also have experienced eviction or other traumas. And even if they were eager to avoid eviction, these tenants might not know how to take full advantage of their rights and available services if their ties do not pass along this information to them.

An important implication of this finding is that disadvantage stems not only from one's individual attributes (e.g., education) or neighborhood characteristics (e.g., crime rate)—but also from the composition of one's social network. Theoretical work on social isolation (e.g., Wilson, 1987) is far more developed than empirical work that maps the ties in which low-income families are enveloped and documents the ramifications of network composition. Our findings suggest that, at least when it comes to avoiding eviction, one's downward ties are more consequential than one's upward ties. Although policymakers have dedicated considerable resources to connecting low-income families to more affluent social networks, we found that such upward connections had no noticeable effect on preventing eviction. However, the level of disadvantage within one's social network can bring about material consequences that exacerbate poverty. From a policy perspective, there is a silver lining to this finding: namely, that lawmakers may be systematically underestimating the benefits of social programs. If, say, reducing drug addiction or preventing family abuse benefits not only former addicts and victims, but also their close family members and friends, then the social and economic return on investment for such interventions may be more widespread than we realize.

Limitations. This study has produced the best evidence to date about which factors are associated with eviction, allowing us to adjudicate between individual-, neighborhood-, and network-level conditions. Nevertheless, it is important to note its limitations. First, this study draws on the *Milwaukee Area Renters Study*, which offers the most comprehensive measures of forced displacement from housing in a large dataset. However, these data pertain only to renters in Milwaukee. We hope that future research will replicate our findings in other locales, especially in unique but important cities with very high housing costs (e.g., New York City, Seattle).

Second, many studies focused on discrimination use field experiments or audit studies to isolate the effect of a characteristic (e.g., race, gender) on an outcome (e.g., job interview, housing access) (Pager and Shepherd, 2008). For a number of practical reasons, however, this approach cannot be applied to many important outcomes, including eviction. For this reason, studies investigating disparities in eviction must rely on observational data, which are vulnerable to omitted variable bias that can compromise causal inference. Using discrete hazard models, we have accounted for a number of factors relevant to eviction and our outcomes, but limitations that apply to all observational studies apply to ours as well.

Third, while our data allowed us to better understand individual-, neighborhood-, and network-level factors associated with an increased likelihood of eviction, we were unable to identify the mechanisms underlying these patterns. How do landlords decide whom to evict and whom to spare? How does a tenant's social network matter when it comes to maintaining residential stability? Qualitative research among tenants and landlords living and operating in low-income neighborhoods could contribute to answering these lingering questions and thereby advance the sociological understanding of forced displacement, housing dynamics, and urban inequality.

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Appendix

Table A1
Demographic composition of the Milwaukee Area Renters Study (MARS) and the American Community Study (ACS), 2010: Means displayed.

	ACS (weighted)	MARS (weighted)
Race/Ethnicity		
White	0.440	0.453
Black	0.424	0.347
Hispanic	0.168	0.135
Education		
Less than HS	0.191	0.135
HS	0.406	0.414
Some college	0.252	0.285
College	0.151	0.166
Household income	35,613	30,726

ACS 2010 sample consists of rent-paying adults.

Table A2
Descriptive statistics for network disadvantage components: What percentage of listed friends and family.

	Family mean	Friends mean
Disadvantage		
Had a child before they were 18	0.203	0.197
Receive government assistance	0.131	0.116
Have a criminal record	0.087	0.117
Had children taken by protective services	0.014	0.014
Have been evicted	0.046	0.049
Have been in jail or prison	0.101	0.105
Are in an abusive relationship	0.020	0.029
Are addicted to drugs	0.028	0.031
Advantage		
Own home	0.360	0.257
Have a college degree	0.298	0.314
Have a full-time job	0.581	0.592
Have a part-time job	0.130	0.139
Receive a pension	0.128	0.056

Notes. These descriptive statistics are unweighted.

Table A3
Correlation matrix for network disadvantage components.

	Fam. teen birth	Fam. gov. help	Fam. crim. rec.	Fam. lost child	Fam. evict	Fam. prison	Fam. relat. abuse	Fam. drug addict
Fam. gov. help	0.252							
Fam. crim. rec	0.140	0.123						
Fam. lost child	0.115	0.121	0.119					
Fam. evict	0.098	0.163	0.237	0.217				
Fam. prison	0.142	0.075	0.680	0.198	0.313			
Fam. abuse	0.103	0.097	0.073	0.181	0.128	0.124		
Fam. drug	0.085	0.140	0.253	0.090	0.347	0.307	0.237	
Fr. birth	0.388	0.120	0.156	0.012	0.092	0.125	0.016	0.048
Fr. gov. help	0.115	0.238	0.107	0.029	0.060	0.091	0.099	0.066
Fr. crim. rec	0.130	0.122	0.821	0.111	0.217	0.542	0.101	0.201
Fr. child	0.154	0.074	0.080	0.068	0.087	0.100	0.041	0.078
Fr. evict	0.106	0.031	0.142	0.036	0.241	0.145	0.087	0.152
Fr. prison	0.188	0.076	0.242	0.032	0.099	0.222	0.050	0.117
Fr. abuse	0.117	0.089	0.173	0.009	0.117	0.149	0.135	0.180
Fr. drug	0.086	0.068	0.129	0.019	0.101	0.119	0.150	0.328

	Friend teen birth	Friend gov. help	Friend crim. rec.	Friend lost child	Friend evict	Friend prison	Friend relat. abuse
Fr. gov. help	0.183						
Fr. crim. rec	0.204	0.136					
Fr. child	0.178	0.101	0.057				
Fr. evict	0.216	0.125	0.161	0.271			
Fr. prison	0.249	0.108	0.236	0.216	0.342		
Fr. abuse	0.183	0.119	0.187	0.113	0.234	0.229	
Fr. drug	0.110	0.138	0.099	0.122	0.216	0.275	0.345

Notes. Variables measure the percentage of a respondent's close ties who have experienced each measure of disadvantage.

Table A4
Descriptive statistics (unweighted).

	N	Mean	St. deviation	Minimum	Maximum
Network characteristics					
Network disadvantage	24,477	0.080	0.086	0	0.578
Network advantage	24,553	0.337	0.156	0	0.792
Milwaukee ties	24,656	5.180	3.641	0	30
Total ties	24,477	7.399	4.191	0	31
Family evictions	24,626	0.046	0.150	0	1
Friend evictions	24,684	0.050	0.164	0	1
Neighborhood characteristics					
Gentrified	19,689	0.092	0.289	0	1
Ungentrified	19,689	0.614	0.487	0	1
Concentrated disadv.	22,410	0.131	0.994	−1.666	3.216

(*continued on next page*)

Table A4 (*continued*)

	N	Mean	St. deviation	Minimum	Maximum
Crime rate	22,786	1.162	0.662	0.01	5.500
Eviction rate	23,140	0.049	0.050	0	0.723
Percentage black	24,482	0.368	0.376	0	1
Individual characteristics					
Payment history	16,660	0.196	0.397	0	1
Lost job prev. year	25,030	0.072	0.258	0	1
Breakup prev. year	25,030	0.066	0.249	0	1
Hispanic tenant	24,970	0.178	0.382	0	1
Black tenant	24,970	0.468	0.499	0	1
Married	24,816	0.162	0.368	0	1
Number of kids	25,057	0.547	1.047	0	7
Number of adults	22,931	0.731	0.900	0	7
Female tenant	25,028	0.625	0.484	0	1
Current income	22,405	1456.068	1044.443	0	6525
Roommate income	25,030	614.641	1493.625	0	54,375
Monthly rent	22,679	594.939	289.637	1	6125
Criminal record	24,851	0.174	0.379	0	1
Felony record	24,690	0.099	0.299	0	1
Less than HS education	24,763	0.208	0.406	0	1
High school education	24,763	0.355	0.478	0	1
Some college education	24,763	0.306	0.461	0	1
Age	24,848	38.434	13.530	15	91
Time since eviction	24,419	51.603	68.920	1	635

Table A5
Percentage of strong ties with select advantages and disadvantages by eviction in last two years.

Percentage of ties who	All (unweighted)	Evicted	Not evicted	All (weighted)	Evicted	Not evicted
Had a child before they were 18	0.214	0.288	0.202	0.171	0.210	0.167
Receive government assistance	0.136	0.195	0.127	0.089	0.101	0.088
Have a criminal record	0.100	0.146	0.093	0.066	0.101	0.063
Had children taken by protective services	0.016	0.023	0.014	0.011	0.011	0.011
Have been evicted	0.050	0.094	0.043	0.032	0.034	0.032
Have been in jail or prison	0.110	0.155	0.103	0.086	0.097	0.085
Are in an abusive relationship	0.025	0.040	0.022	0.030	0.024	0.031
Are addicted to drugs	0.033	0.060	0.029	0.024	0.033	0.023
Own home	0.326	0.285	0.332	0.385	0.404	0.383
Have a college degree	0.326	0.309	0.329	0.335	0.272	0.341
Have a full-time job	0.617	0.586	0.622	0.657	0.592	0.664
Have a part-time job	0.141	0.164	0.138	0.128	0.144	0.126
Have pension	0.097	0.093	0.098	0.113	0.133	0.111

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