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Inaccuracies in Eviction Records: Implications for Renters and Researchers

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ABSTRACT

Administrative court records are increasingly used to study the prevalence of eviction. Yet inaccuracies in court records bias estimates of eviction and distort tenants' true rental histories. This is the first study to systematically assess the prevalence of inaccuracies across jurisdictions. Drawing on over 3.6 million administrative eviction court records from 12 states, we find that, on average, 22% of eviction records contain ambiguous information on how the case was resolved or falsely represent a tenant's eviction history. Adjusting for multiple inaccuracies in the data produces significantly different eviction rate estimates. Cases with increased complexity, such as those involving multiple tenants and lawyers, are more likely to contain inaccuracies. However, inaccuracies vary most prominently between states, indicating that state court system characteristics fundamentally shape the official record of the evicted population.

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In recent years, a growing body of research has focused on eviction. Researchers from different disciplines have employed multiple methods to study the prevalence, causes, and consequences of forced displacement from housing (Brickell, Arrigoitia, & Vasudevan, 2017; Nelson, 2019). Studies have shown that evicted families often face downward residential mobility (Desmond & Shollenberger, 2015) and can become trapped in a cycle of poverty, as eviction has been linked to job loss, depression, and prolonged homelessness (Crane & Warnes, 2000; Desmond, 2016). Accordingly, researchers have begun to analyze the effectiveness of federal, state, and local policies aimed at preventing eviction, from legal interventions such as providing an attorney to tenants in housing court (Greiner, Pattanayak, & Hennessy, 2012; Seron, Martin, Gregg, & Kovath, 2001) to nonhousing related programs such as Medicaid expansion (Zewde, Eliason, Allen, & Gross, 2019).

Recognizing the negative impacts of eviction on families, schools, and communities, policymakers have introduced legislation to lower rates of displacement and promote residential stability. At the municipal level, cities like New York City and San Francisco, California, have recently instituted the right to counsel for families facing eviction (Mironova, 2019), whereas cities like Cleveland, Ohio, have established diversionary community courts that provide tenants with legal aid and social services (Center for Court Innovation, 2019). At the state level, states like Virginia have deepened their investment in affordable housing in direct response to recently published data showing eviction to be widespread in the state (Desmond et al., 2018b; Office of Governor Ralph S. Northam, 2019), whereas states like Washington have passed legislation sealing eviction records, recognizing that those records can negatively affect renters' housing prospects, credit histories, and access to affordable housing programs (Office of Senator Patty Kuderer, 2019). At the federal level, multiple lawmakers have recently introduced legislation aimed at reducing evictions, including the

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bipartisan-sponsored Eviction Crisis Act of 2019, which calls for better nationally representative eviction data, funds local interventions, and extends protections to tenants with false eviction records (Office of Senator Michael Bennet, 2019).

Housing policy researchers and policymakers themselves are increasingly interested in understanding the dynamics of displacement and developing interventions aimed at preventing eviction. Understanding the scope and geography of the problem and evaluating the effectiveness of different policy interventions requires having access to accurate eviction data across multiple local and state jurisdictions. However, there are no comprehensive local or federal statistics (Hartman & Robinson, 2003) or nationally representative surveys (Desmond & Kimbro, 2015) that reliably estimate the number of U.S. households evicted each year. Administrative housing court records from civil courts provide a novel and more comprehensive source of information for estimating the population prevalence of formal eviction.¹ Since administrative records are seldom created with research in mind, they must be critically assessed for omissions, errors, and biases (Loftin & McDowall, 2010; Salganik, 2017).

Housing court records in particular are known to contain data-entry mistakes, vague case outcomes, and the misleading inclusions of unadjudicated cases, all of which can distort estimates of eviction (Kleysteuber, 2006; Spector, 2000). Beyond their impact on statistics, inaccurate or incomplete court records also misrepresent the nature and frequency of tenants' eviction histories. Landlords routinely deny prospective renters who appear to have been previously filed against or evicted (Gold, 2016). Inaccurate court records can therefore prevent tenants from accessing desirable neighborhoods and public housing (Desmond & Shollenberger, 2015; Greiner et al., 2012). For these reasons, auditing eviction court records for errors promotes both statistical accuracy and judicial fairness. It also provides policymakers with a straightforward way to evaluate the soundness of an important source of eviction data.

Drawing on over 3.6 million administrative eviction court records from 12 states, we find that, on average, 22% of eviction records contain ambiguous information on how the case was resolved or falsely represent a tenant's eviction history. We demonstrate that researchers who make different decisions about how to treat eviction data will produce significantly different results from the same data. Cases with increased complexity, such as those involving multiple tenants and lawyers, are more likely to contain inaccuracies. However, inaccuracies vary most prominently between states, suggesting that state court systems fundamentally shape the official record of the evicted population. Accounting for inaccuracies in eviction court data promotes researchers' abilities to conduct evidence-based assessments of eviction- and housing-related policies and to make comparisons across different studies and geographies.

The Challenges of Measuring Eviction

Most estimates of eviction are generated from population surveys that undercount its prevalence. The disadvantaged households who are most at risk of eviction, including the residentially unstable and homeless, are not well represented in standard household sampling frames (Desmond, 2012; Tourangeau, Edwards, & Johnson, 2014). Furthermore, surveys designed to measure eviction in specific metropolitan areas (e.g., Los Angeles Family and Neighborhood Survey, California; Milwaukee Area Renters Study, Wisconsin) or among targeted populations (e.g., Fragile Family and Child Well Being Study) are by design limited in scope. In addition, how eviction-related survey questions are asked may undermine their ability to reveal a complete picture of housing displacement (Desmond & Kimbro, 2015). For example, the American Housing Survey (United States Census Bureau, 2015) only directs eviction questions to those who have recently moved, and both the American Housing Survey and the Panel Study on Income Dynamics (The Institute for Social Research, 2015) provide response categories that group eviction with many other types of forced moves (e.g., foreclosures, job transfers, natural disasters). In total, survey data have yet to produce an accurate and complete accounting of eviction in America.

Administrative data are a more comprehensive source of information about court-ordered evictions. Formal eviction cases are tracked via publicly accessible court records, and researchers have started using these records to estimate eviction prevalence and study its effect on housing displacement (Desmond et al., 2018b; Raymond, Duckworth, Miller, Lucas, & Pokharel, 2016; Shelton, 2018). Yet there are several key barriers to using administrative data for research purposes. For one, comprehensive administrative data sets, including housing court records, are often time-consuming and expensive to build (Hartman & Robinson, 2003; Newman, 2010; Sawicki & Craig, 1996). Once assembled, housing court data are not free from error or bias. One reason we expect inaccuracies in eviction records is the high volume of cases processed by housing courts. Eviction cases are often decided in a matter of minutes, and few tenants are represented by attorneys who could slow down the process or help ensure accurate recordkeeping (Desmond, 2012; Gold, 2016). Indeed, prior scholarship using local data has documented inaccuracies in housing court records including unclear or misleading judgment outcomes, unadjudicated cases that remain on a tenant's eviction history, and cases that show legal evictions when no eviction occurred (Hartman & Robinson, 2003; Kleysteuber, 2006; Spector, 2000).

Eviction data, like other kinds of administrative records, must be carefully examined to avoid producing biased estimates (Connelly, Playford, Gayle, & Dibben, 2016). However, there are no studies that systematically identify eviction record inaccuracies using large, multistate data. As a result, it is unclear whether prior research that draws on court records to assess the causes and consequences of eviction has adequately accounted for court record inaccuracies. For example, two recent articles that analyze eviction court data for Atlanta, Georgia, and Lexington, Kentucky, do not clarify whether or how they accounted for the inaccuracies we identify here (Raymond et al., 2016; Shelton, 2018). In general, this lack of clarity may contribute to ambiguity in how eviction is measured in analyses (which may differ depending on the research questions) and hinder reproducibility of study results by others researchers.

Beyond the impact of faulty records on eviction statistics, inaccurate eviction data are also harmful to tenants. Because landlords routinely discriminate against prospective renters who have a history of involvement with housing court, any false or misleading information in a tenant's file puts them at greater risk of being denied housing in the future (Kleysteuber, 2006). And since eviction records can affect credit scores, inaccurate eviction case information can also detrimentally impact a tenant's borrowing and employment prospects (Greiner et al., 2012). Although the Fair Credit Report Act requires tenant screening companies to verify the accuracy of their reports, lax enforcement disincentivizes them from thoroughly checking for errors (Spector, 2000).

The uncritical use of administrative records disproportionately harms marginalized groups. For example, despite the fact that background checks based on *criminal* court records also contain inaccurate information, they are still routinely used in employment and housing screening (Walter, Viglione, & Tillver, 2017; Yu & Dietrich, 2012). The harm caused by inaccurate criminal records is exacerbated for groups that have disproportionate contact with the criminal justice system, particularly low-income black and Latino men (Western, 2006). By the same token, inaccurate eviction records are more likely to harm the marginalized communities who are most at risk of experiencing an eviction, particularly low-income black and Latina women (Desmond, 2012). Fundamentally, inaccurate eviction court records cause harm by overrepresenting marginalized renters in the data. This differs from many other types of administrative data, which cause harm by underrepresenting marginalized groups and communities (Maantay & Maroko, 2009; Park & Evans, 2018).

Evaluating Eviction Court Records for Inaccuracies

This is the first study to systematically catalog the prevalence and impact of inaccuracies in eviction court data. To do so, we search for two broad types of inaccuracies: *ambiguous records* and *false records*.² *Ambiguous records* are court records that fail to clearly indicate the case's result. They appear in two forms: *unresolved cases* and *opaque cases*. *Unresolved cases* are missing both judgment dates and judgment information, suggesting that the cases were never adjudicated. *Opaque cases* contain

unclear judgment fields that fail to clarify which party, if any, prevailed in court. Opaque cases are particularly troublesome for estimating eviction rates since they represent completed cases but obscure whether a formal eviction was ordered. Both unresolved and opaque cases potentially penalize tenants who may have won or settled their disputes but whose records do not clearly reflect that fact.

False records incorrectly indicate that a tenant was filed against or evicted. They present as *duplicate cases* and *serial cases*. *Duplicate cases* appear in the record multiple times with the exact same case characteristics and are likely the results of recordkeeping mistakes. Duplicate cases can inflate both eviction statistics and tenants' eviction histories since they represent multiple instances of the same case. *Serial cases* are groups of cases involving the same landlord filing repeated eviction claims against the same tenant at the same property. Serial cases often end in an eviction judgment, but the presence of subsequent cases between the same parties indicates that the landlord did not remove the tenant. Serial cases artificially increase displacement statistics and saddle tenants with a distorted eviction history. Unlike duplicate cases, serial cases are genuine case filings and are therefore not strictly recordkeeping errors. Instead, they result from landlords using eviction filings to enforce past-due rent payments rather than clear intentions to remove tenants from a property (Garboden & Rosen, 2019; Immergluck, Ernsthausen, Earl, & Powell, 2019). [Figure 1](#) shows the general progression of eviction cases in courts, including where the types of inaccuracies discussed here are likely to be generated.

Using the above framework to examine inaccuracies in court records we investigate three main questions: What is the prevalence of ambiguous and false records in eviction court data? How do ambiguous and false records affect the estimation of eviction statistics? And what case characteristics predict the likelihood that a case will contain an inaccuracy?

Eviction Court Record Data Used in the Analysis

We obtained statewide eviction court data from 12 states: Alabama, Connecticut, Hawaii, Iowa, Minnesota, Missouri, Nebraska, North Carolina, North Dakota, Pennsylvania, South Carolina, and Virginia.³ The data we received cover a varying number of years. To maximize the comparability of records, we restricted our analytic sample to 3,643,023 cases filed between 2011 and 2015.

Although there was some variation in the information included from each state, most data sets contained the following main fields: case number, county where the case was filed, an identifier of the filing court, case filing date, case judgment date, defendant and plaintiff names, defendant and plaintiff addresses, and information about the outcome of the case. In addition, the data for four states—Nebraska, Pennsylvania, South Carolina, and Virginia—contained variables indicating whether the defendant and plaintiff were represented by an attorney.

We formatted and geocoded the defendant addresses to create a standardized street address. Approximately 93% of the defendant addresses were geocoded at the point or street address level, both of which are precise enough to provide an accurate standardized street address.⁴ We also checked defendant name fields for anonymous monikers: *John/Jane Doe*, *resident*, or *occupant*. Identifying anonymous defendants was an important step in computing the percentage of duplicate and serial cases since those measures look for identical combinations of a tenant's name and address. Finally, we marked and excluded cases that appeared to involve a commercial defendant, using regular expressions to search for terms commonly associated with businesses.⁵

We marked cases *unresolved* if all outcome fields attached to the case, as well as their corresponding judgment date fields, were left blank. We marked cases *opaque* if all of their outcome codes failed to definitively indicate whether the case was decided in favor of the plaintiff or the defendant, or was settled. Opaque codes have values such as *judgment*, *verdict*, *disposed*, and *other*. By comparison, nonopaque codes have values such as *find for plaintiff*, *find for defendant*, *settled*, and *dismissed*. Opaque cases also include those with blank outcome fields but a populated judgment date variable. We classified outcome codes as opaque after confirming with courts that there was no way to identify from the electronic case record which party had prevailed.⁶ We marked cases as ending in

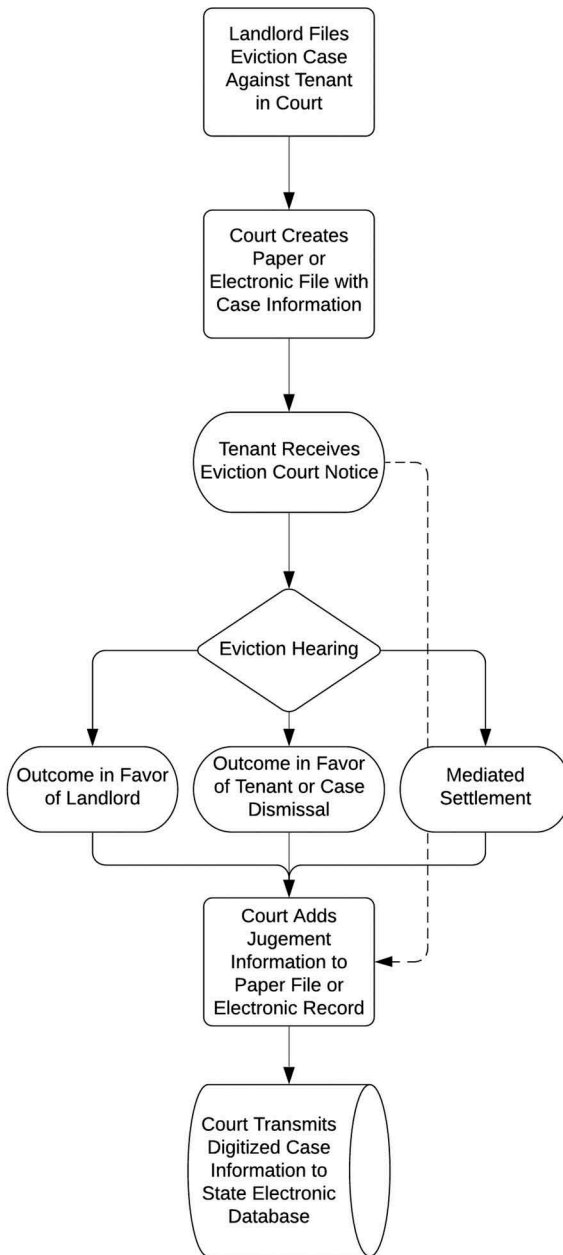


Figure 1. General progression of eviction cases in courts.

Depending on the requirements of the court system, landlords may file the case electronically or via paper forms. Landlords often file cases against tenants behind on rent payments. In some instances, the landlord does not intend to remove the tenant if the past-due rent balance is paid. They may continue to file cases to collect late rent. These repeated filings create **Serial Cases**.

Courts take the documentation submitted by landlords and create an initial paper or electronic record. **Duplicate Cases** may occur as a result of data entry or database errors.

Sometimes landlords and tenants successfully resolve the dispute before the eviction hearing. **Unresolved Cases** may occur if the landlord does not pursue the eviction hearing and the court does not record the agreement reached by the landlord and tenant.

Depending on the jurisdiction, a dozen or more outcome codes may be used to describe one of these three broad results. **Opaque Cases** may occur when the codes courts use are not self-explanatory or well annotated.

Duplicate cases may be created if judgment information is not properly linked to previous case actions, including the original case filing. Cases may appear **Unresolved** if courts fail to properly update judgment information.

States with standardized electronic case management systems can aggregate county case information. **Duplicate, Opaque, or Unresolved Cases** may occur as a result of incomplete transmission of data or other system errors. Paper case records are typically stored locally in the archives of the court where the case was processed.

a definitive eviction judgment if they contained codes like *finding for plaintiff*, *eviction judgment*, *summary judgment*, or similar.

We checked for *duplicate* cases on the basis of six key variables: court identifier, filing date, defendant name, standardized defendant address, case judgment date, and money judgment amount.⁷ We marked a case as a duplicate if any of its defendant listings perfectly matched another

defendant listing on a different case across all six of these fields. Only duplicated cases beyond the first instance were classified as duplicates.⁸ We marked cases as *serials* if they contained any defendants who had been filed against multiple times at the same standardized address but on different dates. All occurrences but the final one of a defendant name–address combination were classified as serials since these nonfinal cases are the ones that, when they end in an eviction judgment, increase eviction rate statistics.⁹

Measuring Inaccuracies in Eviction Court Records

First, we provide statewide descriptive statistics on the prevalence of ambiguous and false eviction records. Second, we analyze the impact of inaccuracies on eviction rates. To do so, eviction statistics are measured at the state level and averaged across the 5-year sample period. When calculating eviction statistics, we distinguish between two main measures: the *case filing rate* and the *eviction rate*. Case filings are all cases filed with a court, regardless of the outcome. We define the *case filing rate* as the number of case filings divided by the number of renter households in the state. The *eviction rate* is the number of filed cases that resulted in an eviction judgment, divided by the number of renter households. To measure the uncertainty introduced by inaccuracies in eviction records, we calculate (a) a baseline unadjusted eviction rate that assumes all opaque outcomes are evictions and includes duplicate and serial cases in eviction counts; and (b) an adjusted eviction rate that assumes all opaque outcomes are not evictions and that excludes duplicate and serial cases.¹⁰

Third, we run a set of logistic regression models to assess whether case characteristics predict the likelihood that a case exhibits a particular inaccuracy. The covariates in these models include case length, number of unique defendants, legal representation, and the filing court's monthly case volume. These variables capture the complexity of each eviction case (e.g., how long it lasted, how many people were involved) as well as each court's capacity to adequately address such complexity. We measured case length by subtracting the filing date from the final action date. We created a variable that counted the number of unique defendant names associated with a case.¹¹ For the four states with attorney information, we generated two dummy variables: one indicating whether attorney names were present for a defendant on a case, and one indicating whether plaintiff attorney names were present.¹² We include legal representation to assess whether there is a relationship between attorneys and the accuracy of eviction records. Finally, we generated a monthly court volume variable by summing the number of cases filed monthly in each county court.

We also include several control variables in the models. Eviction filings often peak during summer months (Desmond, 2012). For this reason, we control for the season in which the case was filed. We also control for case filing year to account for variation in the prevalence of inaccuracies over time. We estimate separate case-level logistic regression models for each state and each type of inaccuracy. Descriptive statistics for all variables are shown in [Table A1](#).

The Difference in Inaccuracy Rates Across States

[Figure 2](#) shows the percentage of cases that contain inaccuracies. We find that, on average, 22% of state eviction cases are ambiguous or false records. The state with the lowest overall inaccuracy rate is Connecticut, where 7.40% of eviction records contain inaccuracies. The state with the highest overall inaccuracy rate is South Carolina, where 46.57% of eviction records contain inaccuracies. Looking at each of the four inaccuracy types individually shows additional variation. Four states—Minnesota, Missouri, North Dakota, and Nebraska—have no unresolved cases. This indicates that some states purge unresolved cases from their systems, do not include unresolved cases in the records released to outside parties, or ensure that all cases are formally closed. By contrast, the remaining five states contain unresolved cases in amounts ranging from 118 in Connecticut to 9,769 in South Carolina. In these states, hundreds or thousands of people whose eviction cases were never

adjudicated remain in the court record. The public release of these cases is potentially harmful to tenants whose truncated contact with the court system may still be noted by landlords.

The overall prevalence of opaque cases is noticeably higher than that of unresolved cases, and it varies more widely between states. In Virginia, only a small percentage of cases have judgment codes that make it impossible to definitively determine the case's outcome. In North Dakota, however, almost 17% of cases have opaque codes. High levels of opacity add uncertainty to research efforts aimed at estimating eviction rates. For tenants, the impact is more complex. Tenants with opaque outcomes who in fact won their cases are potentially harmed since their record does not clearly communicate their victory. However, tenants with opaque outcomes who were in fact legally evicted may benefit from the ambiguity in the record.

The second panel of [Figure 2](#) shows the prevalence of duplicate cases. Overall, state duplicate rates are extremely low, with an average rate across all 12 states of just 0.12%. In five states—Alabama, Connecticut, Hawaii, Nebraska, and North Dakota—there are almost no duplicate records. Despite the small percentage of duplicates, hundreds of defendant listings are still affected in absolute terms, depending on the size of the state.¹³ The number of extra defendant listings gives a fuller picture of the number of tenants impacted by duplicate cases. In Minnesota, for example, duplicate cases affect more than 800 defendant listings. And despite Virginia's modest 0.11% duplicate rate, 1,004 defendant listings are affected.

The second panel of [Figure 2](#) also shows the prevalence of serial cases for each state. Serial case rates are much higher, and vary much more substantially, than duplicate case rates. In Pennsylvania, 173,681 cases (31.02% of total cases) are serial cases in which the same tenant appeared on a subsequent case at the same property. Of these cases, 35.51% showed an eviction judgment in

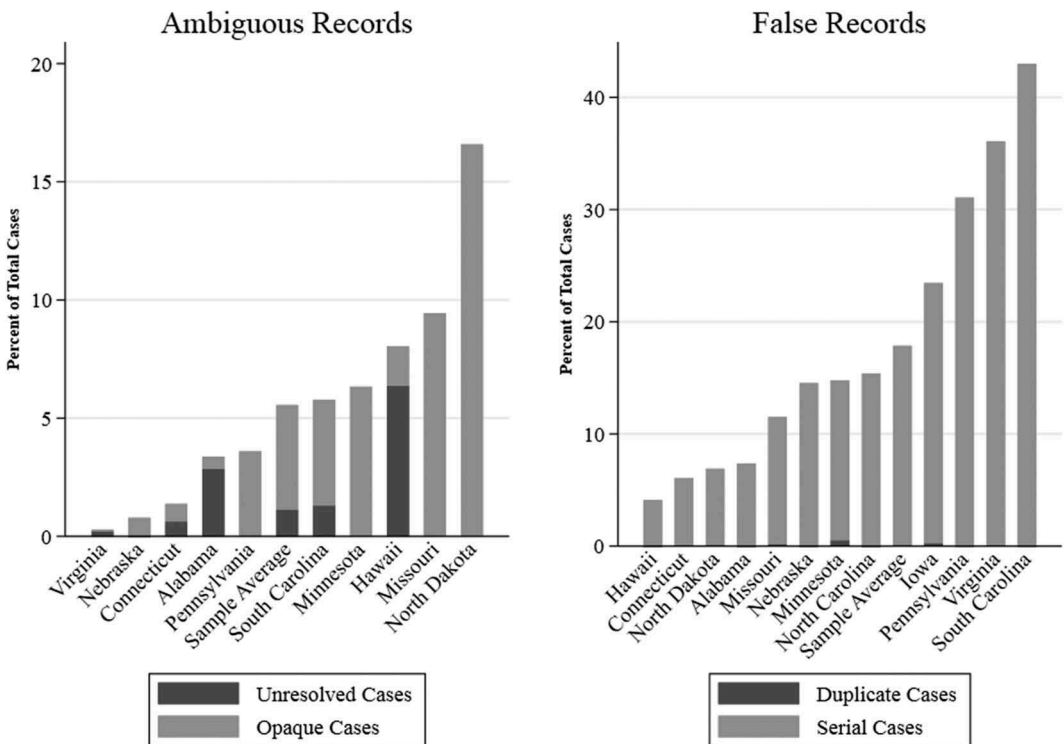


Figure 2. Prevalence of inaccuracies by state and type.

Note. North Carolina did not contain outcome code fields needed to determine unresolved and opaque cases. Iowa courts use a simplistic coding scheme that precludes them from unresolved and opaque analysis.

the official record (see [Table A2](#)) despite the fact that the tenant was never expelled from their home. In total, the substantial differences between state rates for all four inaccuracies suggest that features of each state's court or legal system directly shape the quality and scope of eviction court records.

The Impact of Inaccuracies on Eviction Statistics

[Figure 3](#) shows how opaque, duplicate, and serial eviction records impact statewide eviction rates. We report averages from the 5-year period from 2011 to 2015 and compare an adjusted eviction rate—which excludes opaque, duplicate, and serial cases from eviction counts—with an unadjusted rate that does not account for these inaccuracies. These unadjusted and adjusted measures delineate the range of possible eviction rates that could be produced by researchers analyzing the same court data. The adjusted eviction rate is lower than the unadjusted eviction rate in every state. We document considerable variation in the difference between the two rates across states. In South Carolina, where 43% of cases are serial cases, the unadjusted eviction rate is 21.3%. Removing ambiguous and false evictions from the records lowers the eviction rate to 11.5%, a reduction of 46%. In Missouri, which has a relatively high prevalence of opaque cases, removing ambiguous and false evictions lowers the average annual eviction rate by 19%. Across all states, adjusting for these inaccuracies reduces state eviction rate estimates by an average of 14%.

Some inaccuracies bias eviction rates in more straightforward ways than others. For example, including false records inflates eviction rates because the same household is counted as being evicted multiple times. Ambiguous records, on the other hand, can inflate or deflate rates depending how researchers handle unresolved and ambiguous cases. In some instances, cases may be unresolved because the tenant vacated the property before an eviction was adjudicated. Certainly, some opaque cases result in the household being displaced, even if the outcomes appear less straightforward. As such, removing ambiguous records may overadjust the eviction rate and underestimate the number of households displaced.

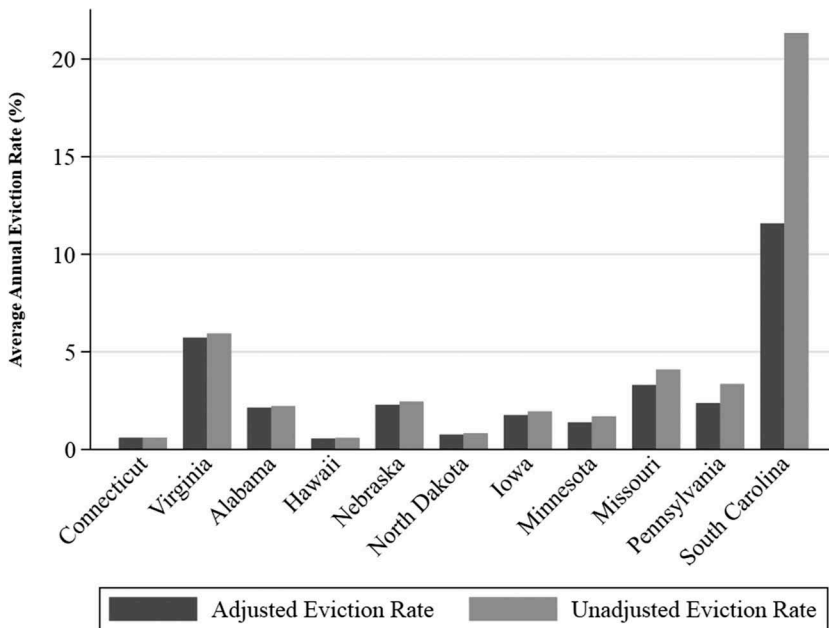


Figure 3. Average annual eviction rates before and after adjusting for inaccuracies, 2011–2015.

Note. States sorted by size of percentage decrease in eviction rates after adjusting for inaccuracies. North Carolina did not contain outcome code fields needed to compute eviction rates. Iowa's adjusted eviction rate does not account for unresolved or opaque cases.

False and ambiguous evictions may differently impact the calculation of eviction measures other than the displacement rate. If researchers are interested in how courts are utilized by landlords in the management of their property, including as a tool to extract rent payments (Garboden & Rosen, 2019; Immergluck et al., 2019), multiple serial filings resulting in eviction judgments against the same household would be an important component of this measure. Most serial cases, regardless of their placement in the chronology of household filings, are resolved. (As shown in Figure 2, many states with high proportions of serial cases still have a very low prevalence of unresolved cases). Although eviction judgments are more common in cases representing the final appearance of a household in the court records, many of the preceding serial cases also result in eviction judgments (see Table A2). This is consistent with previous findings that some landlords who file serial cases are not seeking to evict their tenants and are instead using housing court as a rent collection mechanism. And whereas only serial cases that end in eviction judgments distort measures of displaced households, all serial cases increase the number of landlord–tenant disputes that appear in a tenant’s housing record. Cross-state variation in the percentage of serial cases resulting in eviction judgments demonstrates differences in how these cases are handled by landlords and courts.¹⁴

Court Case Attributes That Predict Inaccuracy

We now examine whether a case’s characteristics predict the likelihood that it contains an inaccuracy. Table 1 displays results for models predicting the likelihood that a case has entirely opaque outcomes. In four states, the coefficients for *number of unique defendants* are both positive and significant, meaning cases with more defendants are more likely to be opaque. In Missouri, for example, each additional unique defendant increases a case’s odds of being opaque by an average of 60%. For these states, the increased paperwork and split judgments common in multiple defendant cases may compromise accurate recordkeeping. Cases with *defendant legal representation* are also more likely to have opaque judgments. In Virginia, for example, a case with a defendant attorney is almost 9 times more likely to be opaque than a case without an attorney. This finding is somewhat counterintuitive, since we might expect that an attorney would help ensure accurate recordkeeping. However, it is possible that defendants with attorneys are able to secure somewhat unique settlements that are poorly captured in the court record. Finally, in five states, cases in courts with *higher monthly court volumes* are less likely to be opaque. This result may be explained by the fact that a higher percentage of cases in high-volume courts are unambiguously labeled default judgments.

Table 2 presents coefficients for models predicting the likelihood that a case is a duplicate. In five states, cases with higher *numbers of unique defendants* are more likely to be duplicates. This relationship is expected since a case with more defendants is by definition more at risk of having a duplicated defendant. By contrast, a *higher monthly court volume* decreases a case’s odds of duplication for North Carolina but has no effect for the remaining states. This mixed result indicates that although there isn’t a strong relationship between court burden and duplicates in eviction records, some states may still be better equipped to handle a heightened burden, perhaps with additional staffing or technological procedures. In all three states with the measure, *having a defendant attorney* increases the likelihood that a case is a duplicate. For example, in Pennsylvania, cases with a defendant attorney have odds of duplication that are over 3 times higher than cases without a defendant attorney. It is possible that by slowing down the process and actively contesting cases, tenants with attorneys increase the number of actions associated with their file and by extension their likelihood of being duplicated.

Table 3 details results for models predicting the likelihood that a case is part of a chain of serial cases. Cases in which tenants are *represented by an attorney* are significantly less likely to be serial cases. In fact, in Pennsylvania, South Carolina, and Virginia, legal representation reduces the odds that a case is a serial case by between 65% and 70%. Several factors may be behind this finding. Tenants showing up to court with an attorney may dissuade their landlord from pursuing

Table 1. Logistic regression results for the likelihood of opaque cases.

	Alabama	Connecticut	Hawaii	Minnesota	Missouri	North Dakota	Nebraska	Pennsylvania	South Carolina	Virginia
Length of case (in 30-day periods)	1.04* (0.02)	1.10*** (0.02)	0.98 (0.02)	1.14*** (0.04)	1.04 (0.03)	1.02 (0.04)	0.96 (0.03)	1.06*** (0.00)	0.95 (0.06)	n/a
Monthly court case volume (in hundreds)	0.30*** (0.10)	1.95 (1.05)	0.26*** (0.04)	1.22* (0.11)	0.98 (0.05)	0.43 (0.40)	0.86 (0.07)	1.29*** (0.06)	1.01 (0.15)	0.95* (0.03)
Number of unique defendants	1.10 (0.15)	0.96 (0.08)	n/a	1.18*** (0.02)	1.60* (0.32)	1.10* (0.05)	1.03 (0.07)	0.89*** (0.00)	n/a	0.93 (0.10)
Defendant attorney	n/a	n/a	n/a	n/a	n/a	n/a	3.73*** (0.80)	2.09*** (0.04)	0.60** (0.12)	9.93*** (2.63)
Plaintiff attorney	n/a	n/a	n/a	n/a	n/a	n/a	0.32* (0.16)	0.71*** (0.02)	n/a	0.66** (0.10)
No. observations	113,878	18,834	11,424	95,216	213,927	5,731	45,199	559,831	741,498	871,316

Note. Separate models run for each state. n/a = variable not available. Coefficients are presented as odds ratios, with standard errors given in parentheses. Data for North Carolina did not contain the outcome code fields needed to compute unresolved and opaque cases. Iowa courts use a simplistic coding scheme that precludes them from unresolved and opaque analysis. Filing season and filing year were included as controls, but their coefficients are not displayed.

* $p < .05$. ** $p < .01$. *** $p < .001$.

Table 2. Logistic regression results for the likelihood of duplicate cases.

	Iowa	Minnesota	Missouri	North Carolina	Pennsylvania	South Carolina	Virginia
Length of case (in 30-day periods)	n/a	1.00 (0.05)	1.01 (0.03)	n/a	1.01** (0.00)	1.05*** (0.01)	n/a
Monthly court case volume (in hundreds)	0.88 (0.07)	1.02 (0.02)	0.92 (0.09)	0.92*** (0.02)	1.00 (0.01)	1.00 (0.09)	0.98 (0.02)
Number of unique defendants	1.48*** (0.13)	1.83*** (0.08)	1.66*** (0.15)	2.15*** (0.32)	1.08 (0.16)	n/a	1.48*** (0.11)
Defendant attorney	n/a	n/a	n/a	n/a	4.04*** (1.57)	14.24*** (8.71)	3.10*** (1.02)
Plaintiff attorney	n/a	n/a	n/a	n/a	2.04** (0.48)	n/a	1.16 (0.29)
No. observations	67,106	95,216	213,927	883,876	559,831	741,498	871,316

Note. Separate models run for each state. n/a = variable not available. Coefficients are presented as odds ratios, with standard errors given in parentheses. Alabama, Connecticut, Hawaii, Nebraska, and North Dakota were omitted because they had less than 25 total duplicated cases each. Filing season and filing year are included as controls, but their coefficients not displayed. * $p < .05$. ** $p < .01$. *** $p < .001$.

a subsequent eviction against them. It is also possible that represented tenants are a select group who, because they are able to secure an attorney, are also more likely to avoid a cycle of serial evictions. Beyond the attorney effect, we find a seasonality pattern in a case's likelihood of being a serial case. In 9 of the 12 states, cases filed in winter months have a higher likelihood of being serial compared with cases filed in the summer. This could reflect a reluctance by landlords to carry out evictions in the winter, when finding new tenants may prove more difficult. It may also reflect additional efforts by tenants to make rent or negotiate with landlords in the colder months.

Although several case-level features predict inaccuracies, few are consistently predictive across all states. The one notable exception is *defendant attorney*, which predicts higher levels of opaque and duplicate cases, as well as lower levels of serial cases, for all states where the measure is available. Overall, the lack of consistency further suggests that state-level factors are primarily responsible for shaping eviction court records.¹⁵

The Significance of Eviction Record Inaccuracies

A growing number of researchers have begun to investigate the dynamics of eviction. Their work has helped to inform several policy interventions, introduced at multiple levels of government, intended to promote residential stability by preventing forced displacement. The findings of this study have implications for researchers who rely on eviction data, policymakers looking to accurately assess the scope of the issue and evaluate the impact of eviction-prevention initiatives, and tenants whose lives are directly affected by false eviction records.

Court data are the most comprehensive source of information about legally sanctioned evictions. But inaccurate or incomplete court records can distort our understanding of who gets evicted and how often. In this study, the first to systematically catalog inaccuracies in eviction records, we examine 3.6 million eviction cases from 12 states. We identified four kinds of inaccuracies in the court records, the frequencies of which vary significantly between states. By contrast, there is little variation within states, and there are few case-level attributes that consistently predict inaccuracy. This suggests that structural factors present in state legal and court systems are responsible for shaping the reliability of eviction records. We find that adjusting for court record inaccuracies reduces annual state eviction rates by an average of 14%. Depending on how they classify false and ambiguous records, researchers who draw on the same data can arrive at significantly different estimates of eviction prevalence.

Accurate estimates of eviction require minimizing the uncertainty and misrepresentation present in administrative court records. Whereas past research using local data identified some of the inaccuracies described here (Hartman & Robinson, 2003; Kleystauber, 2006; Spector, 2000), our

Table 3. Logistic regression results for the likelihood of serial cases.

	Alabama	Connecticut	Hawaii	Iowa	Minnesota	Missouri	North Carolina	North Dakota	Nebraska	Pennsylvania	South Carolina	Virginia
Length of case (in 30-day periods)	0.96** (0.02)	1.03*** (0.01)	0.98*** (0.00)	n/a	0.91 (0.06)	0.91* (0.04)	n/a	1.00 (0.04)	1.02** (0.01)	1.02** (0.01)	1.01 (0.01)	n/a
Monthly court case volume (in hundreds)	1.14*** (0.03)	2.00*** (0.37)	3.87*** (0.96)	1.19*** (0.02)	1.12*** (0.01)	1.03 (0.02)	0.91*** (0.02)	5.47** (3.03)	1.18*** (0.04)	0.99 (0.01)	1.17*** (0.03)	1.06*** (0.01)
Number of unique defendants	1.06 (0.04)	1.01 (0.05)	n/a	1.12*** (0.03)	1.09** (0.03)	1.07* (0.04)	1.10 (0.11)	1.04 (0.09)	1.05 (0.12)	1.02 (0.06)	n/a	1.19*** (0.05)
Defendant attorney	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	0.43*** (0.06)	0.35*** (0.01)	0.28*** (0.03)	0.27*** (0.07)
Plaintiff attorney	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	0.81 (0.15)	1.10 (0.32)	n/a	1.52*** (0.12)
Filing season (ref. = summer) Fall	1.14*** (0.04)	0.97 (0.06)	1.02** (0.01)	1.06 (0.04)	1.13** (0.05)	0.99 (0.03)	0.93*** (0.02)	1.21 (0.14)	1.11*** (0.03)	1.07*** (0.02)	1.01 (0.01)	1.02 (0.02)
Winter	1.47*** (0.05)	1.28*** (0.08)	1.15 (0.09)	1.23*** (0.04)	1.34*** (0.03)	1.35*** (0.04)	1.05 (0.03)	1.27 (0.23)	1.40*** (0.04)	1.27*** (0.04)	1.13*** (0.02)	1.03 (0.03)
Spring	1.16*** (0.03)	1.03 (0.14)	1.28*** (0.08)	1.18*** (0.04)	1.10 (0.06)	1.14*** (0.04)	0.98 (0.03)	1.16 (0.14)	1.18*** (0.06)	1.06* (0.03)	1.17*** (0.02)	1.11** (0.04)
No. observations	113,878	18,834	11,424	67,106	95,216	213,927	883,876	5,731	45,199	559,831	741,498	871,316

Note. Separate models run for each state. n/a = variable not available. Coefficients are presented as odds ratios, with standard errors given in parentheses. Filing year is included as a control, but the coefficients not displayed. The filing season variable is broken down into summer: June, July August; fall: September, October, November; and winter: December, January, February; spring: March, April, May. The small number of cases that are both serial cases and unresolved are not included in the model, since unresolved cases do not have a length of case variable.
*p < .05. **p < .01. ***p < .001.

results provide a framework to help inform researchers drawing on eviction records. Some inaccuracies, including ambiguous records, complicate researchers' abilities to calculate accurate eviction estimates. Unresolved and opaque cases can inflate eviction rates when all cases are included and can deflate rates when all are omitted. In the absence of reliable indicators of how many of these cases result in tenant displacement, researchers should be clear about what outcomes they are categorizing as evictions. Excluding opaque cases produces the most conservative estimates of the eviction rate but also underestimates the true prevalence of displacement. The most conservative estimate is not necessarily the most accurate one.

Alternatively, false records, including duplicate and serial cases, usually inflate eviction rates. Researchers should identify these records and consider how their inclusion will affect eviction estimates. For example, if examining displacement because of eviction, researchers should exclude nonfinal eviction judgments in serial cases. However, for researchers examining landlords' reliance on court systems to collect rent or discipline tenants, or the degree to which tenants are over-represented in the official eviction record, it would be important to include all serial case filings and judgments. Overall, the large gap between unadjusted and adjusted eviction rates makes it critical that researchers carefully communicate how they identified inaccuracies and defined measures of eviction. Doing so will ensure that eviction rates derived from court data can be accurately understood on their own terms as well as compared between studies and between jurisdictions.

Efforts taken to improve the clarity and accuracy of eviction estimates will not only benefit research on this topic, it will also focus the policy debate. If researchers drawing on administrative records produce estimates of eviction without fully considering inaccuracies contained in those records, they invite criticism that may challenge the precision of their estimates and call into question the fundamental nature of the problem. A similar dynamic has played out in the domestic poverty debate in recent years, with arguments over the best way to calculate the U.S. poverty rate compelled not only by scientific commitments but political and normative ones as well (Blank, 2008; Desmond & Western, 2018). Technical differences in measurement practices result in substantially different poverty rates, which in turn motivate drastically different policy responses (cf. Edin & Shaefer, 2015; Meyer & Sullivan, 2012). We believe housing policy researchers can learn from such debates, collaboratively and transparently developing best practices for calculating eviction rates. By contributing to that effort, this study hopes to help move beyond debates about measuring eviction to debates about effective solutions.

Our findings also indicate that where an individual tenant lives directly affects their risk of accruing an unrepresentative eviction history. It is well documented that having any presence in the eviction record is a major impediment to securing future housing and credit (Gold, 2012; Greiner et al., 2012). For this reason, unresolved and opaque cases penalize tenants who, despite winning their cases or successfully negotiating with their landlord, are trailed by records which elide such developments. Tenants living in a state like Minnesota, which does not release unresolved cases to the public and has a low rate of opaque cases, are advantaged compared with tenants living in a state like Hawaii, which has a comparatively higher total rate of ambiguous records. False records are even more problematic, since they add completely unearned records to a tenant's eviction history. In states like Alabama, which has a relatively low duplicate and serial rate, tenants have a much lower risk of accruing a false eviction record compared with those living in a state like South Carolina.

These state-level geographic disparities suggest the need for more consistent judicial recordkeeping procedures. To reduce the confusion caused by unresolved cases, states could adopt policies limiting or prohibiting their release to tenant screening companies. To address opaque cases, states could improve outcome code standards for civil courts. To reduce false records, states could perform regular audits to eliminate duplicates. They could also clearly mark serial cases as one continuing landlord-tenant dispute. In addition, more stringent enforcement of the Fair Credit Reporting Act would provide tenants with more effective

means to challenge inaccuracies in their eviction histories. In total, these reforms would have a direct impact on both the lives of individual tenants and the public's ability to obtain an accurate picture of eviction in their communities.

Notes

1. Formal, court-ordered evictions occur when a landlord files a lawsuit against a tenant seeking the legal right to remove the tenant(s) from the property. Informal evictions occur when landlords coerce or incentivize tenants to vacate the property but do not file a formal eviction lawsuit (Desmond & Shollenberger, 2015).
2. We developed this classification system based on our review of the existing literature and our own analysis of eviction court data.
3. We were only able to analyze 18.13% of the Connecticut data because the remaining data lacked the defendant-specific information needed to compute inaccuracies.
4. We were able to geocode an additional 6% of addresses at less precise geographies (e.g., street name, zip code, administrative place). For the 1.7% cases that contained multiple defendant addresses, we selected the address that fell within the county in which the case was heard. If more than one address fit this criterion, we randomly selected one of the in-county addresses to serve as the case address.
5. Additional details about the data preparation process can be found in Desmond et al. (2018a).
6. It is possible that additional information on the outcome of these cases could be gathered from paper files held in court archives.
7. A case had to contain a nonanonymous defendant name to be classified as a duplicate or serial case.
8. We also checked for defendant records that were duplicated within the same case number. These were more common than duplicate cases, and were usually the product of differences in variables that were outside our interest in this study. Classifying records duplicated within the same case numbers as duplicate cases increases the overall percentage of duplicate cases but does not affect the results of our logistic regression models.
9. Iowa and Minnesota update defendant addresses upon subsequent defendant contact with the court system, which may inflate the number of serial defendants; however, a comparison with alternative data sources that do not update defendant addresses did not reveal substantial differences in the prevalence of serial cases in these states.
10. We do not include a comparison of adjusted and unadjusted *filing* rates. However, we note that an adjusted filing rate would likely *include* unresolved cases and *exclude* duplicate cases. Opaque cases do not affect filing rates, nor do serial cases, which represent genuine filings in eviction court. Unresolved cases do not affect the eviction rate since, by definition, no unresolved cases had recorded eviction judgments in our data; however, the *filing* rate would be biased downward if unresolved cases were excluded from eviction measures. For states that exclude unresolved cases in the public record, there is no reliable way to estimate the prevalence of these cases or how they affect filing rates.
11. We could not measure the number of unique defendants in Hawaii and South Carolina because data from those states did not enumerate individual defendants.
12. We removed instances in which the attorney field was populated with the defendant's name or *pro se*, both of which indicate that the defendant represented themselves.
13. Table A3 lists the number of total defendant records affected by each inaccuracy, since a single case can contain multiple defendant listings.
14. In this study, we define *serial cases* as all *nonfinal* cases filed against the same tenant at a single property. We exclude *final* serial cases from our serial inaccuracy measure because these cases are less likely to represent false evictions.
15. In addition to the case likelihood models presented here, we also ran a series of ordinary least squares regression models to test whether counties that are economically disadvantaged or have overburdened courts are more likely to produce inaccurate records. To do so, we regressed county-year inaccuracy rates within states on court case burden, median property value, and household density. These variables exhibited no significant relationships with rates of unresolved, opaque, or duplicate cases, although densely populated counties with higher property values were associated with higher rates of serial cases. In general, these results show that there is very little variation within states or between counties.

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References

- Blank, R. M. (2008). Presidential address: How to improve poverty measurement in the United States. *Journal of Policy Analysis and Management: The Journal of the Association for Public Policy Analysis and Management*, 27(2), 233–254.
- Brickell, K., Arrigoitia, M. F., & Vasudevan, A. (2017). Geographies of forced eviction: Dispossession, violence, resistance. In K. Brickell, M. F. Arrigoitia, & A. Vasudevan (Eds.), *Geographies of forced eviction* (pp. 1–23). London, England: Palgrave Macmillan.
- Center for Court Innovation. (2019, December 18). Community court grant program. Retrieved from <https://www.courtinnovation.org/community-court-grant-program>
- Connelly, R., Playford, C. J., Gayle, V., & Dibben, C. (2016). The role of administrative data in the big data revolution in social science research. *Social Science Research*, 59, 1–12.
- Crane, M., & Warnes, A. M. (2000). Evictions and prolonged homelessness. *Housing Studies*, 15(5), 757–773.
- Desmond, M. (2012). Eviction and the reproduction of urban poverty. *American Journal of Sociology*, 118(1), 88–133.
- Desmond, M. (2016). *Evicted: Poverty and profit in the American City*. New York, NY: Crown Publishers.
- Desmond, M., Gromis, A., Edmonds, L., Hendrickson, J., Krywokuski, K., Leung, L., & Porton, A. (2018b). Eviction lab national database 1.0. Retrieved from <https://evictionlab.org/>
- Desmond, M., Gromis, A., Edmonds, L., Hendrickson, J., Krywokuski, K., Leung, L., & Porton, A. (2018a). *Eviction Lab Methodology Report Version 1.0*. Retrieved from <https://evictionlab.org/docs/Eviction%20Lab%20Methodology%20Report.pdf>
- Desmond, M., & Kimbro, R. T. (2015). Eviction's fallout: Housing, hardship, and health. *Social Forces*, 94(1), 295–324.
- Desmond, M., & Shollenberger, T. (2015). Forced displacement from rental housing: Prevalence and neighborhood consequences. *Demography*, 52(5), 1751–1772.
- Desmond, M., & Western, B. (2018). Poverty in America: New directions and debates. *Annual Review of Sociology*, 44, 305–318.
- Edin, K., & Shaefer, H. L. (2015). *\$2.00 a day: Living on almost nothing in America*. New York, NY: Houghton Mifflin Harcourt.
- Garboden, P. M., & Rosen, E. (2019). Serial filing: How landlords use the threat of eviction. *City & Community*, 18(2), 638–661.
- Gold, A. E. (2016). No home for justice: how eviction perpetuates health inequity among low-income and minority tenants. *Georgetown Journal on Poverty Law and Policy*, 24, 59–88.
- Greiner, D. J., Pattanayak, C. W., & Hennessy, J. (2012). The limits of unbundled legal assistance: A randomized study in a Massachusetts district court and prospects for the future. *Harvard Law Review*, 126, 901–989.
- Hartman, C., & Robinson, D. (2003). Evictions: The hidden housing problem. *Housing Policy Debate*, 14(4), 461–501.
- Immergluck, D., Ernsthausen, J., Earl, S., & Powell, A. (2019). Evictions, large owners, and serial filings: Findings from Atlanta. *Housing Studies*, 1–22.

- Kleysteuber, R. (2006). Tenant screening thirty years later: A statutory proposal to protect public records. *Yale Law Journal*, 116, 1344–1388.
- Loftin, C., & McDowall, D. (2010). The use of official records to measure crime and delinquency. *Journal of Quantitative Criminology*, 26(4), 527–532.
- Maantay, J., & Maroko, A. (2009). Mapping urban risk: Flood hazards, race, & environmental justice in New York. *Applied Geography*, 29(1), 111–124.
- Meyer, B. D., & Sullivan, J. X. (2012). Identifying the disadvantaged: Official poverty, consumption poverty, and the new supplemental poverty measure. *Journal of Economic Perspectives*, 26(3), 111–136.
- Mironova, O. (2019, March 25). NYC right to counsel: First year results and potential for expansion. Retrieved from <https://www.cssny.org/news/entry/nyc-right-to-counsel>
- Nelson, K. (2019). The microfoundations of bureaucratic outcomes: Causes and consequences of interpretive disjuncture in eviction cases. *Social Problems*, spz050.
- Newman, K. (2010). Go public! *Journal of the American Planning Association*, 76(2), 160–171.
- Office of Governor Ralph S. Northam. (2019, February 28). Governor Northam signs legislation to reduce eviction rates in Virginia [Press Release]. Retrieved from <https://www.governor.virginia.gov/newsroom/all-releases/2019/february/headline-838915-en.html>
- Office of Senator Michael Bennet. (2019, Dec 17). Eviction crisis act. Retrieved from <https://www.bennet.senate.gov/public/index.cfm?p=eviction-crisis-act>
- Office of Senator Patty Kuderer. (2019, May 9). Governor signs bill extending notice for eviction, expanding tenant protections. [Press Release]. Retrieved from <http://sdc.wastateleg.org/kuderer/2019/05/09/governor-signs-bill-extending-notice-for-eviction-expanding-tenant-protections/>
- Park, G., & Evans, G. (2018). Lynch's elements of the city in the digital era. *Journal of the American Planning Association*, 84(3–4), 276–278.
- Raymond, E., Duckworth, R., Miller, B., Lucas, M., & Pokharel, S. (2016). Corporate landlords, institutional investors, and displacement: eviction rates in single-family rentals. Retrieved from SSRN: https://papers.ssrn.com/sol3/papers.cfm?abstract_id=2893552
- Salganik, M. J. (2017). *Bit by Bit: Social research in the digital age*. Princeton, NJ: Princeton University Press.
- Sawicki, D. S., & Craig, W. J. (1996). The democratization of data: Bridging the gap for community groups. *Journal of the American Planning Association*, 62(4), 512–523.
- Seron, C., Martin, F., Gregg, V. R., & Kovath, J. (2001). The impact of legal counsel on outcomes for poor tenants in New York City's housing court: Results of a randomized experiment. *Law and Society Review*, 35(2), 419–434.
- Shelton, T. (2018). Mapping dispossession: Eviction, foreclosure and the multiple geographies of housing instability in Lexington, Kentucky. *Geoforum*, 97, 281–291.
- Spector, M. B. (2000). Tenants' rights, procedural wrongs: The summary eviction and the need for reform. *Wayne Law Review*, 46, 135–210.
- The Institute for Social Research. (2015). Panel study of income dynamics wave 39. Retrieved from <https://psidonline.isr.umich.edu/Guide/documents.aspx>
- Tourangeau, R., Edwards, B., & Johnson, T. P. (2014). *Hard-to-survey populations*. Cambridge, UK: Cambridge University Press.
- United States Census Bureau. (2015). American Housing Survey Computer Assisted Instrument Items Booklet. Retrieved from <https://www.census.gov/content/dam/Census/programs-surveys/ahs/tech-documentation/2015/2015%20AHS%20Items%20Booklet.pdf>
- Walter, R. J., Viglione, J., & Tillyer, M. S. (2017). One strike to second chances: Using criminal backgrounds in admission decisions for assisted housing. *Housing Policy Debate*, 27(5), 734–750.
- Western, B. (2006). *Punishment and inequality in America*. New York: Russell Sage Foundation.
- Yu, P. S., & Dietrich, S. M. (2012). Broken Records. Retrieved from <https://www.nclc.org/images/pdf/pr-reports/broken-records-report.pdf>
- Zewde, N., Eliason, E., Allen, H., & Gross, T. (2019). The effects of the ACA medicaid expansion on nationwide home evictions and eviction-court initiations: United States. *American Journal of Public Health*, 109(10), 1379–1383.

APPENDICES

Table A1. Eviction cases used in analytic sample, and descriptive statistics.

	<i>N</i>	Mean	Median	<i>SD</i>	Min	Max
Unresolved (1 = yes)	2,692,041	0.01	0.00		0.00	1.00
Opaque (1 = yes)	2,692,041	0.03	0.00		0.00	1.00
Duplicate (1 = yes)	3,643,023	0.00	0.00		0.00	1.00
Serial (1 = yes)	3,643,023	0.28	0.00		0.00	1.00
Length of case (in 30-day periods)	2,025,796	1.61	0.77	3.81	0.00	79.37
Monthly court case volume (in hundreds)	3,643,023	6.40	3.41	7.56	0.01	36.33
Number of unique defendants	2,878,931	1.25	1.00	0.52	0.00	27.00
Defendant attorney (1 = yes)	2,227,831	0.01	0.00		0.00	1.00
Plaintiff attorney (1 = yes)	2,227,831	0.32	0.00		0.00	1.00
<i>Filing season</i>						
Summer	3,643,023	0.27	0.00		0.00	1.00
Fall	3,643,023	0.26	0.00		0.00	1.00
Winter	3,643,023	0.24	0.00		0.00	1.00
Spring	3,643,023	0.23	0.00		0.00	1.00
<i>Filing year</i>						
2011	3,643,023	0.21	0.00		0.00	1.00
2012	3,643,023	0.20	0.00		0.00	1.00
2013	3,643,023	0.20	0.00		0.00	1.00
2014	3,643,023	0.20	0.00		0.00	1.00
2015	3,643,023	0.19	0.00		0.00	1.00

Note. *SD* = standard deviation. The *N* column denotes the analytic sample (not all variables are available for all states). The filing season variable is broken down into summer: June, July August; fall: September, October, November; winter: December, January, February; and spring: March, April, May.

Table A2. Portion of nonfinal and final serial cases ending in eviction judgments.

	Total cases	Serial cases (%)	Serial cases ending in eviction judgment (%)	Final cases in serial series (%)	Final cases in serial series ending in eviction judgment (%)
State					
Alabama	117,241	7.34	29.98	6.09	53.17
Connecticut	18,974	6.00	51.05	6.09	76.28
Hawaii	12,631	4.07	22.18	4.01	42.41
Iowa	67,106	23.19	25.36	19.99	61.26
Minnesota	95,219	14.23	21.06	10.87	47.85
Missouri	214,196	11.36	47.42	8.89	69.02
Nebraska	45,222	14.50	30.55	10.91	72.17
North Carolina	883,876	15.37	n/a	8.26	n/a
North Dakota	5,949	6.77	36.97	5.21	78.06
Pennsylvania	559,832	31.02	35.51	15.44	54.01
South Carolina	751,461	42.97	18.96	16.80	32.34
Virginia	871,316	35.97	2.77	14.98	58.24

Note. Serial cases represent the nonfinal cases filed against a household. The data for North Carolina did not contain the outcome code fields needed to compute the percentage of cases ending in eviction judgments.

Table A3. Number of defendant listings affected by inaccuracies.

State	Total cases	Number of defendant listings			Serial
		Unresolved	Opaque	Duplicate	
Alabama	117,241	4,204	772	33	9,932
Connecticut	18,974	309	331	28	1,533
Iowa	67,106	n/a	n/a	214	18,693
Minnesota	95,219	0	9,754	859	17,494
Missouri	214,196	0	33,526	504	29,848
Nebraska	45,222	3	527	211	8,052
North Carolina	883,876	n/a	n/a	22	150,888
North Dakota	5,949	0	1,411	7	480
Pennsylvania	559,832	0	25,126	266	217,275
Virginia	871,316	2,672	1,041	1,004	377,052
Total	2,964,636	7,188	72,488	3,148	831,247

Note. Hawaii and South Carolina are omitted because data from those states lacked information on individual defendants. Iowa courts use a simplistic coding scheme that precludes them from unresolved and opaque analysis. The data for North Carolina did not contain the outcome code fields needed to compute unresolved and opaque cases.