



# A Research Note on the Prevalence of Housing Eviction Among Children Born in U.S. Cities

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Published online: 27 November 2018  
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## Abstract

A growing body of research suggests that housing eviction is more common than previously recognized and may play an important role in the reproduction of poverty. The proportion of children affected by housing eviction, however, remains largely unknown. We estimate that one in seven children born in large U.S. cities in 1998–2000 experienced at least one eviction for nonpayment of rent or mortgage between birth and age 15. Rates of eviction were substantial across all cities and demographic groups studied, but children from disadvantaged backgrounds were most likely to experience eviction. Among those born into deep poverty, we estimate that approximately one in four were evicted by age 15. Given prior evidence that forced moves have negative consequences for children, we conclude that the high prevalence and social stratification of housing eviction are sufficient to play an important role in the reproduction of poverty and warrant greater policy attention.

**Keywords** Eviction · Housing · Material hardship · Poverty · Children

## Introduction

Rising rents and stagnant or declining wages have contributed to increasingly unaffordable housing options for many U.S. households, especially poor urban families with children (Desmond 2015). The majority of low-income households now devote more than one-half of their income to housing (Joint Center for Housing Studies of Harvard University 2017),

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The replication code is available on the Harvard Dataverse: <https://doi.org/10.7910/DVN/BVWFG1>.

**Electronic supplementary material** The online version of this article (<https://doi.org/10.1007/s13524-018-0735-y>) contains supplementary material, which is available to authorized users.

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and housing eviction is a key aspect of America's affordable housing crisis. Drawing on ethnographic evidence, administrative records, and survey data collected in Milwaukee, Desmond (2016:98) claimed, "If incarceration had come to define the lives of men from impoverished black neighborhoods, eviction was shaping the lives of women. Poor black men were locked up. Poor black women were locked out."

Recent studies have bolstered the claim that eviction plays a previously unrecognized role in the reproduction of urban poverty. Forced moves are prevalent among the poorest Milwaukee households (Desmond et al. 2015), and observational studies have suggested that eviction negatively affects mothers' health (Desmond and Kimbro 2015) and neighborhood quality (Desmond and Shollenberger 2015). An emerging consensus indicates that eviction has negative consequences for disadvantaged urban children. What is less clear is the extent to which housing eviction is a common and socially stratified phenomenon for children across U.S. cities. This study seeks to answer these questions.

Table 1 summarizes prior estimates of eviction prevalence, outlining the data source, target population, period covered, and likely biases. In general, eviction research has relied on one of two sources: administrative records or survey data. A major limitation of administrative records is that non-court-ordered or "informal" evictions, frequently the cause of involuntary displacement among low-income renters (Desmond and Shollenberger 2015), are excluded from the estimand. Research using survey data can overcome this limitation but introduces other forms of potential bias, such as misreporting, and often relies on household or telephone sampling frames that exclude those most likely to have experienced residential instability, possibly as a result of eviction.

The most comprehensive analysis of administrative records, conducted by the Eviction Lab at Princeton University, indicated that between 2000 and 2016, the proportion of U.S. rental households experiencing a court-ordered eviction in a calendar year ranged from 2.3 % in 2016 to 3.1 % in 2006 (Desmond et al. 2018). Rates are substantially higher in large U.S. cities, ranging from 2.9 % to 16.5 % (Desmond et al. 2018). Other population estimates that relied on cross-sectional survey data spanned short periods and gave the impression that eviction is a more rare phenomenon. Analyses of the Survey of Income and Program Participation (SIPP), for example, indicated that only 0.3 % of U.S. households experienced eviction in 1998 (Bauman 2003:8). Even in the Detroit metropolitan area during 12 months of the Great Recession, only 2.4 % of households reported experiencing eviction (Gould-Werth and Seefeldt 2012).

We advocate a new focus of study: the proportion of children who were ever evicted during childhood. This estimand is important for those concerned with the well-being of children and the intergenerational transmission of poverty. Prior estimates of eviction prevalence, typically the proportion of households ever evicted over a given year, are likely to be much lower than the proportion of children ever evicted during childhood for two reasons. First, households with children are evicted at higher rates than those without children (Desmond et al. 2013). Second, if a nonzero risk of eviction is typical among disadvantaged families, then a large proportion of children may experience eviction at some point during childhood even if only a small proportion are evicted in any given year.<sup>1</sup> Prior studies have focused on the proportion evicted in a given year, but none have

<sup>1</sup> The misleading nature of annual reports has long been known in poverty research. Duncan and Rodgers (1988) demonstrated that approximately one-third of children under age 4 in 1968 were ever poor by age 15, despite annual estimates representing 1967, 1973, and 1979 showing that the proportion of families with children below the poverty line was only 11 % to 13 % in any given year (Danziger and Gottschalk 1985).



estimated the cumulative probability that a child is ever evicted over the span of childhood. Using panel data on a probability sample, we estimate the proportion of U.S. children born in large cities between 1998 and 2000 who were ever evicted from their home (for nonpayment of rent or mortgage) by age 15 (a parameter we call  $\tau$ ).

In addition to its substantive contribution, this study presents one approach to a persistent problem of missing data common to demographic research about the proportion of people to ever experience an event over the life course (e.g., Amorim et al. 2017; Duncan and Rodgers 1988; Wildeman 2009). Those seeking to estimate such a quantity face two fundamental challenges: (1) survey nonresponse and (2) periods of interest about which no respondents were surveyed. We propose a combination of multiple imputation to address the former and model-based interpolation to address the latter. To translate limited data that do not cover the entire period of interest into transparent estimates with reasonable precision, we assume a parametric model. In other settings with more plentiful data that more completely cover the period of interest, one might prefer a nonparametric machine learning approach; we assess the robustness of our results to one such approach in the [online appendix](#), part 5. Given that no approach yields precise, assumption-free inference when data are incomplete, we state our assumption that missingness is independent of eviction given observed covariates, speculate about likely violations, and place a lower bound on the estimand in the event that assumptions are violated. The approaches used in this study may be useful to demographers who aim to estimate the life course prevalence of a phenomenon with incomplete longitudinal data.

## Data

The Fragile Families and Child Wellbeing Study (hereafter, the Fragile Families Study) is a population-based birth cohort study of 4,898 children born in 20 large U.S. cities between 1998 and 2000. To our knowledge, the Fragile Families Study is the only national panel study to record housing eviction at all follow-up survey waves covering a period from birth through adolescence. Earlier waves of the study have been used to study the consequences of eviction (Desmond and Kimbro 2015). The study includes a stratified, multistage probability sample that oversamples children born to unmarried parents (approximately 3 to 1), resulting in a disproportionately large number of children from low-income families. Because low-income families with children are among those most at risk for eviction (Desmond et al. 2013), the oversample enables greater precision in the estimation of eviction prevalence.

Weighted estimators on the subsample of children born in the 16 probabilistically selected sample cities are unbiased for the true population parameters for all births in 1998–2000 in the 77 U.S. cities with populations greater than 200,000. Weighting is important because of the unequal sample selection probabilities; although 76 % of the unweighted sample of children were born to unmarried parents, weighted estimates suggest that only 40 % of births in the sampling frame were to unmarried parents. The sampling frame is children *born in* large U.S. cities; the target population is births in city hospitals, not births to city residents.<sup>2</sup> For a comparison between our sample and vital records on

<sup>2</sup> Based on address records, we estimate that approximately 20 % of sampled families in the Fragile Families Study resided outside the sample city's municipal boundaries at the time of the focal child's birth.

births to residents of large cities, see the [online appendix](#), part 7. For further details on the sampling design, see Reichman et al. (2001). An advantage of the Fragile Families Study design is that the sampling frame is defined prior to eviction, and attempts are made to follow respondents even if they become unhoused or leave the metropolitan area. This prospective design avoids a common problem with retrospective designs that restrict the sample by potential consequences of eviction, such as whether one lives in a rental unit.

The key outcome variable is based on a question from the SIPP material hardship scale: “In the past twelve months, were you ever evicted from your home or apartment for not paying the rent or mortgage?”<sup>3</sup> (originally adapted from Mayer and Jencks 1989). Parents<sup>4</sup> answered this question when children were approximately ages 1, 3, 5, 9, and 15. Figure 1 presents the prevalence of housing eviction in each report. In most years, approximately 1.5 % of children born in large cities were evicted from their homes, but the prevalence spiked to 3.0 % during the Great Recession, suggesting a role for macroeconomic factors. Unweighted estimates and estimates without multiple imputation are provided in the online appendix, Table A1.

## Overall Prevalence Estimates

What proportion of children born in large cities at the turn of the twenty-first century were *ever* evicted<sup>5</sup> between birth and age 15? The answer to this question is not obvious because some periods have no data available. Figure 2 presents this challenge graphically and summarizes our three approaches to yield a cumulative estimate (for details, see Table A2 in the online appendix).

### Absolute Lower Bound: Observed Evictions

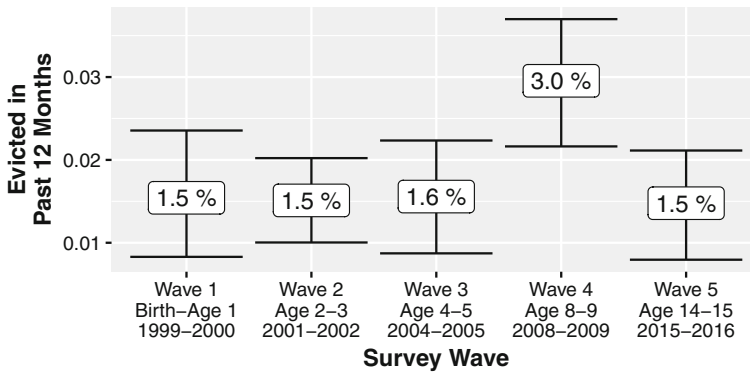
Before introducing more complicated approaches, we begin with a simple assumption: no evictions occurred in years with missing responses or when no data were collected. Because of missing data and attrition, annual reports cover only four of five years for the average child. A long-term recall report covers five additional years (ages 9 to 14) for 74 % of the sample. Using this strategy, which is a lower bound<sup>6</sup> given that some

<sup>3</sup> We estimate that only 14.9 % (unweighted) of parents who reported an eviction lived in an owned home at the previous wave, suggesting that the large majority of evictions (85.1 %) were due to nonpayment of rent. This estimate excludes 26.2 % of eviction reports for which housing status in the prior wave is not known.

<sup>4</sup> For children who live at least one-half of the time with their mothers, we use the mother’s report. Otherwise, for those who live at least one-half the time with their father, we use the father’s report. All others are missing. At age 15, eviction is reported for all children by their primary caregiver.

<sup>5</sup> The proportion of children who have experienced multiple evictions is also an important research question. An absolute lower bound on this proportion is the 1.1 % (CI: 0.1–1.4 %) of the sample that reported eviction in two or more waves. Multiply imputing to fill missing survey reports, we estimate that 1.8 % (CI: 1.0–2.7 %) were evicted in multiple waves. Our parametric model implies that 4.9 % (CI: 3.9–6.1 %) of children born in large U.S. cities in 1998–2000 were evicted in multiple years between birth and age 15. However, these estimates may substantially understate the prevalence of serial evictions because questions asked whether respondents were ever evicted in each reporting period, not the number of evictions. Because serial evictions may occur in quick succession within a single reporting period, we leave more definitive claims about the prevalence of serial eviction to future research.

<sup>6</sup> The point estimate is a lower bound on the weighted sample proportion evicted. The bootstrapped 95 % confidence interval captures estimation uncertainty about the population proportion.



**Fig. 1** Evicted in the past 12 months: Five cross-sectional reports.  $N = 3,442$ . Estimates represent the probability that a child born in 1998–2000 in a U.S. city with population over 200,000 was evicted in the 12 months preceding each interview wave. Missing data are multiply imputed (11 % to 29 % of observations). Error bars represent 95 % bootstrapped confidence intervals. Table A1 in the online appendix summarizes attrition across waves and how estimates change with multiple imputation and weighting. In general, unweighted estimates are slightly higher because the Fragile Families Study oversampled children born to unmarried parents, who are more likely to be evicted.

evictions likely occurred in the unobserved years, we find that 7.9 % (CI:<sup>7</sup> 7.1–8.9 %) of children born in large U.S. cities in 1998–2000 experienced an eviction by age 15.

### Adjusting for Nonresponse: Multiple Imputation

The lower bound estimate understates eviction prevalence because it ignores evictions that are not reported as a result of (1) survey nonresponse (see Table A1 in the online appendix for response rates) and (2) periods in which the study did not ask about eviction (5 of 15 years). To address the first limitation, we determine whether each child with complete data (57 %) was ever evicted given all available reports and then multiply impute missing reports for the remaining children (see the [online appendix](#), part 2, for details). Assuming that eviction is missing at random conditional on covariates, this approach captures the prevalence of eviction over 10 years: the four years preceding ages 1, 3, 5, and 9, and the six years between ages 9 and 15. Using this strategy, we estimate that 9.2 % (CI: 7.3–11.1 %) of children born in large U.S. cities were evicted during this period.

### Preferred Estimate: Multilevel Logistic Regression

As shown in Fig. 2, there were five years in which the study did not ask about eviction (between ages 1–2, 3–4, and 5–8). Both our lower bound and multiple imputation estimators ignore evictions in these periods.

To estimate eviction prevalence over the entire period from birth to age 15, we apply a parametric<sup>8</sup> model: multilevel logistic regression with random intercepts to capture

<sup>7</sup> Throughout, *CI* refers to a 95 % quantile-based bootstrapped confidence interval for frequentist estimates or a 95 % quantile-based posterior credible interval for Bayesian estimates.

<sup>8</sup> Because our primary goal is prediction, we also considered random forests as a nonparametric alternative. For details, see the [online appendix](#), part 5.

unobserved heterogeneity constant within cities of birth or within children.<sup>9</sup> We use bold characters topped by arrows to indicate vectors.

Random intercepts for each city of birth  $c$ :

$$\{\delta_c\} \sim \text{iid Normal}(0, \sigma_\delta^2).$$

Random intercepts for each child  $i$  in each city  $c$ :

$$\{\epsilon_{c[i]}\} \sim \text{iid Normal}(0, \sigma_\epsilon^2).$$

Linear predictor:

$$\eta_{c[i[t]]} = \alpha + \underbrace{\vec{\mathbf{X}}_{c[i]} \vec{\boldsymbol{\beta}}}_{\text{Child-level predictors}} + \underbrace{\text{Age}_{c[i[t]]}\gamma + \text{Recession}_{c[i[t]]}\lambda}_{\text{Time-varying predictors}} + \underbrace{\delta_c + \epsilon_{c[i]}}_{\text{Random intercepts}}.$$

Link function:

$$\underbrace{\pi_{c[i[t]]}}_{\text{Probability (Eviction in year } t \text{ for child } i \text{ born in city } c)} = \text{logit}^{-1}(\eta_{c[i[t]]}).$$

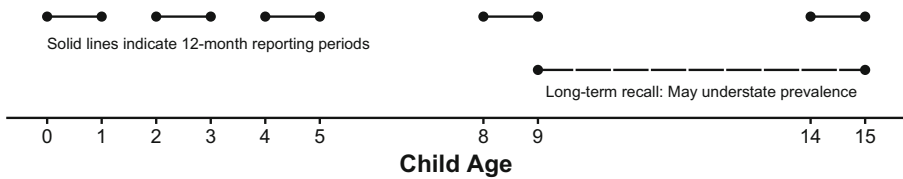
Stochastic component:

$$\underbrace{Y_{c[i[t]]}}_{\text{Eviction in year } t \text{ for child } i \text{ born in city } c} \sim \text{Bernoulli}(\pi_{c[i[t]]}).$$

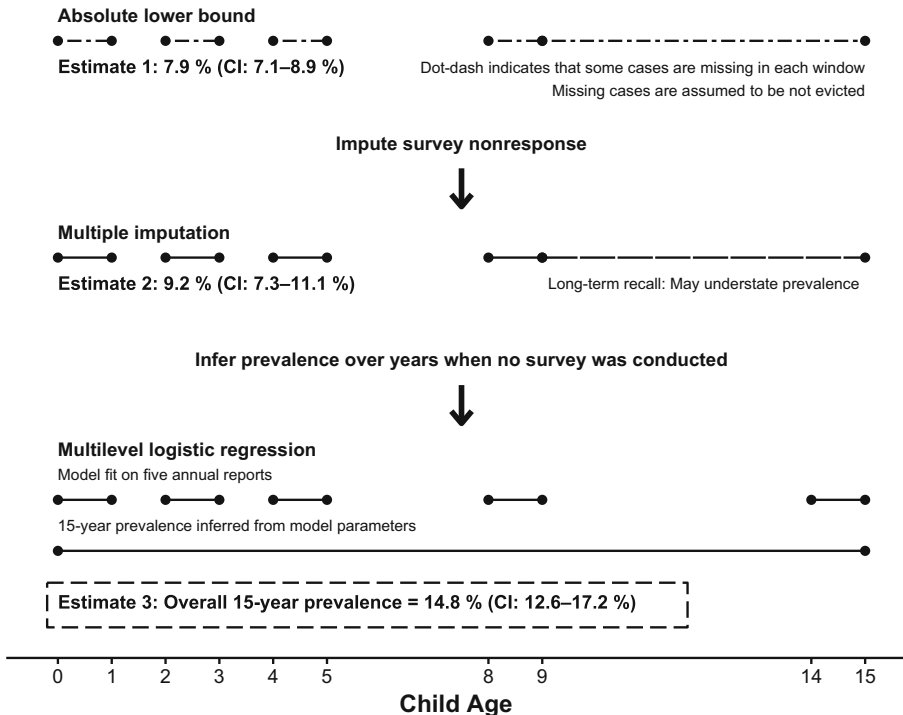
We fit the model on data from the five annual reports. We exclude the six-year retrospective report from the age 15 survey out of concern that the long recall period may understate eviction prevalence. Child-level predictors  $\vec{\mathbf{X}}_{c[i]}$  include race, mother's characteristics, family income relative to needs, type of housing, housing costs, neighborhood context, and city of birth. Time-varying predictors include child age and an indicator for observations in the Great Recession (2008–2009). Table 2 summarizes these variables. We selected these predictors with the goal of choosing variables likely to predict eviction while maintaining a parsimonious model to produce estimates with a reasonable degree of precision. If data were more plentiful, one could use a data-driven approach to select the most relevant predictors, but the limited data in our setting yielded such an approach of limited use (see Fig. A2 in the online appendix). We instead chose the variables based on

<sup>9</sup> Logistic regression estimates are consistent but biased in finite samples, often underpredicting rare events, such as eviction (King and Zeng 2001). Cross-validation suggests that the bias is small in our case (see the online appendix, part 4).

### a. Child ages covered by eviction reports in the Fragile Families Study



### b. Three estimates of the proportion ever evicted by age 15



**Fig. 2** Ever evicted by age 15: Data and estimation approaches. Estimates represent the probability that a child born in 1998–2000 in a U.S. city with population over 200,000 was ever evicted between birth and age 15. All estimates are weighted. Child ages are approximate because all children were not interviewed at precisely age 1, 3, 5, 9, and 15. Table A2 in the online appendix provides more details about the assumptions that produce each estimate.

theory, noting that the final conclusions are reasonably robust to the set of variables chosen (online appendix, Fig. A1).

To facilitate construction of uncertainty estimates, we adopt a Bayesian framework with Cauchy priors on  $\alpha$ ,  $\vec{\beta}$ ,  $\gamma$ , and  $\lambda$ , and half-Cauchy priors on  $\sigma_u$  and  $\sigma_v$ . The Cauchy distribution is weakly informative; the prior density is greatest near 0 but has heavier tails than the normal distribution, thereby allowing the possibility of large parameter values (Gelman et al. 2008). We sample from the posterior by Hamiltonian Monte Carlo implemented in Stan using the R package *rstan* (Carpenter et al. 2017;



Stan Development Team 2017). Variable specifications, modeling details, and coefficient estimates are provided in the [online appendix](#), parts 1–3.

To translate the model output into an estimate of eviction prevalence, we first calculate the predicted probability of eviction for each child  $i$  at every age  $t$  from birth to age 15. In the following notation, characters with hats indicate a single draw from the posterior distribution.

$$\begin{aligned}\hat{\pi}_{c[i|t]} &= \hat{\alpha} + \overrightarrow{X}_{c[i]} \widehat{\beta} + Age_{c[i|t]} \hat{\gamma} + Recess_{c[i|t]} \hat{\lambda} + \hat{u}_c + \hat{v}_{c[i]}. \\ \hat{\pi}_{c[i|t]} &= \text{logit}^{-1} \left( \hat{\eta}_{c[i|t]} \right).\end{aligned}$$

Because we assume conditional independence of eviction across years given the probability of eviction  $\pi_{c[i|t]}$ , we can collapse the age-specific probability estimates to a single cumulative probability estimate  $\hat{\phi}_{c[i]}$  of any eviction between birth and age 15 for each child  $i$  born in city  $c$ .

$$\hat{P}([Ever\ evicted]_{c[i]}) = \hat{\phi}_{c[i]} = 1 - \prod_{t=1}^{15} (1 - \hat{\pi}_{c[i|t]}).$$

A weighted average of the child-specific estimates  $\hat{\phi}_{c[i]}$  over the sample yields an estimate of our target parameter  $\tau$ : the population prevalence of any eviction from birth to age 15.

$$\text{Overall prevalence estimate} = \hat{\tau} = \frac{\sum_{c=1}^{16} \sum_{i=1}^{n_c} w_{c[i]} \hat{\phi}_{c[i]}}{\sum_{c=1}^{16} \sum_{i=1}^{n_c} w_{c[i]}}.$$

By repeating this process for each posterior draw of the parameters, we obtain 10,020 samples of  $\hat{\tau}$  from its posterior distribution. The posterior mean indicates that 14.8 % (CI: 12.6–17.2 %) of U.S. children born in large cities in 1998–2000 were evicted by age 15.

## Eviction Is Socially Stratified

Does eviction exacerbate existing inequalities? Prior work suggests that eviction has negative effects on children and families (Desmond and Kimbro 2015). This section demonstrates that children who are already disadvantaged are more likely to be evicted. To estimate subgroup-specific prevalence, we estimate the weighted average of the posterior cumulative probabilities ( $\hat{\phi}_{c[i]}$ ) over all children in the subgroup. Figure 3 presents subgroup estimates by race/ethnicity and by family income at birth.<sup>10</sup> Eviction

<sup>10</sup> We also examined how eviction varied by city of birth. Prevalence is substantial in all sampled cities, but we found suggestive evidence of some variation from 12.1 % (born in Chicago, CI: 7.0–18.1 %) to 23.5 % (born in Detroit, CI: 18.9–28.7 %). Because estimates are imprecise and because sample cities indicate children's city of birth, not city of eviction, we treat this evidence as suggestive and call for future research on geographic heterogeneity in eviction prevalence. For details, see the [online appendix](#), part 6.

**Table 2** Descriptive statistics for predictors of eviction

	Weighted		Unweighted		Proportion Missing <sup>a</sup>
	Mean	SD	Mean	SD	
Household Characteristics					
Parents married at birth	0.24		0.60		
Permanent (income/poverty line)					
Below 50 %	0.06		0.10		.11–.30
50 % to 100 %	0.15		0.22		
100 % to 200 %	0.29		0.33		
200 % to 300 %	0.20		0.17		
Higher than 300 %	0.30		0.18		
Housing cost/income	0.30	0.18	0.34	0.18	.27–.39
Proportion of years living in an owned home	0.41	0.40	0.26	0.35	.10–.30
Mother's Characteristics					
Race/ethnicity					.00
Black	0.23		0.48		
Hispanic	0.31		0.27		
White/other	0.46		0.25		
Foreign-born	0.25		0.17		.00
Education (child's birth)					
< High school	0.29		0.35		.00
High school	0.30		0.30		
Some college	0.19		0.24		
College	0.22		0.11		
Age at birth	27.10	6.28	25.30	6.05	.00
Impulsivity (child age 3)	0.05	0.99	0.00	1.00	.14
Cognitive skills (WAIS-R, at child age 3)	7.04	2.79	6.70	2.67	.14
Father's Characteristics					
Ever in jail/prison by child age 1	0.20		0.34		.11
Neighborhood Context (census tract characteristics in 1999, residence at birth)					
Racial composition					
Proportion white	0.46	0.34	0.32	0.31	.04
Proportion black	0.25	0.30	0.40	0.37	
Proportion Hispanic	0.24	0.30	0.22	0.26	
Proportion all other	0.06	0.09	0.07	0.10	
Proportion of households below poverty line	0.16	0.15	0.19	0.14	.04
Median rent/household income	0.26	0.05	0.27	0.05	.04

Notes:  $N = 3,442$  children for weighted estimates.  $N = 4,898$  children for unweighted estimates. Missing data are imputed. Details on variable specification are provided in the [online appendix](#), part 1.

<sup>a</sup> When a range is given, the estimate is averaged over five survey waves, with missing data imputed at the wave level before aggregation. The range indicates the least and greatest proportion missing for the variable across waves.



**Fig. 3** Ever evicted by age 15, by race and family income. Estimates represent the probability that a child born in 1998–2000 in a U.S. city with population over 200,000 was ever evicted between birth and age 15. All estimates are weighted. Estimates are based on predicted probabilities from the multilevel logistic regression model. Error bars represent 95 % credible intervals.

was most common among children whose mothers were black (19.2 %, CI: 15.6–23.2 %) and Hispanic (16.7 %, CI: 13.2–20.7 %), compared with children born to mothers of white and other racial and ethnic backgrounds (11.3 %, CI: 8.7–14.3 %). This is consistent with prior evidence from Milwaukee that eviction is most prevalent among black renters (Desmond 2012). Children’s probability of eviction, however, diverges most strikingly by household income. Approximately 28.9 % (CI: 20.4–38.5 %) of children living in deep poverty (permanent income relative to the poverty threshold below 50 %) were evicted. The prevalence of eviction declines monotonically as income rises, yet even the most advantaged children (higher than 300 % of the poverty threshold) faced a 4.7 % (CI: 2.5–7.8 %) probability of eviction.

## Limitations

Our estimators may be biased by three noteworthy limitations: selection into the observed sample, survey question wording, and model specification errors. The first two are likely to lead to an underestimate of eviction prevalence, whereas the direction of the bias is less clear in the third case.

First, our estimates are vulnerable to nonignorable selection into the sample. For example, those at the greatest risk of eviction may have been least likely to consent to

the survey at birth, which would downwardly bias estimates of eviction prevalence. A greater potential source of bias is the assumption that attrition is conditionally ignorable. If eviction disrupts respondents' lives and leads to sample attrition, our estimates would be biased downward.

Second, the survey questions reference eviction due to rent or mortgage nonpayment. Persons evicted from their homes for other reasons, or informally without a court order, frequently do not report having been evicted (Desmond 2016). Fielded in 2009–2011, the Milwaukee Area Renters Study included questions about a variety of moves and found that fewer than one-half of forced moves were court-ordered evictions: the majority were informal evictions (no court order), landlord foreclosures, and building condemnations (Desmond and Shollenberger 2015). Given these findings, our data likely understate eviction prevalence and surely understate the prevalence of forced moves.

Finally, to infer eviction prevalence over 15 years using five annual reports, we assumed a parametric model and interpolated the prevalence of eviction in regions of the covariate space with no data (e.g., child age 7). We concluded that this model-based interpolation is reasonable given the relatively steady prevalence of eviction across childhood (with the exception of the Great Recession). In addition, this modeling approach produced estimates suggesting that eviction is alarmingly prevalent across a range of model specifications (see Fig. A1 in the online appendix). Nonetheless, different modeling assumptions could produce estimates as low as our lower bound or higher than our preferred estimate (see the [online appendix](#), part 3).

The results presented in this article reflect our obligation as social scientists to make the best use of the data available. To provide more rigorous estimates in the future, social scientists will need access to better data. In particular, we recommend improvements on two fronts: surveys and administrative records. Cross-sectional and panel surveys of probability samples should incorporate detailed questions about the timing and nature of eviction (or other forced moves), following examples like the Milwaukee Area Renters Study (Desmond and Shollenberger 2015). Likewise, administrative records already show alarming eviction prevalence and represent a promising source for future research (Desmond et al. 2018). Improvements in these two areas would enable researchers to provide new insights into the prevalence and social stratification of eviction.

## Conclusion

Drawing on a population-based panel study of a birth cohort, we estimate that 14.8 % (CI: 12.6–17.2 %) of children born between 1998 and 2000 in large U.S. cities were evicted from their homes by age 15. Although eviction is widespread across demographic groups and cities, it is most prevalent among children who already face other disadvantages: black children and children raised in poverty. The high prevalence of eviction and its unequal contours support recent ethnographic evidence suggesting that eviction plays an important role in the reproduction of poverty and spatial inequality.

**Acknowledgments** We thank Sara S. McLanahan, Brandon M. Stewart, Matthew J. Salganik, three anonymous reviewers, and members of the Stewart Lab and the Fragile Families Working Group for comments on early drafts. We thank the *Demography* copyeditors for helping to improve our prose. All errors are our own. Research reported in this publication was supported by the Robert Wood Johnson Foundation and by The Eunice Kennedy Shriver National Institute of Child Health & Human Development of the National Institutes of Health under Award Number P2CHD047879. Funding for the Fragile Families Study was provided through Award Numbers R01HD36916, R01HD39135, and R01HD40421, and by a consortium of private foundations. The content is solely the responsibility of the authors and does not necessarily represent the official views of the National Institutes of Health.

## References

- Amorim, M., Dunifon, R., & Pilkauskas, N. (2017). The magnitude and timing of grandparental coresidence during childhood in the United States. *Demographic Research*, 37(article 52), 1695–1706. <https://doi.org/10.4054/DemRes.2017.37.52>
- Bauman, K. J. (2003). *Extended measures of well-being: Living conditions in the United States: 1998* (Current Population Reports: Household Economic Studies Series P70–87). Washington, DC: U.S. Census Bureau.
- Carpenter, B., Gelman, A., Hoffman, M. D., Lee, D., Goodrich, B., Betancourt, M., . . . Riddell, A. (2017). Stan: A probabilistic programming language. *Journal of Statistical Software*, 76(1). <https://doi.org/10.18637/jss.v076.i01>
- Danziger, S., & Gottschalk, P. (1985). *How have families with children been faring?* (Report prepared for the Joint Economic Committee of the Congress). Madison: University of Wisconsin Institute for Research on Poverty. Retrieved from <http://files.eric.ed.gov/fulltext/ED268189.pdf>
- Desmond, M. (2012). Eviction and the reproduction of urban poverty. *American Journal of Sociology*, 118, 88–133.
- Desmond, M. (2015). *Unaffordable America: Poverty, housing, and eviction* (Fast Focus Report No. 22). Madison: University of Wisconsin Institute for Research on Poverty.
- Desmond, M. (2016). *Evicted: Poverty and profit in the American city*. New York, NY: Crown.
- Desmond, M., An, W., Winkler, R., & Ferriss, T. (2013). Evicting children. *Social Forces*, 92, 303–327.
- Desmond, M., Gershenson, C., & Kiviat, B. (2015). Forced relocation and residential instability among urban renters. *Social Service Review*, 89, 227–262.
- Desmond, M., Gromis, A., Edmonds, L., Hendrickson, J., Krywokuski, K., Leung, L., & Porton, A. (2018). *Eviction lab national database: Version 1.0*. Princeton, NJ: Princeton University. Available from [www.evictionlab.org](http://www.evictionlab.org)
- Desmond, M., & Kimbro, R. T. (2015). Eviction's fallout: Housing, hardship, and health. *Social Forces*, 94, 295–324.
- Desmond, M., & Shollenberger, T. (2015). Forced displacement from rental housing: Prevalence and neighborhood consequences. *Demography*, 52, 1751–1772.
- Duncan, G. J., & Rodgers, W. L. (1988). Longitudinal aspects of childhood poverty. *Journal of Marriage and the Family*, 50, 1007–1021.
- Gelman, A., Jakulin, A., Pittau, M. G., & Su, Y.-S. (2008). A weakly informative default prior distribution for logistic and other regression models. *Annals of Applied Statistics*, 2, 1360–1383.
- Gould-Werth, A., & Seefeldt, K. S. (2012). *Material hardships during the Great Recession: Findings from the Michigan Recession and Recovery Study* (National Poverty Center Policy Brief No. 35). Ann Arbor: University of Michigan Poverty Solutions. Retrieved from [http://www.npc.umich.edu/publications/policy\\_briefs/brief35](http://www.npc.umich.edu/publications/policy_briefs/brief35)
- Joint Center for Housing Studies of Harvard University. (2017). *The state of the nation's housing* (Report). Cambridge, MA: Joint Center for Housing Studies. Retrieved from [http://www.jchs.harvard.edu/sites/jchs.harvard.edu/files/harvard\\_jchs\\_state\\_of\\_the\\_nations\\_housing\\_2017.pdf](http://www.jchs.harvard.edu/sites/jchs.harvard.edu/files/harvard_jchs_state_of_the_nations_housing_2017.pdf)
- King, G., & Zeng, L. (2001). Logistic regression in rare events data. *Political Analysis*, 9, 137–163.
- Mayer, S. E., & Jencks, C. (1989). Poverty and the distribution of material hardship. *Journal of Human Resources*, 24, 88–114.
- Reichman, N. E., Teitler, J. O., Garfinkel, I., & McLanahan, S. S. (2001). Fragile Families: Sample and design. *Children and Youth Services Review*, 23, 303–326.
- Stan Development Team. (2017). *RStan: The R interface to Stan* (R package version 2.16.2) [Software]. Available from: <http://mc-stan.org>

- Wildeman, C. (2009). Parental imprisonment, the prison boom, and the concentration of childhood disadvantage. *Demography*, 46, 265–280.