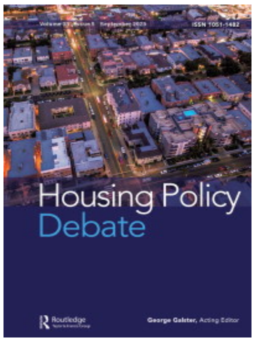

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Which Information Matters? Measuring Landlord Assessment of Tenant Screening Reports

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ABSTRACT

This research studies how tenant screening services' presentation of information influences landlord decisions. Tenant screening services utilize criminal records, eviction records, and credit score databases to produce reports that landlords use to inform their decisions about who to rent to. However, little is known about *how* landlords assess the information presented by tenant screening reports. Through a behavioral experiment with landlords using simulated tenant screening reports, this study shows that landlords use blanket screening policies, that they conflate the existence of tenant records with outcomes (e.g., eviction filings with executed evictions), and that they display, on average, tendencies toward automation bias that are influenced by the risk assessments and scores presented by tenant screening reports. I argue that maintaining blanket screening policies and automation bias, combined with the downstream effects of *creating* and *using* racially biased eviction and criminal records, means that people of color will inevitably experience disproportionate exclusion from rental housing due to perceived "risk" on the part of landlords.

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Eviction filing; racial discrimination; tenant screening; disparate impact

As the real estate industry rapidly develops and adopts new technologies to monitor tenants and automate housing-related decisions, such technologies are changing the conventional relationship between landlords and tenants (Fields, 2022; Porter et al., 2019) and creating new types of discriminatory practices and forms of housing injustices (McElroy, 2019). A coalition of researchers and housing activists, including the author, recently coined the term *landlord tech* to define technology used by property owners in ways that may intrude on the lives of tenants (McElroy et al., 2020). Landlord tech includes, but is not limited to, several contemporary technologies associated with rental listing and property management platforms, as well as surveillance products targeting tenants. These technologies are subjected to rigorous scrutiny because they may perpetuate "the biases of their creators, and of the society at large" (Sisson, 2019, para. 4), disproportionately targeting and potentially endangering marginalized groups (Benjamin, 2019; Eubanks, 2018; McElroy, 2020).

Tenant screening services, one of these landlord technologies, utilize criminal records, eviction records, and credit score databases to source information about individual tenants. Landlords use tenant screening services to make decisions about who to rent their property to (McElroy et al., 2020). Although there is no official registry, it is estimated that there are almost over 2,000 companies that

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offer tenant screening services (Kirchner & Goldstein, 2020). The results are presented as a tenant screening report, but the presentation of the information in the report varies between companies. Some services indicate there are "disqualifying records," but do not show the outcome of the records. Other services calculate a risk score for each tenant based on criminal and eviction records and credit scores using a proprietary algorithm. Other services list returned records without any assessment.

Tenant screening services have been criticized for having high error rates and producing screening reports that are rarely accompanied by a clear explanation of their purpose and use (Kirchner, 2020c; Kirchner & Goldstein, 2020). Moreover, some records in the report must be carefully differentiated from others for accurate assessment—for instance, eviction filings should be differentiated from executed evictions because filings do not reflect the final resolution. Lastly, tenant screening services' use of criminal and eviction records as inputs perpetuates and exacerbates racial inequality due to the fact that incarceration and eviction disproportionately impact Black and Hispanic residents (Desmond, 2012; Ehman, 2015; Gramlich, 2020; Greenberg et al., 2016; Oyama, 2009). One recent law review article interviewing tenants, as well as one federal lawsuit, has shown that landlords maintain "blanket screening policies," which means they deny tenants with criminal or eviction records regardless of the outcome of the case (Franzese, 2018; Smith v. Wasatch Property Management, Inc., 2017).

In building on this formative research, I hope to better understand how landlords use these tools for their decision-making, particularly with regard to how landlords assess the information presented by tenant screening reports. In 2016, the US Department of Housing and Urban Development (HUD) issued a guideline that housing providers should individually assess tenant history, including criminal records (US Department of Housing and Urban Development, 2016). According to a study in which tenants with criminal records and independent landlords were interviewed, most of the landlords did not express explicit racially and/or gendered discriminatory intent. But because they wanted to minimize any potential threats to their real estate investment posed by tenants perceived to be "risky," they relied on tenant screening services to obtain tenants' background information and often used these companies' assessments, "risk scores" or recommendations (Evans v. UDR Inc., 644 F. Supp. 2d 675, 2009; Reosti, 2018).

Toward that end, this study explores how varying content and presentation styles within tenant screening reports influences landlords' decision-making processes. Drawing on algorithmic audit studies (Angwin et al., 2016; Buolamwini & Gebru, 2018; Glymour & Herington, 2019; Green & Chen, 2019), I designed a behavioral experiment that involves Amazon Mechanical Turk (MTurk) workers who identified themselves as landlords living in the US (hereafter referred to as "MTurk landlords") to test the hypothesis that landlords will perceive an eviction record or a criminal record on a potential tenant's report to be a source of risk and, therefore, will avoid renting to them.

This work is particularly important given the housing crisis faced by tenants amid the financial hardship induced by the COVID-19 pandemic. Conceivably, if they were evicted from a property, their future access to rental housing could also be in jeopardy if future rental applications were evaluated with the use of discriminatory screening algorithms. Moreover, if landlords largely conflate eviction filings with executed evictions, tenant screening services would produce further barriers in which tenants who have only eviction filings would be denied, even if the eviction case was settled. In exploring these questions, this work attempts to understand the legal, policy, and regulatory implications of these tenant screening interactions between landlords and tenant screening services.

Literature Review

Emergence of Landlord Tech: Data Capitalism and Algorithmic Discrimination

In recent years, several researchers have turned their attention to new real estate technologies and how such technologies reproduce discrimination in the US housing market (Fields, 2022;

Rugh et al., 2015; Shaw, 2020). Such technologies are related to the emergence of absentee landlords and the development of tools to scale their property management needs. The large volume of houses owned by these absentee landlords necessitated a technological solution to allow property management across long distances. Such needs led to the development of listing services, surveillance products, and tenant screening services (Fields & Uffer, 2016). These technologies enable absentee landlords to minimize risk to their assets, and to create gradable financial securities from them. Critical housing scholars have suggested that the impact of digital transformation in the housing market must be examined from a wider and more critical perspective to understand the transformation's consequences, including who maximizes benefit (Porter et al., 2019). A recent lawsuit filed by HUD against Facebook, which provided an advertising platform for housing and mortgage companies to exclude and target specific racial groups, causing "digital redlining," is an example of this critical perspective (HUD v. Facebook Inc., 2019).

Porter et al. (2019) stress that digital technologies are changing the conventional relationship between landlords and tenants. For instance, digital real estate technologies change the way renters live in homes by deploying numerous surveillance products, including surveillance cameras and automated check-in entry systems, in homes. They also change the way the property is rented and managed by centralizing real estate data that can be analyzed based on profit-maximizing interests, and mediating transactions to support "frictionless flow of capital into landed assets" (Porter et al., 2019, p. 591). This flow creates layers of digitized information about tenants, such as credit scores, for landlords to assess. Sadowski (2019) offers a plausible way of understanding such surveillance products by analyzing data as a form of capital. Surveillance products and networks act as an entry point in the data capitalism pipeline where the stream of data "must keep flowing and growing" (Sadowski, 2019). The data are "extracted" from tenants through surveillance products with murky consent procedures, and are extracted disproportionately from marginalized groups, causing a loop of exposing and augmenting negative histories (Browne, 2015; Eubanks, 2018). Eubanks (2018) shows that tech systems that automate decision-making processes of welfare eligibility, predict for child abuse, and determine housing for unhoused people were designed to "profile, police, and punish the poor" (Eubanks, 2018, p. 38). In parallel, as O'Neil (2016) argued, seemingly neutral and progressive predictive algorithms are usually constructed through "haphazard data gathering and spurious correlations, reinforced by institutional inequalities, and polluted by confirmation bias" (O'Neil, 2016, p. 23). It is worth mentioning that tenant screening systems rely on criminal records, which comprise a kind of "New Jim Crow" by using "color-blinded categories" while ignoring the structural racism of America's criminal justice system. In this manner, tenant screening systems perpetuate and legitimate discrimination against Black people (Alexander, 2020). Benjamin (2019) theorized the increasing deployment of technologies that are seemingly neutral, yet exacerbate racial inequalities as the "New Jim Code." These technologies "reflect and reproduce existing inequalities but … are promoted and perceived as more objective" (Benjamin, 2019, p. 5). Moreover, ProPublica, an investigative journalism outlet, did important empirical work related to such an algorithmic system by auditing the Correctional Offender Management Profiling for Alternative Sanctions (COMPAS), a risk assessment algorithm for recidivism. They found that the recidivism algorithm had higher false-positive rates for a Black defendant than a White defendant (Angwin et al., 2016). Since then, the literature on "algorithmic fairness" has emerged to define and test fairness criteria (Friedler et al., 2019), including empirically auditing algorithmic systems (Buolamwini & Gebru, 2018) and developing methods to intervene in algorithmic systems (Karimi et al., 2021; Venkatasubramanian & Alfano, 2020). However, because there is a lack of adequate historical and intersectional context when optimizing algorithms to meet fairness criteria (Green, 2021), the critical question of whether fairness is structurally even possible still remains.

Fair Housing and Disparate Impact

The Fair Housing Act (FHA) was created to prohibit discriminatory housing policies or practices on the basis of protected classes such as race, religion, sex, disability, familial status, or national origin. Under the FHA, there are two types of discriminatory claims: disparate treatment and disparate impact (Bridges, 2008). Through disparate treatment claims, plaintiffs (tenants in the context of screening services) can allege that the housing providers' decision was motivated by discriminatory *intent*. In addition to that, in 2015, the Supreme Court reaffirmed the lower courts' recognition of disparate *impact* claims on the FHA. In disparate impact claims, plaintiffs are not required to prove discriminatory intent, but instead can argue that a policy or practice has a discriminatory effect against protected classes (Texas Dept. Of Housing and Community Affairs v. Inclusive Communities Project, Inc., 2015). However, when proving disparate impact, the Supreme Court requires plaintiffs to provide statistical evidence that can demonstrate a "robust causality" between the housing provider's policy or practice and the discriminatory effect (Williams, 2018, p. 970). Some legal scholars argue that this robust causality standard makes disparate impact claims unnecessarily complicated because of the burden of proof placed on tenants, who usually do not have legal resources or the required statistical expertise (Bourland, 2017; Schwemm & Bradford, 2016). It is also challenging to isolate a causal relationship between discriminatory policies and protected classes like races because discriminatory impacts are connected with a long and complicated chain of systemic racism, including residential segregation and disinvestment.

Landlords' Decision-Making Process: From Eviction Filing to Tenant Screening

Recent research on eviction has focused on the racialized and gendered effects of residential mobility (Desmond, 2012, 2016; Greenberg et al., 2016), the absence of federally managed eviction data for policy analysis and intervention (Hartman & Robinson, 2003), and the effects of inaccuracies in housing court records (Porton et al., 2021), among other factors. However, in the context of landlord behavior and tenant screening, it is also crucial to understand how eviction records exacerbate housing instability. Practices such as eviction filings, "scraping" by third-party data brokers, and screenings based on eviction histories make it harder for tenants who have had prior dealings with eviction courts (regardless of how their cases actually turn out) to find rental housing in the future.

Eviction has been understood to be time-consuming and costly for landlords because if they evict a tenant who does not pay rent, the possibility of recovering lost rent is extremely low. Additionally, after eviction, their property sits vacant until they find a new tenant. For these reasons, landlords, especially those with a small portfolio of rental properties, may use various negotiation tactics with tenants, including forgiving back rent, finding rental assistance, "cash for keys," or asking tenants to perform a service in lieu of paying rent on time (Balzarini & Boyd, 2021; Shiffer-Sebba, 2020). Recently, housing scholars have examined the broader ramifications of eviction *filing* (Garboden & Rosen, 2019; Immergluck et al., 2020; Leung et al., 2021). For instance, Garboden and Rosen (2019) argue that landlords rely on the "threat of eviction" (Garboden & Rosen, 2019, p. 649) because there is a relative financial advantage in threatening eviction rather than actually evicting tenants and leaving their premises vacant. Through the process of filing for eviction and starting the eviction process, landlords can eventually collect unpaid rents *plus* late fees, and the tenant continues living in their property. Through this process, eviction *filing* transforms the landlord–tenant relationship into a collector–debtor relationship with state-assisted debt collection. As a result, many eviction filings are dismissed as the cases proceed, and almost half of the eviction filings are associated with serial filings (Leung et al., 2021; Public Justice Center, 2015). With regards to tenant screening services, eviction filing has harmful effects on tenants' ability to obtain rental housing in the future because even if their case is dismissed, it will still show up in records and be flagged by tenant screening services, which may result in rejection by a future potential landlord.

Each county's housing court has its own system to manage and publish such eviction records. However, these eviction records are scraped by third-party, private-sector data brokers like LexisNexis (Kimble, 2020), not a federally owned and managed database (Hartman & Robinson, 2003). These scraped data are then sold to tenant screening services. Such eviction records are often vague about whether or not a case was resolved, and the court system of each state also fundamentally shapes the characteristics of eviction records (Porton et al., 2021). Moreover, if third-party data brokers obtain inaccurate records, it is incredibly difficult to backtrack to correct, seal, or expunge the records because the "black box" of data networks makes it hard to track the trajectory of the data afterward (Kirchner, 2020a).

Through tenant screening, landlords are able to rely on housing court records when making a rental decision by using eviction as a proxy for "riskier" tenants who could potentially cause additional financial burdens such as late rent or eviction filing fees (Greif, 2018). Using housing court histories to make rental decisions penalizes tenants who were previously involved in an eviction case from obtaining future housing even if an eviction case is dismissed or the tenant prevails (Franzese, 2018). The mere presence of a housing court record in the prospective tenant's history can be scraped by data brokers and used in tenant screening services' reports. This represents the final step of the convoluted picture of how practices around eviction records contribute to the potential housing insecurity of vulnerable tenants. In particular, these "algorithmic proxies" (Rosen et al., 2021, p. 789)—credit scores, eviction records, and criminal records—being used to represent tenants who pay rent on time and do not damage property should be understood through the lens of systemic racism, which is multifaceted and multidimensional, as opposed to interpersonal racial prejudice. The data used for estimating such algorithmic proxies operate within the frame of "color-blind racism," where current socioeconomic conditions are considered as given in race-neutral frames (Bonilla-Silva, 2018). These tenant screening algorithms still exacerbate racial inequality (Benjamin, 2019; Eubanks, 2018) because the data used in seemingly race-neutral algorithms are correlated both with the outcome (e.g., creditworthiness) and with race (Bartlett et al., 2020; Hepburn et al., 2020). Nevertheless, these algorithmic proxies are still institutionally sanctioned and widely used, supporting and exacerbating interpersonal racial bias and "giv[ing] the dominant group economic, political, and social power" (Rosen et al., 2021, p. 793).

Tenant Screening Services

The availability of digitized personal background information, including credit scores, eviction records, and criminal records, led to an expansion of private companies providing background check services, including tenant screening services (Dunn & Grabchuk, 2010). The choice of data used by tenant screening services relies on and reinforces the assumption that a tenant's past history will correlate with the future. However, future performance, such as paying rent on time and not damaging the property, is inherently unobservable (Rosen et al., 2021). Some scholars have challenged such assumptions, arguing that "past evictions become virtually useless as a proxy for potential future evictions" because the specificity of individual evictions makes it extremely difficult to generalize (Kleysteuber, 2007, p. 1377). In addition, other scholars have argued that these seemingly neutral data sets actually demonstrate disparate impacts because they rely on court records of the US criminal justice system, which disproportionately impacts Black and Hispanic men, whereas evictions disproportionately affect Black women (Desmond, 2012; Greenberg et al., 2016).

Therefore, it has been argued that tenant screening services are liable under the FHA, because even though tenant screening services and landlords may not have an explicit intent to discriminate, the court records used to make algorithmic judgments on potential tenants perpetuate discrimination using criminal and eviction records (Bhatia, 2020). In 2016, noting the disproportionate impact of criminal records on minoritized people, HUD issued new guidance for real estate transactions, prohibiting blanket policies—for instance, rejecting all tenants with any criminal record (US Department of Housing and Urban Development, 2016). But in practice, this guidance may not impact daily housing decisions if housing providers do not operationalize this policy. According to a study that interviewed tenants with criminal records and independent landlords, most of the landlords did not express explicit racist and gendered discrimination in their practice (Reosti, 2018). Yet at the same time, landlords wanted to exercise the maximum discretion on their property and also wanted tenant screening services to make decisions on their behalf because of the time, cost, and labor associated with the tenant screening process. Therefore, whereas landlords might be accountable for FHA violations if they directly use discriminatory data as inputs, if they use tenant screening services to help choose a tenant, landlords could plausibly deny that they "activat[e] stigmatizing implicit associations between an ostensibly neutral status marker and an ascribed trait, such as criminal record and race" (Reosti, 2018, p. 15). Tenant screening services make racialized data available to landlords but at the same time conceal systemic racism through the use of algorithmically determined scores or delivering insufficient details of court records. Some tenant screening services also provide recommendations in their reports, such as stressing that landlords should avoid tenants with any sort of eviction record.

When rejected by tenant screening services, tenants with criminal or eviction records have to search for substandard housing that does not require tenant screening services, causing additional economic, social, and health costs (e.g., paying tenant screening fees multiple times as an applicant for rental housing until being accepted into housing with mold). Furthermore, tenants are also unable to adequately mobilize in response to a potential violation of their housing rights, because it is extremely difficult to prove discrimination by landlords. When landlords reject applications, they are not required to reveal the exact reason for doing so, and often just tell applicants that they chose better-qualified applicants, potentially hiding discriminatory acts against protected classes (Reosti, 2018).

This research seeks to contribute to this literature by exploring how landlords use tenant screening services to make renting decisions. In particular, I suggest that it is important to carefully consider how landlords' assessment of tenants based on screening reports, combined with the use of racially discriminatory data by tenant screening services, creates a discriminatory effect against protected classes. As the interviews with independent landlords suggest, landlords often actively respond to regulations in tenant screening processes to protect their rental discretion (Reosti, 2018). The policy and legal implications coming from the landlords' report usage patterns require further exploration.

Research Design

The research design is inspired by audit studies that consist of field experiments to detect and test discrimination by randomizing a set of heterogeneous "testers" to observe the effect of their characteristics (Gaddis, 2018). This technique has been widely used in studying the housing (Evans, 2016) and employment contexts (Pager, 2003). The experimental set-up of audit studies benefits from isolating causal factors that are challenging to pinpoint in observational studies. I hypothesize that landlords would disqualify reports containing *any* criminal or eviction records, no matter the outcome, conditions, or context. This hypothesis is designed to test whether the content and presentation of tenant screening reports affect landlord behavior. The treatment includes showing detailed information (e.g., regarding conviction) or showing the risk score of the reports. It also compares how landlords differently assess and disqualify reports between eviction and criminal records. Overall, I aim to achieve the following:

1. To understand how landlords assess the content and/or presentation of tenant screening reports and use these reports in their rental decision.
2. Specifically, to understand how landlords make decisions when presented with data about tenants' prior evictions and criminal records.

However, there were several challenges in testing the research hypotheses. First, tenant screening companies are not subject to any disclosure requirements—unlike, for instance, banks, which must disclose their mortgage lending decisions (Haupert, 2022). Second, there are numerous privacy concerns and potential harms when conducting tests using data from real tenants. For instance, there is the chance of negatively affecting tenants' credit scores when tenant screening services request their credit score. I addressed these issues by *generating* simulated tenant screening reports based on an analysis of sample tenant screening reports, as a way of measuring how landlords use diverse information shown in these reports without using real tenants' information. The following section introduces how this study addressed such challenges by designing a behavioral experiment using these synthesized tenant screening reports.

Analysis of Sample Tenant Screening Reports

The sample reports were collected from two sources: public housing agencies' Freedom of Information Act (FOIA) responses requested by the Markup, an investigative journalism outlet (Kirchner, 2020b); and sample reports that tenant screening companies published to advertise their services. These sample reports provide a way of analyzing what is contained in actual tenant screening reports that cannot be made public due to privacy concerns and/or proprietary claims—particularly, what data fields they use, how they present personal data, and so on.

Data Fields in Tenant Screening Reports

Most sample reports include a credit score, eviction records, and criminal records, but their presentation varies. For instance, among the 25 sample reports I obtained from 20 companies (see Table A1 in the Supplementary material for the full list of companies), one service (Corelogic CrimSAFE) hides the critical data fields to consider, four services (Naborly, Corelogic Safetenant, National Tenant Network, and Yardi) show the score that is calculated by their algorithm, and the rest list the records without assessment. Each report contains different data fields and styles of presentation to show criminal and eviction records.

Some data fields are more critical to assessing a record than others (see Tables A2 and A3 in the Supplementary material for the full list of data fields). For eviction records, the two most critical data fields are case type and judgment. For instance, if a record is coded as a "civil new filing" type of case, but there is no follow-up "civil judgment" in the case, that record is not the final eviction judgment. Furthermore, many eviction cases are dismissed by a judge, or settled between tenants and landlords; for instance, tenants often pay past-due rent after an eviction filing. Additionally, although less critical than the former two factors, additional consideration might be needed if the case is too old (for instance, the Fair Credit Reporting Act (FCRA) prohibits arrest records over 7 years old from being shown, but conviction records can be shown even if the case is older than 7 years), or if the case involves those who were evicted during a disastrous event, like COVID-19 (e.g., filed after March 2020). For criminal records, four data fields are critical for assessment: disposition, offense degree, types of charge, case type, and any dates. For disposition, landlords should check whether a conviction is recorded or not. For the degree of offense, landlords might want to check whether the charge was a felony or a misdemeanor.

Landlords may also need to check the exact charge to determine whether the charge is related to causing property damage or posing a threat to public safety. They should also check whether the criminal record is just an arrest record, or whether the case was ultimately dismissed/dropped by a judge or a prosecutor. Lastly, if any of the dates indicate that a record is "too old" (e.g., more than 10 years), landlords might additionally take this into consideration.

Some sample tenant screening reports omit these data fields. Although these are "sample" reports, I argue that this analysis is valid for critiquing tenant screening services, because sample reports must be created using an existing system by being fed either with dummy variables or with real applicants' data and redacting sensitive information. This process is detailed in multiple sample reports from the FOIA responses. Therefore, through such processes, even if the data in the sample reports are not real, the underlying data structure is exposed in the sample reports. Some might argue that the availability of data fields may differ with each sample report because each housing court has different data fields and maintains its data structure independently. However, even if we assume that other real reports from the same company would include a certain type of data, it is important to note that the *mechanism* of creating such a sample report—which is the same as or very similar to that used to create a real screening report—omits such structure. For instance, when a tenant screening report includes a case type field, such as "civil new filing" or "civil judgment," but does not present a value in that field, this means the data structure is there, and the company makes a point of showing the case type field, but in this case there is no relevant data for that field. However, if a tenant screening report does not include a given case type field at all, this might indicate that the company does not have a structure for showing that case type field. In these circumstances, it could be challenging to assess such reports because the case type will never be visible.

This possibility of omission is critical because it would indicate an "overinclusive" trend of tenant screening services, whereby these services include tenants' records even if the records are incomplete or imperfect. Indeed, many sample reports include incomplete records or empty data fields. Particularly regarding criminal records, many of the sample reports appear to treat sequences of criminal justice procedures, including arrest, charge, disposition, and sentencing, as a single event. However, discerning such sequences is crucial for accurate assessment because these procedures imply very different consequences. According to the New York Division of Criminal Justice Services, for instance, among the 123,594 felony arrests in 2019, only 23,359 (18.9%) led to final convictions (NYS Division of Criminal Justice Services, 2020). In this case, one might incorrectly assess a felony arrest record that was eventually downgraded to a misdemeanor as a convicted felony case if the report treated that information as a single event or omitted relevant data fields and sequences of criminal justice procedures from arrest to conviction. Information from eviction records is similarly conflated. For instance, one sample report shows only a dollar amount without a clear explanation of whether that was the amount filed by landlords (eviction filing) or ordered by a judge (executed eviction). Furthermore, there is a lack of basic graphic design that might suggest to the reader how to assess the report, such as calling attention to critical information with bold formatting or highlighting. Finally, the use of jargon and acronyms, without including glossaries or data dictionaries, adds to the confusion when reading reports.

Simulated Tenant Screening Reports

Drawing on the sample report analysis, I generated tenant screening reports for a behavioral experiment with landlords. Each wass designed to represent a condition where the prospective tenant's screening report contains a unique criminal record or eviction record. I set all the reports' credit scores to "fair"—with some variation to make the simulated tenant screening reports more realistic—to control the confounding effect that might be coming from credit scores.

Table 1. Risk scoring criteria used in generating tenant screening reports for the experiment.

Record type (residential history/ criminal history)	Score	Examples
Had no records	Low	
Residential history: Had a filed, dismissed, or settled eviction record (eviction filings)	Mid	Case 1: Civil new filing eviction record. No follow-up records; we don't know what finally happened from just this record. Case 2: Civil judgment: Dismissed without prejudice, meaning that it was dismissed by a judge. Case 3: Civil judgment: Settled, meaning that the case was settled between the landlord and the tenant.
Criminal history: Had a convicted misdemeanor or not-convicted criminal record	Mid	Case 1: A misdemeanor case filed record. Type of charge: Assault. No disposition. Case 2: A felony arrested record. Type of charge: Possession of cocaine. No disposition. Case 3: A convicted misdemeanor record. Type of charge: Principal: Burglary 2nd degree. Disposition: Convicted—guilty.
Residential history: Had an eviction order record	High	Case 1: Civil judgment: $2,536, meaning that plaintiffs prevailed with that amount. Case 2: Civil judgment: Amended eviction, failure to vacate, meaning that an eviction order was amended by a judge because a tenant failed to vacate. Case 3: Civil judgment: RP $1,878 NPR restitution of premises (RP), meaning that an eviction order was issued by a judge.
Criminal history: Had a convicted felony or registered sex offender record	High	Case 1: A felony disposed record. Type of charge: Armed robbery. Disposition: Convicted—guilty. Case 2: A registered sex offender record. Type of charge: Criminal sexual conduct with a minor 1st. Disposition: Convicted—guilty.

Note. The criteria were based on the 2016 HUD guideline for using criminal records in housing transactions.

Table 1 shows the categorization of report types. The risk scores were set as "low" for the reports that had no criminal or eviction records whatsoever. The risk scores were set as "mid" for the reports that included eviction filings or misdemeanor criminal records. If the report included a convicted felony record or eviction judgment record, the risk score was set as "high." The goal of scoring was not to develop a precise risk assessment algorithm but to group various types of records that can be factored in for the analysis. These scores (low, mid, high) were shown in only one type of tenant screening report (Type 2) as one of the treatments in the experiment and were used for the later analysis. In terms of residential history, it is important to see how landlords assess eviction filings (currently scored as mid) compared to executed evictions (high). This is because eviction filings are not final resolutions in particular cases and only a small portion of overall eviction filings are executed. In essence, eviction filings are reflective of landlords' motives and incentives to evict tenants, not evidence of tenants' bad behavior—because prior research on eviction filings identified that some landlords do not even want to evict tenants but file evictions because it is an effective way to turn the state into a debt collector and evade property vacancy (Garboden & Rosen, 2019). On criminal history, similarly, it is crucial to see how landlords assess arrest records and convicted misdemeanors (mid) relative to felonies and registered sex offenders (high).

Behavioral Experiment

Each individual MTurk landlord checked 25 simulated tenant screening reports and made 25 decisions. I randomly assigned one of the three report types to each of the 25 reports, as Figure 1 shows. The three report types are the following:

- *Type 1: Show records, no detail, no risk score* (see Figure A1 in the Supplementary material for the report example). Reports indicate that there is a criminal or eviction record, but they do

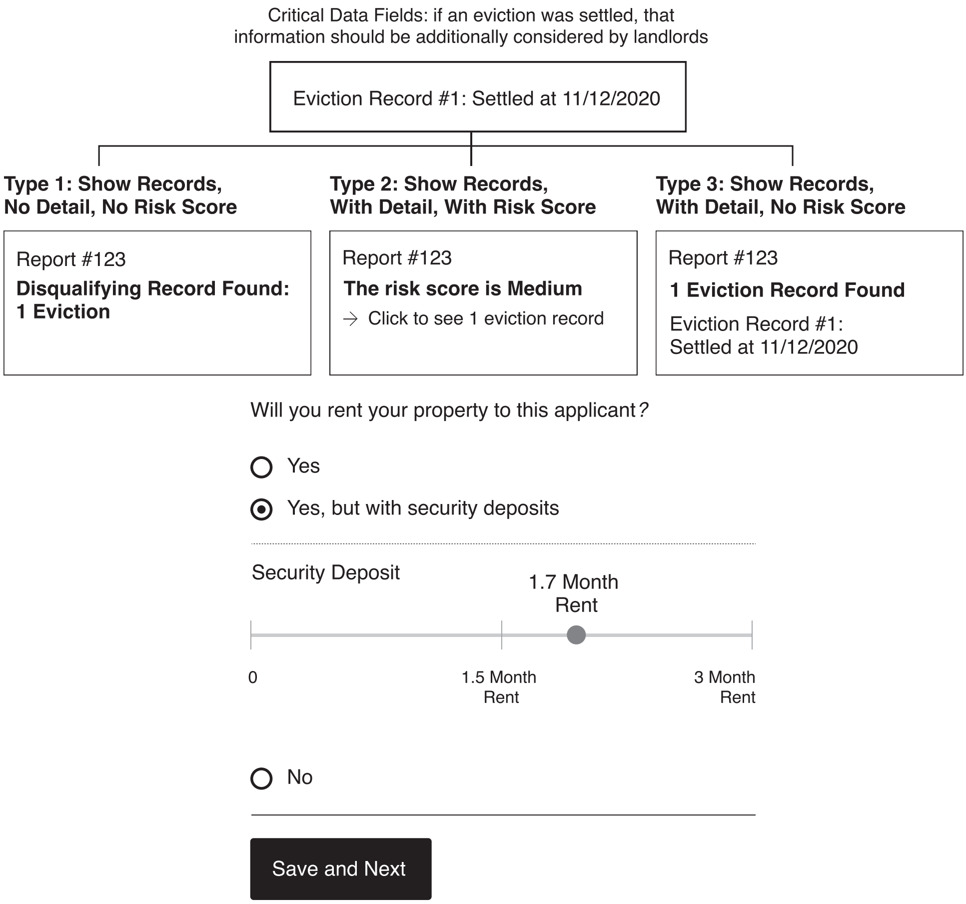

Figure 1. Design for a behavioral experiment testing three types of tenant screening reports.

not provide any critical details about such a record. Landlords can only see that there is a record. This is the type of report that was involved in the 2018 lawsuit (CFHC v. Corelogic, 2018).

- *Type 2: Show records, with detail, with risk score* (see Figure A2 in the Supplementary material for the report example). Reports show the risk score of the criminal or eviction record on a categorical scale (low, mid, high; see Table 1), but they provide the details only if the prospective landlord opens the summary link. Landlords mainly see the risk score, and the details of a record are shown only when they decide to click on the link. Among the sample reports, I identified three tenant screening services that provide this report type.
- *Type 3: Show records, with detail, no risk score* (see Figure A3 in the Supplementary material for the report example). Reports give all the details of criminal or eviction records. Landlords see the details of a record, but are not provided with risk scores or other methods of assessment. Among the 25 sample reports I obtained, 21 are Type 3.

The report types are reflective of the sample reports that I gathered. The experiment did not include a report type that did not show details but did show risk scores, because I could not identify any reports of this type among the sample reports that I gathered. To recruit landlords from MTurk, I used MTurk's worker requirements for participation and further limited the workers' eligibility in the experiment. When I initiated the requester's batch, for instance, I set the workers' requirements as follows:

1. Their task approval rate (known as HIT in MTurk) is over 90%.
2. Their current residence is owned.
3. They currently live in the US.

Then, on the landing page of the experiment, I stated that only a landlord who is currently renting out their property to a tenant could participate in the experiment. To further collect reliable responses, I prohibited repeated participation using the same account. I also required participants to take at least 1 minute to look at each report and make a decision (the total assessment time had to be 25 minutes or higher to be compensated). Furthermore, I used an algorithm that would not allow participants to complete the experiment if they made the same decision in every case (e.g., 25 yes responses). Lastly, I required them to write out the criteria by which they made their rental decisions (minimum 50 words).

However, there are still considerations and limitations to consider regarding sampling people through MTurk. The user-experience-driven tactics I described partially mitigate the reliability of the responses, but researchers have pointed out there are still potential limitations of using MTurk. These challenges include repeated participation, anonymity and resulting data quality, and selection bias (Landers & Behrend, 2015). For instance, I prohibited repeated participation using one account, but that could not stop a user from creating multiple accounts and participating with each account. Also, there is debate regarding whether anonymity contributes to obtaining truthful responses—one study shows that respondents exhibit less social desirability bias with anonymity (Ong & Weiss, 2000), but there is also research showing that face-to-face interaction can encourage more honest opinions (Van Zant & Kray, 2014). In the case of MTurk, researchers have no means to directly verify the workers' information or responses. Lastly, because MTurk fundamentally involves convenience sampling, some scholars have tried to show there are demographic differences between MTurk worker samples and population-based samples in the US (Huff & Tingley, 2015; Paolacci & Chandler, 2014).

Despite these limitations, recent research suggests that recruiting through MTurk is a viable convenience sampling method (Berinsky et al., 2012; Buhrmester et al., 2011; Woo et al., 2015). For instance, several replication studies produce similar findings using MTurk workers compared with the original studies using population-based samples (Berinsky et al., 2012; Buhrmester et al., 2011; Crump et al., 2013; Horton et al., 2011). An extensive verification study using IP addresses shows that MTurk workers' self-reported information is largely correct, which contributes to the trustworthiness of MTurk responses (Rand, 2012). Overall, while acknowledging the limitations, I felt confident designing this study based on recent findings that using MTurk is a viable option for conducting experimental research (Garcia & Abascal, 2016).

Relatedly, one specific limitation is that the recruited sample was disproportionately representative of small-scale landlords (see Table 2). In the sample of this paper's study, 87% of the sampled landlords managed fewer than 10 units. The underrepresentation of large-scale landlords in this study can be attributed to the fact that MTurk workers are individuals. Recent research found that large-scale landlords were more likely to rely on algorithmic software and formal and protocol-based decision-making, whereas small-scale landlords are less likely to use algorithmic software and rely more on "gut checks" and informal relationships with tenants (Gomory, 2022; Rosen et al., 2021). In particular, Rosen et al. (2021) noted that around half of small-scale landlords (managing 1–5 units) conduct algorithmic tenant screening (44% for credit check, 59% for eviction record check, and 56% for criminal record check). In essence, the results of this study should be applied mainly to the understanding of tenant screening technologies used by small-scale landlords.

Table 2. Attributes of the participants in the experiment.

	All $N = 209$	Type 1 $N = 65$	Type 2 $N = 73$	Type 3 $N = 71$
Gender (%)				
Female	46.6	40.0	45.2	54.1
Male	53.3	60.0	54.7	45.8
Number of units managed (%)				
1 unit	30.0	29.2	31.5	29.1
2–4 units	36.1	35.3	34.2	38.8
5–10 units	20.9	23.0	23.2	16.6
11–50 units	8.0	9.2	5.4	9.7
>50 units	4.7	3.0	5.4	5.5
Race and ethnicity (%)				
White	78.5	75.3	82.1	77.7
Black	9.0	10.7	6.8	9.7
Asian	6.6	6.1	9.5	4.1
Hispanic	4.2	4.6	1.3	6.9
Native American	0.9	3.0	0	0
Other	0.4	0	0	1.3
Income level (%)				
Under $40,000	7.1	6.1	4.1	11.1
$40,001–$60,000	19.5	21.5	17.8	19.4
$60,001–$80,000	23.3	29.2	23.2	18.0
$80,001–$100,000	21.4	24.6	20.5	19.4
$100,001–$120,000	11.9	6.1	12.3	16.6
More than $120,000	16.6	12.3	21.9	15.2

Note. The null hypothesis that the proportions of each row in the three types (Type 1, 2, 3) are the same was tested at a statistical significance level of .05. All rows had $p > .05$. This indicates that given the proportions, participants in Types 1, 2, and 3 are not statistically different.

A total of 5,225 decisions from 209 landlords were made in the experiment. When setting effect size as medium (0.15) according to Cohen (2013), with 80% power and a .05 significance level, the estimated sample size was 159 when the number of predictors in a regression was 21. Landlords who completed the experiment first gave informed consent in accordance with policies of the Institutional Review Board of my institution. Then each landlord was asked the number of rental units they oversee as well as their gender, race and ethnicity, and income level. Next, they were presented with a short tutorial on how to use the survey app, and were shown five tenant screening reports with no records (low risk), five reports with a mid-scored criminal record, five reports with a mid-scored eviction record, five reports with a high-scored criminal record, and five reports with a high-scored eviction record (25 reports). The order of these reports was shuffled; thus, there was no recognizable pattern of reports shown. Participants either accepted or rejected each report, or they could add between 0.1 and 3 month's worth of rent as security deposit if they wanted to conditionally accept a tenant. The assumption for imposing the security deposit was that landlords would be familiar with measuring the perceived risk of the tenant in question through the means of security deposits (Avail, 2020; Hatch, 2017).

However, there are limitations to asking landlords to impose security deposits as a way of measuring the risk of the report. First, the 3-month maximum allowed in the experiment might exceed the limit in the landlord's state—because the maximum security deposit is regulated at the state level (Hatch, 2017)—and landlords might not want to impose security deposits higher than the state ceiling, which could cause bias. Second, in real circumstances, landlords might set a fixed security deposit prior to soliciting applications, even if applicants are low risk. This means that no matter how they perceive the risk through the report, they might set a fixed security deposit for every applicant. Acknowledging these limitations, the analysis of security deposits is used to measure the perception of the risk shown on the report as well as how landlords quantify this perception in financial terms. It also offers a more nuanced picture of "within-yes" applications—that is, within conditionally accepted applications, the analysis of security deposits can provide a picture of how criminal and eviction records are penalized, with a specific focus on data representation in tenant screening reports.

After reviewing the 25 reports, participants were asked if they think it is okay for a landlord to never rent to people with a criminal or eviction record and to describe the overarching strategies of their decision-making processes. All three report types redacted applicants' names to control the implicit bias of names, which several audit studies have highlighted (Bertrand & Mullainathan, 2003; Quillian et al., 2017). This is because this study is not meant to test the racial bias that comes from the landlords' racially discriminatory intent but to test their behavior when facing criminal and eviction records, which are considered "color-blind categories" yet are still related to racialized and discriminatory effects.

Analysis

The possible decisions for each report were "Yes," "Yes with security deposit (ranging from 0.1 to 3.0 months)," and "No." Among the predictors, there are two main factors: type of report (Type 1, Type 2, Type 3; see Figure 1) and report score (low, mid, high; see Table 1). The analysis consists of two parts. First, I ran a logistic regression of the rental decision (a binary decision of yes or no) on two predictors, then added landlord-level covariates, including their income, number of units managed, race, gender and whether they think that it is okay to reject tenants with any criminal or eviction records. The logistic regression model with landlord-level covariates takes the following form:

$$ln\left(\frac{p}{1-p}\right) = \alpha + \beta_1 \text{Score}_{ij} + \beta_2 \text{Type}_{ij} + \beta_3 \text{Score}_{ij} \times \text{Type}_{ij} + \gamma X_j, \;\; p = \Pr\left(\text{decision}_{ij} = 1\right)$$

where each report i is allocated to landlord j, α is the intercept, β_1 is the causal effect of showing different report scores, β_2 is the causal effect of showing different types of reports, β_3 is the interaction term between types of reports and scores of reports, and X_j is landlord-level covariates. Then, among conditionally accepted decisions with security deposit, I ran an ordinary least squares (OLS) linear regression of both rental decisions without covariates and with landlord-level covariates. The OLS model with landlord-level covariates takes the following form:

$$Y_{ij} = \alpha + \beta_1 \text{Score}_{ij} + \beta_2 \text{Type}_{ij} + \beta_3 \text{Score}_{ij} \times \text{Type}_{ij} + \gamma X_j + \epsilon_{ij}$$

where Y_{ij} is a security deposit imposed on report i by landlord j, α is the intercept, β_1 is the causal effect of showing different report scores, β_2 is the causal effect of showing different types of reports, β_3 is the interaction term between types of reports and scores of reports, and X_j is landlord-level covariates. Cluster-robust standard errors were used to account for the clusters of decisions made by one landlord. The mid-scored reports should be assessed with particular care because they have room for consideration (e.g., arrested records, dismissed eviction records). Therefore, assessing the interaction terms of mid-scored reports was the key to the experiment.

Results

I analyzed how the presentation of tenant screening report information in three different ways affected landlords' decision-making processes. Table 3 shows the impact of the three types of reports and risk scores on rental decisions, for all of the decisions. Table 4 shows the impact on rental decisions only for those reports that include eviction or criminal records. Table 5 shows the impact on security deposits of the three types of reports and risk scores for conditionally accepted decisions. For Type 1 reports ("Show records, no details, no scores"), landlords were only shown whether or not a report contained a criminal or eviction record. Type 1 decisions

Table 3. Impact of three types of reports and risk scores on rental decisions (Yes or No).

	Dependent variable: Pr (Rental decision = Yes)	
	(1)	(2)
Type 2	1.650 (0.741)	1.675 (0.783)
Type 3	1.602 (0.673)	1.507 (0.652)
Mid score	0.258*** (0.094)	0.240*** (0.085)
Mid × Type 2	0.346* (0.178)	0.337* (0.176)
Mid × Type 3	0.554 (0.276)	0.549 (0.277)
High score	0.248*** (0.087)	0.250*** (0.092)
High × Type 2	0.142*** (0.078)	0.134*** (0.074)
High × Type 3	0.347* (0.175)	0.337* (0.172)
Constant	11.037*** (3.295)	11.869*** (3.742)
N of observations	5,225	5,225
N of landlords	209	209
Deviance	5,747.92	5,547.74
Pseudo R^2	0.11	0.14
Landlord controls	No	Yes

Note. Cluster-robust standard errors are given in parentheses. The unit of the coefficients is an odds ratio except constant (odds). The reference group is Type 1 low-scored reports. Landlord controls include landlords' gender, number of units managed, race and ethnicity, linearized income level, and a dummy variable capturing whether they think it is appropriate for a landlord to never rent to people with a criminal or eviction record. The likelihood ratio test between two models is $\chi^2(10) = 150.4,\ p < 0.001$.
$^{\dagger}p < .1.\ ^{*}p < .05.\ ^{**}p < .01.\ ^{***}p < .001.$

Table 4. Impact of three types of reports and risk scores on rental decisions (Yes or No), for only reports that have either an eviction record or a criminal record.

	Dependent variable: Pr (Rental decision = Yes)			
	Eviction (1)	(2)	Criminal (3)	(4)
Type 2	0.645 (0.194)	0.696 (0.227)	0.507* (0.151)	0.494* (0.156)
Type 3	1.011 (0.326)	1.002 (0.338)	0.789 (0.232)	0.774 (0.240)
High score	0.939 (0.094)	0.935 (0.099)	1.154 (0.145)	1.161 (0.152)
High × Type 2	0.415*** (0.080)	0.387*** (0.080)	0.402*** (0.086)	0.383*** (0.086)
High × Type 3	0.766 (0.132)	0.752 (0.138)	0.513*** (0.089)	0.496*** (0.091)
Constant	2.869*** (0.665)	3.195*** (0.822)	2.611*** (0.588)	2.784*** (0.667)
N of observations	2,090	2,090	2,090	2,090
N of landlords	209	209	209	209
Deviance	2,571.7	2,429.7	2,669.6	2,567.76
Pseudo R^2	0.043	0.096	0.049	0.085
Landlord controls	No	Yes	No	Yes

Note. Cluster-robust standard errors are given in parentheses. The unit of the coefficients is an odd ratio except constant (odds). The reference group is Type 1 mid-scored reports because there are no low-scored reports that have eviction or criminal records. Landlord controls include landlords' gender, number of units managed, race and ethnicity, and linearized income level, and a dummy variable capturing whether they think it is appropriate for a landlord to never rent to people with a criminal or eviction record. The likelihood ratio tests between (1) and (2) and between (3) and (4) are $\chi^2(12) = 141.92,\ p < 0.001$ and $\chi^2(12) = 101.93,\ p < 0.001$, respectively.
$^{\dagger}p < .1.\ ^{*}p < .05.\ ^{**}p < .01.\ ^{***}p < .001.$

represent landlords' blanket screening policy—because they need to make a decision without having details on each criminal/eviction record. Type 2 reports ("Show records, with details, with risk scores") show the effect of using risk scores to assess tenants. Type 3 reports ("Show records, with details, no risk scores") represent the effect of showing detailed eviction or criminal records but without a risk score. With landlord controls, the patterns of coefficients and statistical significance largely remained unchanged; thus, the assessment of the coefficients and confidence intervals (CIs) is based on the models without landlord controls except when the statistical significance changed.

Table 5. Impact of three types of reports and risk scores on security deposits among conditionally accepted reports.

	Dependent variable: Security deposit (0.1–3.0 months of rent)	
	(1)	(2)
Type 2	−0.141 (0.173)	−0.125 (0.169)
Type 3	0.194 (0.176)	0.182 (0.164)
Mid score	0.020 (0.131)	−0.003 (0.129)
Mid × Type 2	0.352* (0.179)	0.342† (0.184)
Mid × Type 3	0.107 (0.184)	0.142 (0.181)
High score	0.097 (0.129)	0.062 (0.128)
High × Type 2	0.400* (0.190)	0.412* (0.195)
High × Type 3	0.0066 (0.188)	0.115 (0.186)
Constant	1.393*** (0.130)	1.429*** (0.119)
N of observations	2,110	2,110
N of landlords	209	209
R^2	0.04	0.14
Landlord controls	No	Yes

Note. Cluster-robust standard errors are given in parentheses. The unit of the coefficients is the month of rent. The reference group is Type 1 low-scored reports. Controls include landlords' gender, number of units managed, race and ethnicity, and linearized income level, and a dummy variable capturing whether they think it is appropriate for a landlord to never rent to people with a criminal or eviction record. The ANOVA test between two models $F(12) = 14.79$, $p < 0.001$.
†$p < .1$. *$p < .05$. **$p < .01$. ***$p < .001$.

Blanket Screening Policies

Even when more detailed information was displayed, MTurk landlords tended not to translate this information into fairer decisions for tenants. On rental decisions, among mid-scored reports, there was no statistically significant difference in the odds ratio between accepting based on reports that include detailed information (such as convictions) and accepting based on reports that do not provide such information (Mid × Type 3, Table 3; 95% CI: 0.209–1.472). This means that even when landlords had enough detail to assess the outcome of a criminal or eviction record in the report (such as an eviction case being dismissed or settled), they still tended to conflate the existence of the record with a negative outcome for the tenant—that is, the mere presence of an eviction record was interpreted as evidence of an executed eviction. On conditionally accepted tenant screening reports, similarly, there was no statistically significant difference in security deposit amount imposed between accepting tenants with Type 3 reports versus Type 1 reports among mid-scored reports (Mid × Type 3, Table 5; 95% CI: −0.253 to 0.467). In contrast, it appears that landlords translated the detailed information into negative impacts on rental decisions when reviewing high-scored tenant screening reports. Among high-scored reports, Type 3 reports (High × Type 3, Table 3) were statistically significantly associated with an additional 65.3% decrease in the odds of acceptance ($p < .05$). On conditionally accepted reports, however, there were no statistically significant differences in security deposits between Type 3 high-scored reports and Type 1 high-scored reports (High × Type 3, Table 5; 95% CI: −0.361 to 0.375).

Similarly, Table 4 shows that MTurk landlords tended to treat eviction filings or dismissed eviction records (mid-scored) and executed evictions (high-scored) similarly. On rental decisions, there was no statistically significant difference in the odds of acceptance between mid- and high-scored reports when showing detailed information (Type 3). Because the reference category for report type was Type 1, this means that landlords tended to treat eviction filings as indications of executed evictions. As Table 4 shows, only when the score of an eviction order case was displayed as "high" (High × Type 2, Model (1) in Table 4) were the reports significantly associated with an additional (58.5%) decrease in the odds of acceptance. This potentially illustrates landlords' homogeneous understanding of different types of eviction records, as opposed to the acceptance pattern found with criminal records. MTurk landlords assessed the high-scored criminal records (records of either convicted felonies or registered sex offenders) with greater sensitivity: Type 3 high-scored criminal records (High × Type 3, Model (3) in Table 4) were significantly associated with an additional 48.7% decrease in the odds of acceptance.

Automation Bias

Rather than using additional details to make decisions, MTurk landlords tended to rely on the risk scores shown on the reports. On rental decisions, among mid risk score reports, tenant screening reports that displayed risk scores (Mid × Type 2, Table 3) were significantly associated with an additional 65.4% decrease in the odds of acceptance ($p < .05$), whereas when MTurk landlords saw reports that showed detailed information but did not show the scores (Mid × Type 3, Table 3), there was no statistically significant difference observed. This means landlords did not assess the detailed information in the reports, such as an eviction case that was actually dismissed, but rather were influenced by the report's assessment where provided. Similarly, among high-risk scored reports, reports that displayed risk scores (High × Type 2, Table 3) were significantly associated with an additional 85.8% decrease in the odds of an acceptance ($p < .001$). A statistically significant difference was also observed with reports that showed critical data fields but did not show the scores (Type 3). The additional decrease in the odds of acceptance was 65.3%. This means that landlords were less influenced by the details of a criminal or eviction record and more influenced by the risk score of the reports.

With conditionally accepted reports, similar patterns were observed. For both mid- and high-scored reports, displaying risk scores (Mid × Type 2, Table 5) was statistically significantly associated with an additional 0.352 months of rent for mid scores and 0.4 months of rent for high scores in terms of security deposits. When landlord controls were added to the model, the statistical significance of the coefficient of showing mid scores of reports (Mid × Type 2, Model (2) in Table 5) changed to the $p < .1$ level, but the coefficient itself was largely unchanged (0.342). Additionally, there was no statistically significant difference between these reports and reports that showed critical data fields but did not show the scores (High × Type 3, Table 5), whereas there was statistically significant evidence that MTurk landlords imposed on average 0.4 months more rent as a security deposit with the reports that display high-risk scores (High × Type 2, Table 5). This means that MTurk landlords, on average, tended to penalize tenants more when they saw high-risk scores on the reports, rather than utilizing detailed information to make more precise judgements (e.g., convictions for felonies). Overall, this pattern suggests that MTurk landlords exhibit automation bias, specifically *commission errors* where decision-makers follow the directives of the automated system even when there is additional valid and legitimate information (Skitka et al., 1999).

Decision Strategy

I examined the answers MTurk landlords provided about their decision-making process, particularly focusing on how and why they maintained blanket screening policies or assessed records in detail. Overall, MTurk landlords answered that they gave more latitude in considering criminal records than eviction records. They maintained blanket screening policies more frequently in relation to eviction records than criminal records, meaning that landlords tended to conflate eviction filings with executed evictions. Furthermore, many landlords noted that they consider eviction records to represent a higher risk than criminal records.

Almost a third of the landlords—29% ($N = 33$)—answered that they automatically added a security deposit and did not consider the conditions of criminal records in doing so. Many of them applied their blanket screening policies to both criminal and eviction records. Nearly half of the landlords—49% ($N = 54$)—answered that they maintain blanket screening policies for eviction records. They considered the eviction process itself to be painful (e.g., "Having to go through the eviction process is time consuming and not worth the risk," P209), and some noted that eviction records are a more severe threat to landlords than criminal records are (e.g., "I put more weight into the eviction records," P208). They also feared that eviction would affect their financial situation (e.g., "Financial issues were a bigger deal, especially evictions. Who wants to deal with that headache?," P222). However, they did not distinguish between different types of evictions or consider eviction details; that is, eviction filings and eviction judgments were perceived to be the same in terms of risk. Among the answers, only one landlord noted that even though they were aware of different outcomes from eviction filings, they still said "No" to all types of eviction records ("I basically wouldn't rent to anyone with an eviction, it doesn't matter how long ago or how the case was disposed," P507). Most other landlords, however, did not distinguish between eviction records with different details, such as dismissals or settlements.

By contrast, 60% ($N = 66$) of the landlords noted that they did consider various details of criminal records. This may be because criminal records have more data fields to consider. For example, some landlords mentioned precise types of charges ("I wouldn't let someone selling or doing cocaine in my rental. But if it was just a marijuana possession then I would not mind," P112; "I avoided anybody who might be to[o] rowdy, or related to property theft," P232); the date of the crime ("I look at those with criminal convictions differently, as long as it was in the past," P539); the degree of the charge ("Tenants are acceptable [… if] they are not a felon […] and are not a sex offender," P11); conviction ("If a case is dropped, I would consider it, but I will definitely not consider convicted criminals," P247) and so on.

Discussion and Policy Implications

Assessment of Tenant Screening Reports

This study's aim is to understand how landlords assess tenant screening reports using different ways of presenting information about prior eviction and criminal history. Accordingly, what this study measures is (a) whether landlords assess eviction and criminal records differently when they provide more detailed information, and if so, whether they turn that assessment into equitable rental decisions; and (b) how landlords perceive the risk scores shown in the reports. In this section, I discuss the implications of assessing evictions and criminal records and discuss the pattern of imposing security deposits on lower-income tenants. I then discuss the critical power of algorithmic scoring and automation bias. Lastly, I discuss the specific implications for small-scale landlords based on the behavior that prior research has identified.

Eviction Records

With regards to eviction records, one of the most noticeable harms this study identifies is that during the tenant screening process, landlords do not distinguish between eviction filings and actually executed evictions. This is particularly alarming given that many landlords file numerous evictions *without the intention of or a sound rationale for* actually evicting tenants (Garboden & Rosen, 2019). Furthermore, this study replicates the finding of "professional solidarity" among landlords (Garboden & Rosen, 2019, p. 647). Eviction filings are a tacit tenant screening measure meant to issue a warning to other landlords against taking on the tenant in question (Garboden & Rosen, 2019; Leung et al., 2021). Furthermore, landlords often file multiple evictions on the same tenant—this is frequently called "serial filing" (Immergluck et al., 2020; Leung et al., 2021). As a result, in Washington, DC, for example, among all eviction records, only 5.5% of evictions filed in 2018 were executed (McCabe & Rosen, 2020). This means that 94.5% of filed evictions were not executed. *As this study has shown, those records may be interpreted, erroneously, as evictions by landlords and will likely still negatively affect tenants' future housing search* (Phillips, 2020). Additionally, recent research shows that neighborhoods where corporate landlords are concentrated were able to initiate a large share of serial eviction filings because it is an effective way to collect rents and increase revenue (Leung et al., 2021). In contrast to criminal records—HUD's 2016 guidance did not allow landlords to maintain a blanket policy of rejecting any tenant with arrest records (US Department of Housing and Urban Development, 2016)—there is no such protection for eviction records. Therefore, it would be hard for a tenant to challenge blanket screening policies on eviction filings.

The results of this study, along with prior studies regarding eviction filing practices and legal challenges, have several implications for tenant screening policy and research. First, if landlords conflate eviction filings with executed evictions in tenant screening, then tenants who experience the frustrating eviction filings process but thought they sorted everything out by paying rent and late fees will still face a barrier to future housing. Rather than seeking remedies for financial hardship before filing an eviction, or properly assessing eviction filings when screening tenants, conflating eviction filings with executed evictions means landlords complete the cycle of punishment against tenants who may be experiencing financial insecurity. Further research is required on effective interventions to provide rental assistance and/or means for overcoming financial hardship before the eviction filing process is initiated.

Second, taking into consideration HUD's regulation on blanket screening policies using criminal records, similar regulations should be enacted to prevent blanket screening policies using eviction filings. In other words, landlords who want to assess tenants' eviction records should be obligated to check the details of eviction records and assess them accordingly. Relatedly, further research is required to understand landlords' perception of eviction filings in the tenant screening process, with a specific comparison to executed evictions: Are landlords aware of the difference? If they would still desire to hold eviction filings against applicants, what are their reasons? Lastly, this study calls for further research on how corporate landlords automate the processes of (a) filing evictions and (b) screening tenants. These two processes should require greater human interaction with tenants who are experiencing or who have experienced financial hardship, but the structure of large, corporate landlords risks further reinforcing automation bias and scaling blanket screening policies for the optimization of their business logic (Fields, 2022).

Criminal Records

There are considerations and implications involved in the assessment of criminal records. First, this study shows that MTurk landlords may differentiate serious types of crimes (e.g., sex offenders) from less serious ones (e.g., shoplifting) and/or may differentiate according to the disposition. In contrast, the prior section described how MTurk landlords treat filings and executed evictions similarly. These differences might suggest that landlords are less familiar with how evictions are executed than with how criminal justice procedure works (e.g., charge under criminal procedure and conviction/acquittal), because eviction records are a specific type of civil procedure—landlord–tenant disputes.

However, in the mid-scored reports, there is statistical evidence that showing the report's risk score (Type 2) caused MTurk landlords to deny tenant applications more frequently, whereas there is no statistical evidence that having detailed information in the report (Type 3) caused MTurk landlords to do the same. This result indicates a need for further research and policy formulation on algorithmic scoring of tenant records (Smith & Voguell, 2022), with a specific focus on how landlords construct proxies of desirable tenants through two perspectives from this study: (a) the difficulties of assessing mid-scored criminal records (e.g., arrest records and misdemeanors) and, therefore, (b) reinforcing landlords' potential reliance on algorithmic decisions provided by reports.

In mid-scored criminal records, landlords would have more discretion in terms of how to assess tenants, depending on the type of charges or the disposition of the case. HUD prohibits denying housing by holding arrest records against tenants. But apart from that, landlords who would like to construct proxies of undesirable tenants using criminal records must assess which criminal records would relate to tenants' behavior (e.g., damaging their property and/or adversely affecting other tenants). However, it is incredibly challenging to identify the causal relationship between how and which past misdemeanors cause particular future tenant behaviors. Moreover, legal jargon and abbreviations on the report could make it harder for landlords to understand criminal records in the first place. These factors, as a result, could contribute to landlords' reliance on the scores provided by the report shown in the experiment.

Algorithmic scoring using criminal records is problematic because training data—a data set that is used to train a machine learning model—is inaccurate and the outcome variable ("desirable tenants") is unclear. For instance, the tenant screening company RealPage produces 11,000 reports using "abbreviated" criminal records, which are cheaper to acquire than full criminal records but do not include details of the resolution (Kirchner & Goldstein, 2020). An inaccurate model is highly likely to result from tenant screening services using these kinds of abbreviated data, given that it is important to include the final resolution of criminal justice procedures for proper assessment. Moreover, it would be challenging to set an outcome variable for developing this kind of algorithm because it is hard to project a certain criminal outcome into "good" tenant behaviors.

Security Deposit

It is important to note that within conditionally accepted reports, similar patterns of blanket screening policies and automation bias are exhibited when landlords impose security deposits. These results may corroborate a paired-test study that shows that Black tenants have less favorable terms and conditions, including security deposits, in rental agreements (Ross & Turner, 2005). One additional finding of the experiment is that algorithmic scoring can exacerbate this racially unequal landscape in rental agreements not just because the algorithm may be inaccurate, but because landlords may want to follow the risk assessment made by the tenant screening report. This is alarming for low-income tenants, particularly housing voucher holders. Security deposits are one of the most significant barriers to obtaining housing for voucher holders, because vouchers do not pay security deposits but most private landlords require them (Rosenblatt & Cossyleon, 2018). Given that voucher holders have exceptionally low income (usually less than 50% of area median income) and might experience more housing insecurity (rental debts and eviction-related experiences), imposing greater security deposits on voucher holders almost equates to denying them housing—yet these decisions could be justified by algorithmic scoring if tenant screening services employ it. Therefore, further research and policy intervention are required—like the Milwaukee County HOME Security Deposit Assistance Program, which provides voucher holders up to $1,000 that can be used to pay security deposits (Rosenblatt & Cossyleon, 2018). Furthermore, in assessing voucher holders' data, it is questionable to hold nonpayment eviction records against applicants before obtaining housing vouchers, given the financial hardship regarding rent payment was resolved and because most of the rent is guaranteed by the voucher and the tenant's portion is adjusted relative to their income. Hence, it is crucial to further study the impact of imposing more financial burdens in rental agreements, particularly with a specific focus on low-income tenants and housing voucher holders.

Automation Bias

This study finds that landlords tend to rely more on the automated system's judgment: when a report noted that a tenant was either medium or high risk, landlords showed a higher tendency toward rejection, or, if conditionally accepted, they imposed a higher security deposit. This indicates that tenant screening services' risk scoring may critically affect landlords' decision-making. Given that there is no regulation pertaining to producing and deploying such algorithms, and given the inherent inaccuracies of eviction data (Porton et al., 2021) and widespread, serial eviction filings (Garboden & Rosen, 2019), particularly automatic eviction filings activated by digitized property management systems and large, corporate landlords (Fields, 2022; Gomory, 2022; Immergluck et al., 2020), tenant screening services very likely contribute to perpetuating algorithmic inequality (Eubanks, 2018) by denying qualified applicants—disproportionately from protected groups—access to housing.

Small-Scale Landlords

These findings mainly represent the behavior of small-scale landlords. Therefore, the results should be understood in the context of the scale of landlords. Landlord practices vary with scale, as do their familiarity with and need to outsource screening tasks. For instance, recent research shows that landlords with smaller portfolios tend to rely more on implicit bias and informal screenings, including checking the cleanliness of tenants' children and current residences, and often explicitly associating certain races and genders with "less desirable" tenants (Rosen et el., 2021). Furthermore, when small-scale landlords do use tenant screening services, often there is room for negotiation.

In small-scale landlords' decision-making process, this study may show how "gut feelings" identified in the previous research influence the understanding of the detailed information shown in the report (Type 3). This influence may be due to the following: (a) the information shown in the report might be difficult to interpret for small-scale landlords who often do not have the legal knowledge to assess the reports, including differentiating between eviction filings and executed evictions; or (b) they are aware of the difference between eviction filings and executed evictions but their implicit bias toward eviction proceedings renders records with eviction filings still less desirable than those without. Given that prior research shows that small-scale landlords often have more room for negotiation in screening (Rosen et al., 2021), at the least, tenant screening reports should provide an explicit assessment guide to differentiate between eviction filings and executed evictions listed on the report. This would then create the conditions for negotiation between landlords and applicants. On the other hand, the automation bias pattern can be attributed to the following: either (a) small-scale landlords unconditionally believe what the reports score or (b) the score confirms their "gut feelings" regarding eviction filings (confirmation bias). Both could reflect the critical power of tenant screening services' algorithmic scoring. The reports' decisive scoring creates less room for negotiation and limits individual consideration in screening processes. Currently, these reports' scoring algorithms are a black box and not under regulation. Therefore, more scrutiny is required to understand and regulate tenant screening services' logics of scoring and risk assessment.

Compared to small-scale landlords, I argue that large-scale landlords would likely exhibit even more blanket screening policies and automation bias because their business model requires a streamlined process with more strict rules for managing large units (Fields, 2022). Because it is economically impracticable to assess every single applicant in a case-by-case manner when managing large-scale properties, they are eager to set a standardized policy and like to use third-party services that can make an instant tenancy decision that could theoretically comply with fair housing regulations (although this is clearly debatable). Prior research also shows that landlords with larger portfolios tend to rely more on automated screening algorithms and strict rules (Rosen et al., 2021). However, is it challenging to develop a "fair" tenant selection algorithm not only because of the aforementioned limitations on developing training data and identifying outcome variables, but also because the final decision is complicated by individual and institutional presuppositions and biases. Therefore, again, this calls for more research on how large-scale landlords operate and automate their decision-making in the tenant selection pipeline, including how this relates to eviction filings and tenant screening.

Sealing and Expunging Housing Court Data

Numerous housing activists and policy scholars have demanded that records be sealed and/or expunged because of the harm and inherent limitations of using court data for screening tenants (Polk, 2020). I also argue that it is appropriate to seal and expunge housing court records, because of the inadequate assessment and conflation of different judgment levels of records identified in this study. Relatedly, a number of state and municipal jurisdictions have established a policy of sealing and expunging housing court data. California and Nevada, for example, require eviction records to be automatically sealed immediately after filing; records are unsealed only if the landlord prevails (Cal. Civ. Proc. Code, 2021; Nev. Rev. Stat, 2017). Third-party data brokers easily scrape records as soon as they are published online. Washington, DC, recently passed an amendment that proposes to seal eviction records as well (Hearing on B24-94, Eviction Record Sealing Authority Amendment Act of 2021, 2021). These states advocate sealing records immediately after filing, not after the judgment. At the same time, a Connecticut bill proposes to grant access to eviction records to legal service professionals and academic scholars (H.B. 6528.1, 2021). Preventing third-party data brokers and tenant screening services from scraping eviction filings and even eviction cases that were decided in the landlords' favor would be the most effective solution (Dada & Duarte, 2022), given the pattern of assessment identified in this study for screening tenants.

In addition, we must collectively keep advocating for the establishment of a national-level eviction database for policy analysis regarding eviction and other policy formulations such as the distribution of rental assistance (Hepburn & Panfil, 2021). As Hepburn and Panfil (2021) argue, one of the keys to creating such a database is fully anonymizing data points to prevent unnecessary identification by tenant screening services. However, because of innovations of machine learning and the possibility of inferring anonymized individuals' identities (de Montjoye et al., 2013; Montjoye et al., 2015), I argue that we need to take an additional step to limit access only for policy analysis, research, and legal aid, similar to the proposed Connecticut bill (H.B. 6528.1, 2021). In this case, the default setting would be to show fully anonymized and aggregate-level data, and individual-level data access would be granted only for research purposes or legal service provision.

How Tenant Screening Contributes to Racial Discrimination: The Downstream Effect of "Race-Neutral" Data

This study shows how racial discrimination in tenant screening works through a system of "color-evasive" racism (Annamma et al., 2017), in which current racial disparities are considered to be either unintentional outcomes in an otherwise fair operation of market dynamics or the result of intentionally racist individuals (Bonilla-Silva, 2018). However, both of these explanations miss the systemic nature of discrimination in "racialized social systems," where political, social, and economic aspects of everyday life are structured by a racialized hierarchy (Bonilla-Silva, 2018), in which even interpersonal racism and racial hatred can be attributed to institutionally reinforced racial hierarchies (Feagin, 1991).

In the upstream of this seemingly race-neutral data, records of tenants are generated by landlords, housing courts, and credit bureaus, reflecting the substandard conditions of tenants such as low credit scores or eviction and criminal histories. Although these appear to be neutral, they are in fact highly racialized. Due to a long history of discriminatory policies and practices, including racial covenants, redlining (Winling & Michney, 2021), exclusionary zoning (Rothstein, 2018), lending discrimination (Steil et al., 2018), and predatory lending (Taylor, 2019), and because of the broadly racialized criminal justice system (Alexander, 2020), certain groups, particularly Black and Hispanic people, are disproportionately affected. This history thus exposes how minoritized people have a greater likelihood of living in substandard housing, and in a segregated neighborhood, with fewer opportunities for social mobility. Given that these groups of people are overrepresented in criminal and eviction records (Hepburn et al., 2020) and eviction filings are generated disproportionately on low-income, Black and Hispanic, and women tenants, as a result (Garboden & Rosen, 2019; Hepburn et al., 2020; Leung et al., 2021), there will inevitably be discriminatory effects when using these data to make decisions.

It is important to note the "downstream effects" of color-evasive racism in which it permeates the system from data brokers to the tenant screening process. Tenant screening services compile supposedly race-neutral data while ignoring the underlying racial disparities within the data sets. Although the final decision of accepting or rejecting a prospective tenant's application ostensibly rests on landlords' perception of "good" tenants, this study finds that by deciding not to critically disentangle the content of the report and basing their assessment on the decisions or scores of the tenant screening report, landlords perpetuate implicit racial discrimination. Rosen et al. (2021) observed that landlords who use tenant screening algorithms delegate their decision to the software so as to plausibly deny flouting fair housing laws. However, this delegation does not result in "fair" or less discriminatory outcomes; rather, it shows how implicit bias is coded into the structure of tenant screening and how landlords "'unthinkingly discriminate' without having any idea they are doing so" (Manegold, 1994, para. 1). Through these algorithmic proxies that tenant screening services provide using ostensibly race-neutral data, landlords are able to justify their choices by relying on tenant screening services' conveniently compiled information and risk scores (Rosen et al., 2021).

Because of such downstream effects, law scholars and legal services providers have been focusing on whether the disparate impact standard in the FHA can provide a robust framework for determining when apparently neutral data is being used for housing transactions and whether there is a correlation between protected classes and those data (Vesoulis, 2020). As of April 2021, the disparate-impact liability against tenant screening services under the FHA is controversial as there are conflicting verdicts in the lower courts (Bhatia, 2020). I argue that upholding the liability of tenant screening services through the disparate impact standard would be crucial for protecting tenants' rights from these tenant screening patterns. More broadly, upholding the disparate impact claims of discriminatory systems like tenant screening services' use of criminal and eviction records would contribute to recognizing that persistent racial disparities are a result of the historical and systematic oppression of minoritized groups and that policies and practices that perpetuate adverse impacts on those groups should be prohibited (Steil, 2022).

Overall, enforcing tenant screening using those data created from "upstream" means creating racially subordinated boundaries and othering Black and Hispanic renters in the "downstream" of tenant selection. Tenant screening creates a structure of housing injustice in which racial injustices, including historical housing discrimination and the racial wealth gap, disproportionate incarceration rates, and wrongful conviction can effectively work to discriminate against historically marginalized renters, particularly Black and Hispanic renters. Housing providers should think about the broader meaning of "fairness" in tenant selection, beyond adopting technologies that merely comply with fair housing laws—because these seemingly racially neutral technologies are still deeply bounded by the racialized social systems in which we are living.

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No potential conflict of interest was reported by the author(s).

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References

Alexander, M. (2020). *The new Jim Crow: Mass incarceration in the age of Colorblindness* (Tenth anniversary edition). The New Press.

Angwin, J., Larson, J., Mattu, S., Kirchner, L. (2016, May 23). Machine Bias. *ProPublica*. https://www.propublica.org/article/machine-bias-risk-assessments-in-criminal-sentencing

Annamma, S. A., Jackson, D. D., & Morrison, D. (2017). Conceptualizing color-evasiveness: Using dis/ability critical race theory to expand a color-blind racial ideology in education and society. *Race Ethnicity and Education*, *20*(2), 147–162. https://doi.org/10.1080/13613324.2016.1248837

Avail. (2020, February 4). Security deposit collection: Minimize your risks. *Avail Blog*. https://www.avail.co/education/articles/security-deposit-collection-minimize-your-risks

Balzarini, J., & Boyd, M. L. (2021). Working with them: Small-scale landlord strategies for avoiding evictions. *Housing Policy Debate*, *31*(3–5), 425–445. https://doi.org/10.1080/10511482.2020.1800779

Bartlett, R. P., Morse, A., Wallace, N., Stanton, R. (2020). *Algorithmic discrimination and input accountability under the Civil Rights Acts* (SSRN Scholarly Paper ID 3674665). Social Science Research Network. https://doi.org/10.2139/ssrn.3674665

Benjamin, R. (2019). *Race after technology: Abolitionist tools for the New Jim Code* (1st edition). Polity. https://doi.org/10.1093/sf/soz162

Berinsky, A. J., Huber, G. A., & Lenz, G. S. (2012). Evaluating online labor markets for experimental research: Amazon.com's Mechanical Turk. *Political Analysis*, *20*(3), 351–368. https://doi.org/10.1093/pan/mpr057

Bertrand, M., & Mullainathan, S. (2003). *Are emily and greg more employable than Lakisha and Jamal? A field experiment on labor market discrimination* (Working Paper No. 9873; Working Paper Series). National Bureau of Economic Research. https://doi.org/10.3386/w9873

Bhatia, S. (2020). To "otherwise make unavailable": Tenant screening companies' liability under the Fair Housing Act's disparate impact theory. *Fordham Law Review*, *88*(6), 2551.

Bonilla-Silva, E. (2018). *Racism without racists: Color-blind racism and the persistence of racial inequality in America* (Fifth edition). Rowman & Littlefield.

Bourland, N. (2017, May 8). When causation is too "ROBUST": Disparate impact in the crosshairs in de reyes. *Cuny Law Review*. http://www.cunylawreview.org/nick-bourland/

Bridges, K. A. (2008). Justifying facial discrimination by government defendants under the Fair Housing Act: Which standard to apply. *Missouri Law Review*, *73*, 19.

Browne, S. (2015). *Dark matters: On the surveillance of blackness*. Duke University Press.

Buhrmester, M., Kwang, T., & Gosling, S. D. (2011). Amazon's mechanical turk: A new source of inexpensive, yet high-quality, data? *Perspectives on Psychological Science*, *6*(1), 3–5. https://doi.org/10.1177/1745691610393980

Buolamwini, J., Gebru, T. (2018). Gender shades: Intersectional accuracy disparities in commercial gender classification. *Conference on Fairness, Accountability and Transparency*, 77–91. http://proceedings.mlr.press/v81/buolamwini18a.html

Cal. Civ. Proc. Code, § 1161. 2 (2021).

CFHC v. Corelogic, 18-cv-00705-VLB (2018). (S.D. Connecticut April 24, 2018).

Cohen, J. (2013). *Statistical power analysis for the behavioral sciences* (0 ed.). Routledge. https://doi.org/10.4324/9780203771587

Crump, M. J. C., McDonnell, J. V., & Gureckis, T. M. (2013). Evaluating Amazon's mechanical turk as a tool for experimental behavioral research. *PLoS One*, *8*(3), e57410. https://doi.org/10.1371/journal.pone.0057410

Dada, T., Duarte, N. (2022). *How to seal eviction records: Guidance for legislative drafting* (p. 43). Upturn. https://www.upturn.org/static/files/how-to-seal-eviction-records-071322.pdf
de Montjoye, Y.-A., Hidalgo, C A., Verleysen, M., & Blondel, V D. (2013). Unique in the crowd: The privacy bounds of human mobility. *Scientific Reports*, *3*, 1376. https://doi.org/10.1038/srep01376
Desmond, M. (2012). Eviction and the reproduction of urban poverty. *American Journal of Sociology*, *118*(1), 88–133. https://doi.org/10.1086/666082
Desmond, M. (2016). *Evicted: Poverty and profit in the American city* (First Edition). Crown Publishers.
Dunn, E., & Grabchuk, M. (2010). Background checks and social effects: Contemporary residential tenant-screening problems in Washington State. *Seattle Journal for Social Justice*, *9*(1), 13. https://digitalcommons.law.seattleu.edu/sjsj/vol9/iss1/13
Ehman, M. (2015). *Fair housing disparate impact claims based on the use of criminal and eviction records in tenant screening policies*. https://www.nhlp.org/wp-content/uploads/Merf-Ehman-FH-DI-Claims-Based-on-Use-of-Criminal-and-Eviction-Records-Sept.-2015.pdf
Eubanks, V. (2018). *Automating inequality: How high-tech tools profile, police, and punish the poor*. St. Martin's Press.
Evans, D N. (2016). The effect of criminal convictions on real estate agent decisions in New York City. *Journal of Crime and Justice*, *39*(3), 363–379. https://doi.org/10.1080/0735648X.2016.1166068
Evans v. UDR Inc., 644 F. Supp. 2d 675, 7:07-CV-136-FL (2009). United States District Court, E.D. North Carolina, Southern Division, March 24, https://casetext.com/case/evans-v-udr-inc
Feagin, J R. (1991). The continuing significance of race: Antiblack discrimination in public places. *American Sociological Review*, *56*(1), 101–116. https://doi.org/10.2307/2095676
Fields, D. (2022). Automated landlord: Digital technologies and post-crisis financial accumulation. *Environment and Planning A*, *54*(1), 160–181. https://doi.org/10.1177/0308518X19846514
Fields, D., & Uffer, S. (2016). The financialisation of rental housing: A comparative analysis of New York City and Berlin. *Urban Studies*, *53*(7), 1486–1502. https://doi.org/10.1177/0042098014543704
Franzese, P A. (2018). A place to call home: Tenant Blacklisting and the denial of opportunity. *Fordham Urb. L.J.*, *45*, 661.
Friedler, S. A., Scheidegger, C., Venkatasubramanian, S., Choudhary, S., Hamilton, E. P., Roth, D. (2019). A comparative study of fairness-enhancing interventions in machine learning. *Proceedings of the Conference on Fairness, Accountability, and Transparency* (pp. 329–338). https://doi.org/10.1145/3287560.3287589
Gaddis, S. M. (2018). An introduction to audit studies in the social sciences. In S. M. Gaddis (Ed.), *Audit studies: Behind the scenes with theory, method, and nuance* (pp. 3–44). Springer International Publishing. https://doi.org/10.1007/978-3-319-71153-9_1
Garboden, P M., & Rosen, E. (2019). Serial filing: How landlords use the threat of eviction. *City & Community*, *18*(2), 638–661. https://doi.org/10.1111/cico.12387
Garcia, D., & Abascal, M. (2016). Colored perceptions: Racially distinctive names and assessments of skin color. *American Behavioral Scientist*, *60*(4), 420–441. https://doi.org/10.1177/0002764215613395
Glymour, B., Herington, J. (2019). Measuring the biases that matter: The ethical and casual foundations for measures of fairness in algorithms. *Proceedings of the conference on fairness, accountability, and transparency* (pp. 269–278). https://doi.org/10.1145/3287560.3287573
Gomory, H. (2022). The social and institutional contexts underlying landlords' eviction practices. *Social Forces*, *100*(4), 1774–1805. https://doi.org/10.1093/sf/soab063
Gramlich, J. (2020). Black imprisonment rate in the US has fallen by a third since 2006. *Pew Research Center*. https://www.pewresearch.org/fact-tank/2020/05/06/share-of-black-white-hispanic-americans-in-prison-2018-vs-2006/
Green, B. (2021). *Escaping the "impossibility of fairness": From formal to substantive algorithmic fairness* (SSRN Scholarly Paper ID 3883649). Social Science Research Network. https://doi.org/10.2139/ssrn.3883649
Green, B., Chen, Y. (2019). Disparate interactions: An algorithm-in-the-loop analysis of fairness in risk assessments. *Proceedings of the conference on fairness, accountability, and transparency* (pp. 90–99). https://doi.org/10.1145/3287560.3287563
Greenberg, D., Gershenson, C., & Desmond, M. (2016). Discrimination in evictions: Empirical evidence and legal challenges. *Harvard Civil Rights-Civil Liberties Law Review*, *51*, 115.
Greif, M. (2018). Regulating landlords: Unintended consequences for poor tenants. *City & Community*, *17*(3), 658–674. https://doi.org/10.1111/cico.12321
Hartman, C., & Robinson, D. (2003). Evictions: The hidden housing problem. *Housing Policy Debate*, *14*(4), 461–501. https://doi.org/10.1080/10511482.2003.9521483
Hatch, M E. (2017). Statutory protection for renters: Classification of state landlord–tenant policy approaches. *Housing Policy Debate*, *27*(1), 98–119. https://doi.org/10.1080/10511482.2016.1155073
Haupert, T. (2022). The racial landscape of fintech mortgage lending. *Housing Policy Debate*, *32*(2), 337. https://doi.org/10.1080/10511482.2020.1825010
H.B. 6528.1. (2021). https://trackbill.com/bill/connecticut-house-bill-6528-an-act-concerning-the-sealing-of-eviction-records/2049122/
Hearing on B24-94, Eviction Record Sealing Authority Amendment Act of 2021. (2021).

Hepburn, P., Louis, R., & Desmond, M. (2020). Racial and gender disparities among Evicted Americans. *Sociological Science*, *7*, 649–662. https://doi.org/10.15195/v7.a27

Hepburn, P., & Panfil, Y. (2021, January 28). Opinion | The Black Hole at the heart of the eviction crisis. *The New York Times*. https://www.nytimes.com/2021/01/28/opinion/eviction-crisis-moratorium.html

Horton, J J., Rand, D G., & Zeckhauser, R J. (2011). The online laboratory: Conducting experiments in a real labor market. *Experimental Economics*, *14*(3), 399–425. https://doi.org/10.1007/s10683-011-9273-9

Huff, C., & Tingley, D. (2015). Who are these people?" Evaluating the demographic characteristics and political preferences of MTurk survey respondents. *Research & Politics*, *2*(3), 205316801560464. https://doi.org/10.1177/2053168015604648

Immergluck, D., Ernsthausen, J., Earl, S., & Powell, A. (2020). Evictions, large owners, and serial filings: Findings from Atlanta. *Housing Studies*, *35*(5), 903–922. https://doi.org/10.1080/02673037.2019.1639635

Karimi, A.-H., Schölkopf, B., & Valera, I. (2021). Algorithmic recourse: From counterfactual explanations to interventions. *Proceedings of the 2021 ACM Conference on Fairness, Accountability, and Transparency* (pp. 353–362). https://doi.org/10.1145/3442188.3445899

Kimble, M. (2020, December 9). How evictions haunt tenants for years. *The Texas Observer*. https://www.texasobserver.org/evictions-texas-housing/

Kirchner, L. (2020a). When Zombie data costs you a home. *The Markup*. https://themarkup.org/locked-out/2020/10/06/zombie-criminal-records-housing-background-checks

Kirchner, L. (2020b, May). How we investigated the tenant screening industry. *The Markup*. https://themarkup.org/show-your-work/2020/05/28/how-we-investigated-the-tenant-screening-industry

Kirchner, L. (2020c, September 24). Can algorithms violate fair housing laws? *The Markup*. https://themarkup.org/locked-out/2020/09/24/fair-housing-laws-algorithms-tenant-screenings

Kirchner, L., & Goldstein, M. (2020). Access denied: Faulty automated background checks Freeze Out Renters. *The Markup*. https://themarkup.org/locked-out/2020/05/28/access-denied-faulty-automated-background-checks-freeze-out-renters

Kleysteuber, R. (2007). Tenant screening thirty years later: A statutory proposal to protect public records. *The Yale Law Journal*, *116*(6), 1344–1388. https://doi.org/10.2307/20455760

Landers, R N., & Behrend, T S. (2015). An inconvenient truth: Arbitrary distinctions between organizational, mechanical turk, and other convenience samples. *Industrial and Organizational Psychology*, *8*(2), 142–164. https://doi.org/10.1017/iop.2015.13

Leung, L., Hepburn, P., & Desmond, M. (2021). Serial eviction filing: Civil courts, property management, and the threat of displacement. *Social Forces*, *100*(1), 316–344. https://doi.org/10.1093/sf/soaa089

Manegold, C. S. (1994, September 27). "Glass ceiling" is pervasive, secretary of labor contends. *The New York Times*. https://www.nytimes.com/1994/09/27/us/glass-ceiling-is-pervasive-secretary-of-labor-contends.html

McCabe, B. J., & Rosen, E. (2020). *Eviction in Washington, DC: Racial and geographic disparities in housing instability* (p. 42). Georgetown University. https://www.stout.com/-/media/pdf/evictions/dc-eviction-report-ada.pdf

McElroy, E. (2019, November 6). *Disruption at the Doorstep*. Urban Omnibus. https://urbanomnibus.net/2019/11/disruption-at-the-doorstep/

McElroy, E. (2020). Property as technology. *City*, *24*(1–2), 112–129. https://doi.org/10.1080/13604813.2020.1739910

McElroy, E., So, W., Whittaker, M., Fried, G., Raji, D., Smooke, J., Ruiz, D. (2020). *Landlord Tech Watch*. Landlord Tech Watch. https://antievictionmappingproject.github.io/landlordtech

Montjoye, Y.-A d., Radaelli, L., Singh, V. K., & Pentland, A. "S. (2015). Unique in the shopping mall: On the reidentifiability of credit card metadata. *Science*, *347*(6221), 536–539. https://doi.org/10.1126/science.1256297

Nev. Rev. Stat, § 40. 2545. (2017).

NYS Division of Criminal Justice Services. (2020). *Disposed adult arrest demographics*. https://www.criminaljustice.ny.gov/crimnet/ojsa/dispositions-adult-arrest-demographics/2019/NYS.pdf

O'Neil, C. (2016). *Weapons of math destruction: How big data increases inequality and threatens democracy* (First edition). Crown.

Ong, A. D., & Weiss, D. J. (2000). The impact of anonymity on responses to sensitive question. *Journal of Applied Social Psychology*, *30*(8), 1691–1708. https://doi.org/10.1111/j.1559-1816.2000.tb02462.x

Oyama, R. (2009). Do Not (Re)Enter: The rise of criminal background tenant screening as a violation of the Fair Housing Act. *Michigan Journal of Race and Law*, *15*(1), 181–222.

Pager, D. (2003). The mark of a criminal record. *American Journal of Sociology*, *108*(5), 937–975. https://doi.org/10.1086/374403

Paolacci, G., & Chandler, J. (2014). Inside the Turk: Understanding mechanical turk as a participant pool. *Current Directions in Psychological Science*, *23*(3), 184–188. https://doi.org/10.1177/0963721414531598

Phillips, R. (2020). *Breaking the record: Dismantling the barriers eviction records place on housing opportunities*. Community Legal Services of Philadelphia. https://clsphila.org/wp-content/uploads/2020/12/Breaking-the-Record-Report_Nov2020.pdf

Polk, K. (2020). Screened out of housing: The impact of misleading tenant screening reports and the potential for criminal expungement as a model for effectively sealing evictions. *Northwestern Journal of Law & Social Policy*, *15*(3), 338.

Porter, L., Fields, D., Landau-Ward, A., Rogers, D., Sadowski, J., Maalsen, S., Kitchin, R., Dawkins, O., Young, G., & Bates, L. K. (2019). Planning, land and housing in the digital data revolution/the politics of digital transformations of housing/digital innovations, PropTech and Housing – The view from Melbourne/Digital Housing and Renters: Disrupting the Australian Rental Bond System and Tenant Advocacy/Prospects for an Intelligent Planning System/What are the prospects for a politically intelligent planning system? *Planning Theory & Practice*, *20*(4), 575–603. https://doi.org/10.1080/14649357.2019.1651997

Porton, A., Gromis, A., & Desmond, M. (2021). Inaccuracies in eviction records: Implications for renters and researchers. *Housing Policy Debate*, *31*(3–5), 377–394. https://doi.org/10.1080/10511482.2020.1748084

Public Justice Center. (2015). *Justice diverted: How renters in Baltimore are Processed in the Baltimore City Rent Court*. https://abell.org/sites/default/files/files/cd-justicediverted216.pdf

Quillian, L., Pager, D., Hexel, O., & Midtbøen, A. H. (2017). Meta-analysis of field experiments shows no change in racial discrimination in hiring over time. *Proceedings of the National Academy of Sciences*, *114*(41), 10870–10875. https://doi.org/10.1073/pnas.1706255114

Rand, D. G. (2012). The promise of mechanical Turk: How online labor markets can help theorists run behavioral experiments. *Journal of Theoretical Biology*, *299*, 172–179. https://doi.org/10.1016/j.jtbi.2011.03.004

Reosti, A. C. (2018). *Tenant screening and fair housing in the information age* [Thesis]. https://digital.lib.washington.edu:443/researchworks/handle/1773/42546

Rosen, E., Garboden, P. M. E., & Cossyleon, J. E. (2021). Racial discrimination in housing: How landlords use algorithms and home visits to screen tenants. *American Sociological Review*, *86*(5), 787–822. https://doi.org/10.1177/00031224211029618

Rosenblatt, P., & Cossyleon, J. E. (2018). Pushing the boundaries: Searching for housing in the most segregated metropolis in America. *City & Community*, *17*(1), 87–108. https://doi.org/10.1111/cico.12288

Ross, S. L., & Turner, M. A. (2005). Housing discrimination in Metropolitan America: Explaining Changes between 1989 and 2000. *Social Problems*, *52*(2), 152–180. https://doi.org/10.1525/sp.2005.52.2.152

Rothstein, R. (2018). *The color of law: A Forgotten history of how our Government Segregated America*. (Reprint Edition). Liveright.

Rugh, J. S., Albright, L., & Massey, D. S. (2015). Race, space, and cumulative disadvantage: A case study of the subprime lending collapse. *Social Problems*, *62*(2), 186–218. https://doi.org/10.1093/socpro/spv002

Sadowski, J. (2019). When data is capital: Datafication, accumulation, and extraction. *Big Data & Society*, *6*(1), 205395171882054. https://doi.org/10.1177/2053951718820549

Schwemm, R., & Bradford, C. (2016). Proving disparate impact in fair housing cases after inclusive communities. *N.Y.U. Journal of Legislation & Public Policy*, *19*(4), 685–770.

Shaw, J. (2020). Platform Real Estate: Theory and practice of new urban real estate markets. *Urban Geography*, *41*(8), 1037. https://doi.org/10.1080/02723638.2018.1524653

Shiffer–Sebba, D. (2020). Understanding the divergent logics of landlords: Circumstantial versus deliberate pathways. *City & Community*, *19*(4), 1011–1037. https://doi.org/10.1111/cico.12490

Sisson, P. (2019, December 17). *Housing discrimination goes high tech*. Curbed. https://www.curbed.com/2019/12/17/21026311/mortgage-apartment-housing-algorithm-discrimination

Skitka, L. J., Mosier, K. L., & Burdick, M. (1999). Does automation bias decision-making? *International Journal of Human-Computer Studies*, *51*(5), 991–1006. https://doi.org/10.1006/ijhc.1999.0252

Smith, E., Voguell, H. (2022). How your shadow credit score could decide whether you get an apartment. *ProPublica*. https://www.propublica.org/article/how-your-shadow-credit-score-could-decide-whether-you-get-an-apartment

Smith v. Wasatch Property Management, Inc, 2::2017cv00501 (S.D. Wash. October). (2017). https://www.aclu.org/legal-document/smith-v-wasatch-property-management-complaint

Steil, J. (2022). Antisubordination planning. *Journal of Planning Education and Research*, *42*(1), 9–18. https://doi.org/10.1177/0739456X18815739

Steil, J. P., Albright, L., Rugh, J. S., & Massey, D. S. (2018). The social structure of mortgage discrimination. *Housing Studies*, *33*(5), 759–776. https://doi.org/10.1080/02673037.2017.1390076

Taylor, K.-Y. (2019). *Race for profit: How banks and the real estate industry undermined black homeownership*. University of North Carolina Press. https://doi.org/10.5149/9781469653686_taylor

Texas Dept. Of Housing and Community Affairs v. Inclusive Communities Project, Inc., No. 13-1731 (Supreme Court June 25, 2015).

US Department of Housing and Urban Development. (2016). *Office of general counsel guidance on application of Fair Housing Act standards to the use of criminal records by providers of housing and real estate-related transactions*. https://www.hud.gov/sites/documents/HUD_OGCGUIDAPPFHASTANDCR.PDF

HUD v. Facebook Inc. (2019).

Van Zant, A. B., & Kray, L. J. (2014). I can't lie to your face: Minimal face-to-face interaction promotes honesty. *Journal of Experimental Social Psychology*, *55*, 234–238. https://doi.org/10.1016/j.jesp.2014.07.014

Venkatasubramanian, S., Alfano, M. (2020). The philosophical basis of algorithmic recourse. *Proceedings of the 2020 Conference on Fairness, Accountability, and Transparency* (pp. 284–293). https://doi.org/10.1145/3351095.3372876

Vesoulis, A. (2020, February 20). How housing voucher programs can hurt the low-income families they're designed to help. *Time*. https://time.com/5783945/housing-vouchers-discrimination/

Williams, C. (2018). Inclusive communities and robust causality: The constant struggle to balance access to the courts with protection for defendants. *Minnesota Law Review*, *102*, 969–1017.

Winling, L. C., & Michney, T. M. (2021). The roots of redlining: Academic, governmental, and professional networks in the making of the new deal lending regime. *Journal of American History*, *108*(1), 42–69. https://doi.org/10.1093/jahist/jaab066

Woo, S. E., Keith, M., & Thornton, M. A. (2015). Amazon mechanical turk for industrial and organizational psychology: Advantages, challenges, and practical recommendations. *Industrial and Organizational Psychology*, *8*(2), 171–179. https://doi.org/10.1017/iop.2015.21