

Eviction, Healthcare Utilization, and Disenrollment Among New York City Medicaid Patients



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Introduction: Although growing evidence links residential evictions to health, little work has examined connections between eviction and healthcare utilization or access. In this study, eviction records are linked to Medicaid claims to estimate short-term associations between eviction and healthcare utilization, as well as Medicaid disenrollment.

Methods: New York City eviction records from 2017 were linked to New York State Medicaid claims, with 1,300 evicted patients matched to 261,855 non-evicted patients with similar past healthcare utilization, demographics, and neighborhoods. Outcomes included patients' number of acute and ambulatory care visits, healthcare spending, Medicaid disenrollment, and pharmaceutical prescription fills during 6 months of follow-up. Coarsened exact matching was used to strengthen causal inference in observational data. Weighted generalized linear models were then fit, including censoring weights. Analyses were conducted in 2019–2021.

Results: Eviction was associated with 63% higher odds of losing Medicaid coverage (95% CI=1.38, 1.92, $p<0.001$), fewer pharmaceutical prescription fills (incidence rate ratio=0.68, 95% CI=0.52, 0.88, $p=0.004$), and lower odds of generating any healthcare spending (OR=0.72, 95% CI=0.61, 0.85, $p<0.001$). However, among patients who generated any spending, average spending was 20% higher for those evicted (95% CI=1.03, 1.40, $p=0.017$), such that evicted patients generated more spending on balance. Marginally significant estimates suggested associations with increased acute, and decreased ambulatory, care visits.

Conclusions: Results suggest that eviction drives increased healthcare spending while disrupting healthcare access. Given previous research that Medicaid expansion lowered eviction rates, eviction and Medicaid disenrollment may operate cyclically, accumulating disadvantage. Preventing evictions may improve access to care and lower Medicaid costs.

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INTRODUCTION

The U.S. is undergoing a housing affordability crisis, making eviction a regular feature of poor and working-class communities' lives.^{1–3} This is especially true in cities, where rent burden is severe.^{3,4} Available evidence suggests that evictions worsen material deprivation, sort families into lower-quality housing in more disadvantaged neighborhoods, disrupt social networks, and erode mental health.^{5–11} Accordingly, evictions have been linked to a growing list of physical health outcomes across the life course, including birth outcomes, injection

drug use, infectious disease, self-rated health, and mortality.^{7,12–17}

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As yet understudied are eviction's impacts on health-care utilization. Broadly, unresolved questions about eviction's links to health care fall in 2 buckets. First, does eviction interrupt health care access, such as displacement away from known primary care providers,¹⁸ difficulty refilling or storing prescriptions or adhering to their directed use,^{13,19,20} or loss of health insurance coverage? Such gaps could hypothetically arise if, for example, evictees are forced into far-away neighborhoods,⁵ outside the catchment area or vicinity of their health care providers and pharmacies; if managing housing instability exhausts people's capacity to attend to their health¹⁹; or if sudden changes of address impede the renewal of public health care benefits. Second, does the stress and deprivation caused by eviction lead to higher health care utilization? To date, only 1 study has examined whether health care visits of any kind spike after an eviction (focused on emergency room visits),¹⁰ and evidence directly examining whether eviction interrupts health care access is scarce.²¹

In this paper, 2017 New York City (NYC) eviction data are linked to New York State (NYS) Medicaid records to test whether, among Medicaid enrollees, eviction is prospectively associated with (1) number of ambulatory care visits, (2) number of acute care visits, (3) health care spending, (4) Medicaid disenrollment, and (5) pharmaceutical prescription fills. Except for acute care visits, this study is the first to directly test links between eviction and these outcomes. It does so by matching evicted enrollees with otherwise similar, non-evicted enrollees, using social, demographic, and geographic factors as well as past health care utilization. To capture health care outcomes caused by the sudden stress, deprivation, and disruption eviction causes, outcomes were examined during the 6 months following eviction.

METHODS

Eviction Data

Data were provided by NYC OpenData²² on all 2017 court-ordered residential evictions in NYC voluntarily reported by marshals (officials who execute evictions), including execution date, address, and unit number. A total of 28 of 39 marshals employed in 2017 reported to OpenData, representing the majority of court-ordered evictions.

Medicaid Health Care Data and Linkage to Evictions

Utilization data were derived from the NYS Medicaid claims file,²³ which contains detailed information on all patients ever enrolled in Medicaid in NYS. These data were accessed through the New York University Health Evaluation and Analytics Lab. Claims data included patient enrollment status, address history, demographics, medical spending, and health care utilization.

Patient addresses in the claims file had been previously geocoded by the New York University Health Evaluation and Analytics Lab to the NYC tax parcel system. To link patients with evictions, eviction addresses were geocoded with geocode.io, a commercial service, and the Google Maps application programming interface (API), then linked via spatial merge to parcel shapefiles using ArcGIS, version 10.6.²⁴ All but 289 evictions (1.4%) were assigned parcel identifiers, yielding 20,521 parcel-linked evictions. Patients were considered evicted if their most recent Medicaid enrollment information, as of the eviction execution date, indicated that they lived in the unit number and building of an eviction.

Outcomes

A total of 5 outcomes were assessed during the 6 months after an eviction: Medicaid disenrollment (i.e., loss of coverage), total medical spending (U.S. dollars), number of ambulatory care visits, number of acute care visits (emergency department visits plus hospitalizations; an emergency department visit immediately followed by a hospital admission was considered 1 visit), and number of pharmaceutical prescription fills. Outcomes included 2 definitions of disenrollment: (1) disenrollment for any amount of time during follow-up and (2) disenrollment for a period of ≥ 91 days. The latter definition may be more meaningful because NYS Medicaid will retroactively reimburse medical costs for uninsured periods of up to 90 days. Health care spending was analyzed with a 2-part "hurdle" model,²⁵ predicting (1) odds of any health care spending and (2) spending among those who generated $> \$0$; marginal predictions from the 2-part model provided estimates of the average overall spending difference between evicted and non-evicted patients.

Measured Confounders

Confounders for matching and regression-based adjustment were derived from Medicaid claims data—measured during a 6-month baseline (pre-eviction) period—and included patient age, binary sex, race/ethnicity, NYC borough of residence, immigration status, and baseline health care data (health care spending, number of acute and ambulatory care visits, number of pharmaceutical prescription fills). Sex and race/ethnicity were included as imperfect proxies for risk of sexism and racism exposures (e.g., in housing and health care).^{26,27} Residential census tract poverty rates were also included, with rates drawn from 2017 American Community Survey 5-year estimates.

Sequential "Target Trials" Framework and Inclusion Criteria

This analysis draws on causal inference developments on "target trials," in which the researcher conceives of a hypothetical RCT that could be conducted to answer the research question, then analyzes observational data in a way that seeks to emulate that hypothetical trial.^{28,29} These are sometimes imagined as a sequence of trials—in this case, in which each month of 2017 could be imagined as a separate "trial" testing the impact of eviction.³⁰ This sequential "target trial" framework accommodates scenarios in which individuals can switch between exposure states, potentially multiple times, between trials. This study attempted to emulate a series of trials in which, each month, Medicaid patients were grouped on the basis of similar levels of preintervention

healthcare utilization, insurance coverage, demographics, and eviction history and then randomized to be evicted or not evicted, with outcomes measured over the ensuing 6 months.

To do this, groups with matching covariates were first identified, starting with a first “trial” examining evictions in January 2017. For each NYC resident on Medicaid in January 2017, a *baseline period* was defined as the 180 days preceding the date of the eviction (for patients who were evicted) or 180 days preceding January 15 (for patients who were not evicted). Similarly, the *follow-up period* was defined as 180 days beginning with the eviction execution date or the middle of the month for those not evicted. This process was repeated for each month, yielding 12 study samples, which were then combined into a single data set. The same individual could therefore appear in the data set up to 12 times if they met the inclusion criteria for each “trial.”

Inclusion criteria were based on each patient’s 180-day baseline period. These were: an NYC address of residence, residence in private sector housing (public housing evictions are not executed by marshals), residence in a tax parcel with only 1 street address (to ensure correct building identification), no address changes reported (to minimize the risk of mis-assigning evictions, since addresses are updated infrequently), no evictions identified during the 6-month baseline period (to control for eviction history through restriction), continuously enrolled in Medicaid (to ensure baseline healthcare use data were fully available), and not dual-eligible for Medicare (Medicaid claims alone are not reliable indicators of healthcare use for this subpopulation).

Statistical Analysis

First, coarsened exact matching was used, a nonparametric processing step that improves causal inference in observational data by reducing model dependence and eliminating positivity violations. Continuous confounding variables were temporarily “coarsened” into categorical variables using Sturges’ rule.²⁹ The coarsened exact matching algorithm then sorted patients in the same study month into strata that shared exact values for all measured confounders. All available data for which matches existed were analyzed, with matching weights accounting for varying stratum sizes.

Weights were additionally estimated to account for differential loss to follow-up due to Medicaid disenrollment during the follow-up period.³¹ These inverse probability of selection weights allowed models to estimate the effects of eviction on, for example, healthcare spending had no patients lost Medicaid coverage in the follow-up period. Predictors of selection included eviction, study month, and the previously specified baseline confounders. Two sets of inverse probability of selection weights were estimated: one defined *censoring* as loss of Medicaid (patients fell out of the claims file) for any amount of time, and the other, included as a sensitivity analysis, defined *censoring* as loss of Medicaid for a period of ≥ 91 days during follow-up.

Using the matched, weighted data, quasi-binomial logistic models were fit for binary outcomes (both definitions of disenrollment; any healthcare spending), quasi-Poisson models were fit for ambulatory and acute care visits, and a log-link generalized linear model assuming a gamma distribution was fit for healthcare spending among those whose medical spending was $> \$0$. Models for disenrollment were weighted by the matching weights only (since censoring was the outcome itself), whereas all other models were weighted using combined weights (the matching weight

multiplied by the selection weight). To minimize residual confounding, uncoarsened matching variables were included in outcome models. Clustered SEs accounted for the inclusion of the same patients multiple times.

In robustness checks, (1) the sample was restricted to exclude repeat evictions, and (2) month-by-month pretrends were examined during the 6-month baseline period to assess whether evicted patients and their matches exhibited diverging healthcare utilization trends leading up to eviction.

Analyses were performed in R, version 3, during 2019–2021 (details are in Appendix, available online). This study was approved by the New York University IRB.

RESULTS

For 2017, NYC OpenData reported 20,810 residential evictions. A total of 6,922 NYC Medicaid patients were classified as evicted.

In the unmatched sample (Table 1), NYC Medicaid patients who were evicted were more likely to be male, Black or Hispanic, Bronx residents, and U.S. citizens. The mean census tract poverty rate was also higher for evicted patients. During the baseline period, average medical spending was higher for evicted than for non-evicted patients, as was healthcare use, though evicted patients filled slightly fewer pharmaceutical prescriptions. Pretrends in healthcare utilization were similar for evicted patients and their matches (Appendix, available online).

After applying inclusion criteria (Figure 1), excluding patients with missing baseline data, and matching evicted to non-evicted patients, the final analytic data set included 1,312 evicted “patient-trials” (the number of patients multiplied by the number of times each was included in the analysis) comprising 1,300 unique patients and 375,553 non-evicted patient-trials (261,855 unique patients). Fully 95.3% of evicted patients were matched to ≥ 1 non-evicted controls.

In outcome models (Table 2), eviction was associated with markers of impeded access to care. Evicted patients had 1.63 times the odds of losing Medicaid coverage for any length of time during follow-up (95% CI=1.38, 1.92, $p<0.001$) and 1.43 times the odds of losing coverage for ≥ 91 days (95% CI=1.12, 1.84, $p=0.005$) compared with controls. Evicted patients filled 0.68 times the number of prescriptions (95% CI=0.52, 0.88, $p=0.004$) and had 0.72 times the odds of generating any healthcare spending (95% CI=0.61, 0.85, $p<0.001$). Eviction was also associated with fewer ambulatory care visits (incidence rate ratio=0.60, 95% CI=0.36, 1.04, $p=0.069$), although marginally statistically significantly so.

Conversely, evicted patients who utilized care generated 20% more healthcare spending (95% CI=1.03, 1.40, $p=0.017$) on average; imprecise estimates indicated a 22% higher incidence rate of acute care visits (95% CI=0.97,

Table 1. Sample Descriptives and Matching Performance Among 2017 NYC Medicaid Patients

Variables	Means before matching			Matched data (weighted) ^a		
	Evicted	Non-evicted	Absolute difference	Evicted	Non-evicted	Absolute difference
Age, years	24.3 (19.1)	26.7 (18.1)	2.4	23.5 (18.9)	23.4 (18.8)	0.1
Census tract poverty, %	29.1	24.4	4.7	29.1	29.1	<0.1
Binary sex, %						
Male	54.9	46.6	8.3	55.2	55.4	0.18
Female	45.1	53.4	—	44.8	44.6	—
Race/ethnicity, %						
White, non-Hispanic	7.9	16.5	8.6	7.3	7.2	0.1
Black, non-Hispanic	40.2	21.3	18.8	40.7	40.3	0.4
Asian, non-Hispanic	3.6	18.5	14.9	3.6	3.6	0.1
Hispanic/Latino	35.5	26.0	9.6	35.7	36.2	0.4
Other, non-Hispanic	12.8	17.7	4.9	12.7	12.7	0.0
Citizenship status, %						
U.S. citizen	89.0	79.2	9.8	89.6	89.6	<0.1
Noncitizen	11.0	20.8	—	10.4	10.4	—
Borough of residence, %						
Manhattan	11.5	9.4	2.2	11.4	11.4	<0.1
Brooklyn	23.2	35.1	11.9	52.4	52.3	0.1
Bronx	52.3	24.5	27.8	23.6	23.8	0.1
Queens	11.3	27.1	15.8	11.1	11.1	<0.1
Staten Island	1.7	3.9	2.3	1.5	1.5	<0.1
Baseline medical variables						
Medical spending, USD	4,702 (18,726)	3,043 (13,033)	1,659	2,947 (9,597)	2,762 (8,552)	185
Ambulatory care visits	3.8 (11.2)	3.5 (7.9)	0.4	2.9 (7.8)	3.1 (7.8)	0.2
Acute care visits	0.4 (1.3)	0.2 (1.0)	0.2	0.3 (1.0)	0.3 (0.8)	0.1
Pharmaceutical prescriptions filled	7.8 (16.2)	8.0 (15.4)	0.2	6.6 (14.1)	6.7 (14.1)	0.1
Lost Medicaid coverage while under observation, %						
... For any amount of time	16.6	11.0		16.5	11.3	
... For ≥91 days	6.3	4.7		6.2	4.6	
N	1,377	21,354,066		1,312	375,553	
N unique	1,364	2,294,875		1,300	261,855	

Note: The statistics presented are means (displayed as percentages for binary variables) for uncensored patients. SDs are in parentheses for continuous variables.

^aMatched data were weighted to account for different matching ratios for evicted to non-evicted patients. Of the 1,377 evicted patient-trials that met inclusion criteria and had no missing baseline covariates, 1,312 were matched (95.28%) to a total of 261,855 non-evicted patient-trials. NYC, New York City; USD, U.S. dollar.

1.53, $p=0.082$). On balance, marginal predictions from the 2-part spending model suggested that evicted patients generated more healthcare spending on average (estimated difference=\$158, 95% CI= −9, 326, $p=0.063$), despite generating \$0 more often than controls. Results from sensitivity analyses based on an alternative definition of loss to follow-up (inverse probability of selection weights based on a gap in coverage ≥ 91 days rather than any gap) were functionally identical—although overall spending differences were slightly larger (\$177, 95% CI=11, 342, $p=0.037$)—as were results excluding observed, repeat eviction trials ($n=12$) and their matches.

DISCUSSION

This 6-month follow-up study of Medicaid patients in NYC found that eviction was associated with markers of impeded healthcare access and higher healthcare spending. Compared with similar controls, evicted patients had increased odds of losing Medicaid coverage, filled fewer prescriptions, had fewer ambulatory care visits, and had higher odds of generating \$0 of healthcare spending—of receiving no care at all. Yet, evicted patients who did access care generated more costs and had more acute care visits, though 95% CIs for acute (and ambulatory) care

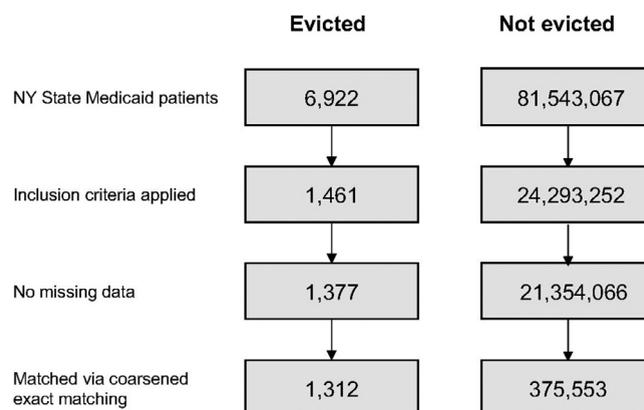


Figure 1. Sample sizes for evicted and non-evicted Medicaid patients.

Note: These are not counts of unique patients. The final data set is a combination of 12 monthly data sets, 1 for each month in 2017; an individual can appear up to 12 times.

NY, New York.

crossed the null. The only other study on eviction and acute care visits, using assignment to more or less tenant-friendly housing court judges in NYC as an instrument, similarly found increased emergency room visits after an eviction, especially in the first 2 years.¹⁰ Thus, despite apparent barriers to care, imprecise estimates suggested that eviction was associated with potentially substantial additional medical spending during follow-up.

These results suggest 2 co-occurring effects of eviction, at least in the short term. On the one hand, evictions may drive poor health, increasing patients' healthcare needs. On the other, evictions may impede patients' healthcare access, either because managing urgent housing needs competes (in time and in psychological energy) with patients' need to access ambulatory care, fill prescriptions, or recertify their Medicaid eligibility¹⁹ or because physical displacement makes it difficult to access known primary care providers or pharmacies. Data sets that would allow analyses of these mediating paths are needed.

Limitations

This study has important limitations. Most obviously, confounding and selection bias were likely not fully eliminated, though the robustness of these findings is supported by strict inclusion criteria and equivalent results under multiple definitions of selection. "Acute care visits" and "ambulatory care visits" are also heterogeneous categories, including both treatment and prevention, requiring careful interpretation. The following discussion focuses on 3 less-apparent limitations, related to (1) misclassification of eviction status, (2) limited generalizability, and (3) reasons for Medicaid disenrollment.

First, patients' eviction histories may have been misclassified: data linkage was based on dates and locations rather than on patient names, patient addresses in Medicaid could be inaccurate, and 11 of 39 marshals did not report to NYC OpenData. Suggesting that a high proportion of the patients classified as evicted were in fact evicted, 18% of evicted patients in the sample filed a new Medicaid address in the 6 months after their eviction (vs

Table 2. Six-Month Changes in Healthcare Utilization/Coverage Associated With Eviction

Outcomes	Interpretation	Estimate	95% CI	p-value
Losing Medicaid for any length of time	OR	1.63	1.38, 1.92	<0.001
Losing Medicaid for ≥91 days	OR	1.43	1.12, 1.84	0.005
Total healthcare spending (USD)				
Whether spending >\$0	OR	0.72	0.61, 0.85	<0.001
Total healthcare spending among those with spending >\$0	Spending ratio	1.20	1.03, 1.40	0.017
Acute care visits	IRR	1.22	0.97, 1.53	0.083
Ambulatory care visits	IRR	0.60	0.35, 1.04	0.069
Pharmaceutical prescription fills	IRR	0.68	0.52, 0.88	0.004

Note: Boldface p-values indicate statistical significance ($p < 0.05$).

Estimates for each outcome come from separate models in the same matched population of 1,312 evicted patient-trials comprising 1,300 unique patients and 375,553 non-evicted patient-trials (261,855 unique patients).

IRR, incidence rate ratio; USD, U.S. dollar.

4% of controls), despite patients generally only updating addresses when prompted (e.g., at doctor's visits). More pressingly, many evictions are informal, such as via landlords making apartments uninhabitable or vastly increasing rent overnight, which are not captured in this analysis—ditto evictions not carried out, or not reported, by marshals.^{5,32} This suggests that un-evicted people were more likely to be misclassified as un-evicted than evicted people were to be misclassified as evicted; results would then be interpreted as underestimates.

Second, on generalizability, the strict inclusion criteria exclude 79% of identified evictees. Excluded cases include patients who experienced recent housing instability, who were not dual-eligible for Medicare, or who (re-)enrolled in Medicaid within the last 6 months. Retained sample members are thus a relatively housing-secure, non-elderly, and socioeconomically stable minority of evicted patients. The association between eviction and healthcare utilization or Medicaid disenrollment may be stronger among the excluded population; the chaos and deepening deprivation of repeat housing instability or repeatedly falling on and off health insurance may heighten stress and erect even more trying logistical barriers to Medicaid recertification. The strict inclusion criteria may also account for differences between the sample's demographics and those of previous research, which has found, for example, that women are at higher risk of eviction than men,³³ contrary to the information in [Table 1](#) (although these data provide binary sex only, not gender identity).

Third, there are multiple reasons for Medicaid disenrollment, which this study cannot differentiate. Some people who were evicted may have moved out of state and enrolled in another state's Medicaid program, meaning that this study's results for a ≥ 91 -day disenrollment should be interpreted carefully. A "Medicaid disenrollment" interpretation is nonetheless strengthened by the fact that among patients who disenrolled for ≥ 91 days, evicted and non-evicted patients were equally likely to have remained in the state a year after the end of follow-up (as measured by re-enrolling in NYS Medicaid), suggesting that rates of out-of-state moves may have been roughly equal across evicted and non-evicted patients who faced ≥ 91 -day disenrollment.

Similarly, although rarer, patients can lose Medicaid by becoming ineligible—for example, acquiring higher-paying jobs, which may sponsor private insurance.^{34,35} Because eviction can damage economic prospects,³⁶ it may be that disenrollments among matches were disproportionately accompanied by private insurance enrollment, whereas disenrollments among evicted patients disproportionately comprised insurance loss. If true,

models underestimate the relative increase in evicted patients' odds of losing health insurance.

Finally, Medicaid patients in NYS only need to recertify their Medicaid eligibility once per year. A portion of each trial's sample was therefore not eligible for disenrollment because their recertification date did not fall within that trial's 6 months of follow-up. This should not introduce bias to models estimating patients' odds of disenrollment as long as the proportion of people not eligible for disenrollment did not differ by eviction status, but this is an additional, necessary assumption.

CONCLUSIONS

To the extent that this study detected a causal signal, results suggest that preventing eviction may both improve access to health care and lower healthcare costs. Programs within Medicaid to prevent disenrollment (e.g., making recertification easier and less frequent³⁷) and to proactively support patients in accessing care after an eviction are warranted and may be cost-effective. Further upstream, policies that would increase housing stability and prevent evictions—such as minimum wage increases, more funding for affordable housing, expansion of multifamily residential zoning,³⁸ "just cause" eviction legislation,³⁹ and legal representation in housing court⁴⁰—may yield offsetting savings in the Medicaid budget while safeguarding the health of low-income Americans.

Results on Medicaid disenrollment are striking alongside previous work showing that Medicaid expansion lowered eviction rates.^{41,42} That work suggests that enrolling in Medicaid protects low-income families from being evicted, preserving their health and working hours and obviating the need to spend money on private health insurance premiums. That is, this study suggests that eviction increases patients' risk of losing Medicaid coverage, and that coverage loss may then increase their risk of future eviction. Eviction and Medicaid loss may thus operate as a cycle of health disadvantage. Research using stronger causal inference designs outside of NYC is needed to establish that evictions leading to Medicaid disenrollment is a national pattern. If results hold, state and federal policymakers must take those cycles into account when anticipating the costs and savings of intervening to prevent evictions or expand public insurance coverage.

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CREDIT AUTHOR STATEMENT

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SUPPLEMENTAL MATERIAL

Supplemental materials associated with this article can be found in the online version at <https://doi.org/10.1016/j.amepre.2021.07.018>.

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