****DRAFT. DO NOT CITE, QUOTE, OR FURTHER SHARE WITHOUT PERMISSION FROM THE AUTHORS****

Going Against the Record: How Algorithms Shape the Way Landlords Make Exceptions for Bad Background Checks

Working Paper

August 28, 2023

Barbara Kiviat,[1] Sara Sternberg Greene,[2] and Hesu Yoon[1]

[1]Stanford University Department of Sociology
[2]Duke University School of Law

Abstract: Organizations have long used records of individuals' pasts to assess risk, and increasingly they do so with algorithms. This may seem to eliminate the possibility of leniency for people with problematic pasts, yet scholars note that algorithms do not erase discretion, only relocate it. We ask what differences in exception-making follow. We turn to the case of tenant screening, where gatekeepers consult credit reports, criminal records, and eviction histories, but some do so with rules-based algorithms, while others employ traditional methods of judgment. Interviews with landlords, property managers, and executives at real estate and tenant screening companies reveal surprising similarity and meaningful difference. To move from documents to decisions, gatekeepers of all sorts mobilize cultural understanding—via situational and temporal re-embedding—but with algorithms, exception-worthy situations must be codified into counter-rules before tenants come along, in ways interoperable with records' classification systems. The result: only applicants with the most culturally salient and institutionally legible circumstances benefit. We discuss implications for theories of algorithms and for scholars studying the influence of personal records on life chances.

Acknowledgements: For helpful comments and guidance, the authors thank Laura Adler, Angèle Christin, Carly Knight, Kim Pernell, Eva Rosen, and Mitchell Stevens, as well as audiences at Boston University's Precarity Lab, the Berkeley Department of Sociology, SCANCOR Stanford, and the 2021 annual meeting of the American Sociological Association. The authors also thank Kiersten Hasenour, Natasha Overmeyer, Liann Yamashita, and Pamela Zabala for skillfully conducting interviews, and Amanda Boltax, Angela He, and Dana Zhao for excellent research assistance. The authors gratefully acknowledge funding from the UPS Endowment Fund at Stanford University. Joanna Weiner created Figures 1, 2, and 3, and the authors thank her for the graphic design expertise. Direct correspondence to bkiviat@stanford.edu and greene@law.duke.edu.

INTRODUCTION

Organizations have long used records of individuals' pasts to make risk assessments, and increasingly they do so with algorithms—sets of rules, which, in their most sophisticated form, exist as computer code. The goal is to identify people whose pasts suggest future problems. Lenders consult credit reports to pinpoint borrowers who may not repay; judges review rap sheets to gauge whether defendants are likely to recidivate; insurers look at accident history to flag drivers prone to filing claims; social workers consider case files to predict if parents will neglect their children; and so on (Bosk 2018; Fourcade and Healy 2013; Werth 2019).

Traditionally, moving from records of a person's past to an understanding of the risk they pose moving forward involved an expert reading records and applying professional judgment.[1] Yet increasingly organizations use the data in records in rules-based, actuarial, and automated ways—modes broadly known as "algorithmic" (Levy, Chasalow, and Riley 2021; Rona-Tas 2020; Simon 1988). With this shift from judgmental to algorithmic analysis has come concern that, in a faithful enactment of Weber's iron cage, organizations now coldly and mechanically link individuals' pasts to their future opportunities, with little room for discretion, exception, or what in this article we call "going against the record" (Burrell and Fourcade 2021; Eubanks 2017; Harcourt 2007; Issar and Aneesh 2022). Data, it may seem, become destiny.

However, as the burgeoning literature on algorithms shows, reality is often more complicated. As organizations adopt algorithms, the exercise of judgment and discretion is not simply done away with but is instead relocated (Brayne and Christin 2021; Gray and Suri 2019; Seaver 2018). This insight echoes broader understandings about how organizations work,

[1] We use the colloquial (and in our data, emic) meaning of the word risk: exposure to danger, harm, or loss. Other scholars reserve the word for quantified representations of future loss (e.g., Knight 1921).

including the tendency for practice to become de-coupled from rules and for discretion to perennially re-appear (Crozier 1964; Lipsky 1980; Meyer and Rowan 1977). Taken together, the literature suggests two things. First, we should expect that even with rules-based risk analysis there will be openings for organizations and their employees to over-ride the written record and categorize a problematic past as not, in fact, disqualifying. And second, who has this ability and where they sit in an organization is likely to be different based on whether record use is judgmental or algorithmic. Yet is this difference in who wields exception-making power the only one we should expect? We suspect not.

In this article, we seek to identify other ways that going against the record takes shape differently when organizations use personal data algorithmically. This investigation is theoretically significant, but also important in a real-world sense, given that exception-making is a pathway by which people with marred records can at times still gain access to resources (Canales 2014; Kiviat 2019a; Prottas 1979). Exception-making can introduce bias, to be sure, but it can also reflect compassion for extenuating circumstances. In this article, we define exception-making as either ad hoc *or systematic* instances of gatekeepers deciding that a blemished record will not prevent a person from gaining access to a resource. For risk-averse organizations, this sort of going against the record is seemingly antithetical to risk minimization goals. Yet for various reasons, including economic constraints, decision-makers often feel as though they cannot simply screen out everyone with a checkered past. How, then, do they decide which problematic pasts can be overlooked?[2]

For our empirical case, we turn to tenant screening, where scholars have begun to note the importance of personal record use (e.g., Reosti 2018, 2020; Rosen, Garboden, and Cossyleon

[2] Risk-*embracing* organizations, such as subprime lenders, may actively seek out individuals with marred records. That is a business model different from the one we consider in this paper.

2021). In the U.S., most landlords and property managers consider potential tenants' credit reports, criminal records, and eviction histories, which they get from background check companies (Consumer Financial Protection Bureau 2022). This is consequential for the more than 100 million Americans with marred records, so-called "negative credentials" (Maroto 2012; Pager 2003).[3] Landlords may reject upwards of a quarter of at least some rental populations.[4] Tenant screening is a strategic case for understanding how exception-making plays out differently with algorithm use, because the field of housing rental is split between landlords that use records judgmentally and those that process them algorithmically. We can thus compare respondents using essentially the same data in different ways. We draw on interviews with 78 landlords and property managers in two U.S. metropolitan areas, as well as interviews with 10 current or former tenant screening company executives. Interviews with these executives, as well as executives at major real estate and property management companies, offer the first sociological look at the upper levels of tenant screening decision-making—the first glimpse into the black box of rental housing algorithms.

Comparing exception-making in judgmental and algorithmic contexts, we find both surprising similarity and meaningful difference. Both settings involve plenty of going against the record—of selectively ignoring background check blemishes—but with algorithms, decisions about which infractions to ignore are made far in advance, removed from details about applicants, and codified into what we call counter-rules. Nonetheless, the executives who create these counter-rules engage in the same processes of cultural meaning-making as gatekeepers

[3] We estimated this figure from the number of Americans with criminal records, debts in collection on their credit reports, and evictions filed against them each year (Gromis et al. 2022; Leasure and Andersen 2016; Ratcliffe et al., 2014). We believe this is a conservative estimate.
[4] Our data suggest it would not be uncommon for 15 to 20% of applicants to be rejected, although this may vary by market context. Other sources suggest the figure may be higher (personal correspondence with staff at the National Housing Law Project).

evaluating one applicant at a time. Both sorts of decision-makers turn to narrative and analogy as they undertake what we call situational and temporal re-embedding, an interpretive process that breathes life into bureaucratic records that present a thin version of people's pasts. Yet counter-rules, which must be written in advance and interoperable with the categories records already contain, change the variety of exceptions that landlords make. Only applicants with the most culturally salient and institutionally legible circumstances benefit.

The rest of this paper proceeds as follows. First, we explain the differences between judgmental and algorithmic risk assessment; highlight how organizations across domains have come to deploy algorithmic methods for making risk-related decisions about individuals; and mine the literatures on algorithms and organizations for guidance on what this means for the exercise of judgment and discretion. Next, we turn to our case, detailing how landlords and property managers use credit reports, criminal histories, and eviction records in rental decisions, and why this milieu is a useful one for addressing our theoretical concern. Then, we describe our data and methods and present our findings. Finally, we discuss the implications of our results for theories of algorithms and exception-making, as well as for scholars more broadly attentive to the increasing influence of personal records on life chances.

RISK ASSESSMENT, ALGORITHMS, AND GOING AGAINST THE RECORD

In markets and other domains of social life, organizations and the decision-makers who work for them often seek to assess how much risk an individual poses. Equipped with records of a person's past, evaluators of risk follow two main modes of moving from data to predictions of future behavior. The first relies on professionals closely reading dossiers one at a time and applying expert judgment. The second uses pre-determined and codified rules to mechanically assess the data contained in documents. Scholars across a variety of settings have identified these two approaches to risk assessment, variously referring to the first as clinical, unstructured, subjective, and character-based, and to the second as mechanical, automated, black-boxed, and, when rules capture known correlations, actuarial (Grove et al. 2000; Meehl 1954; Underwood 1979; Werth 2019). In this article, we refer to the first mode as judgmental and the second as algorithmic.[5] By "algorithm" we simply mean a set of rules one follows to make a decision; this could be as straightforward as a flowchart or computationally complex.

Both judgmental and algorithmic assessments have long been with us, but over time many domains have shifted from the former to the latter (Christin 2020b; Rona-Tas 2020). This is true for risk assessments in markets, such as those that allocate credit and insurance (Krippner and Hirschman 2022; Straka 2000), as well as for risk assessments in more social realms, such as criminal justice and child welfare (Bosk 2018; Eubanks 2017; Werth 2019). At times, scholars characterize judgmental assessment as idiosyncratic, though decision-makers do apply standards, just informal ones, like rules of thumb (Daston 2022; Meehl 1954; Rona-Tas and Guseva 2014). What is different is not a lack of patterned thinking, but the absence of rigid rules articulated in advance of any particular decision. Judgmental decision-makers are free to selectively ignore a record that, on first pass, indicates risk (i.e., a negative credential). Those following pre-set rules are less able to do so, which is why algorithmic assessment is often held up as a way to reduce bias, including those related to race and gender (Bielby 2000; Reskin 2000).[6]

When rules are taken to the extreme, however, that same rigidity is what leads to Weber's dystopian vision of the iron cage. Making decisions "without regard for persons" cuts both ways

[5] In using the word "judgmental," we follow in the tradition of consumer lending, where practitioners and others have long used the term to distinguish individualized, interpretive decision-making from that which is rules-based or statistical (e.g., Guseva 2008; Krippner 2017; Lauer 2017).
[6] This doesn't always work as intended (Ajunwa 2020; Dobbin, Schrage, and Kalev 2015).

(Weber 1978:975). Extracting human judgment and discretion also boxes out pro-social forms of partiality, such as those arising from empathy and consideration of special circumstance. As organizations increasingly rely on algorithms to assess risk and make decisions about individuals, the danger, social theorists argue, is that personal records, especially those that carry the imprimatur of institutions like the state, will unyieldingly control people's fates (Burrell and Fourcade 2021; Eubanks 2017; Harcourt 2007). In terms of the market, algorithmic "sorting and slotting," fueled by profit motive, means that those registering as risky will be automatically excluded or confined to less desirable options (Fourcade and Healy 2013, 2017; O'Neil 2016).

Yet while that may hold true in a general sense, the burgeoning literature on algorithms in organizational context shows that real-life practice is often more nuanced. The ability to go against a record that, on its face, indicates risk rarely disappears completely. This is true in part because organizational leaders at times intentionally leave ways for evaluators close to particular cases to override the recommendations of algorithms, especially in marginal situations (e.g., Albright 2019; Moulton 2007). Many child welfare authorities, for example, allow caseworkers to discount the results of actuarial tools designed to predict if parents will harm their children (Bosk 2020; De-Arteaga, Fogliato, and Chouldechova 2020).

But even when organizations do intend to excise human judgment, intuition, and discretion from risk-assessment and decision-making, they are effectively unable to do so. That is because effort to erase these modes of thinking only pushes them to other parts of the environment (Brayne 2021; Brayne and Christin 2021; Christin 2017; Gillespie 2018; Gray and Suri 2019). Consider what happened when legislators imposed sentencing algorithms on judges: discretionary power flowed to prosecutors, who still had leeway to decide what charges to bring, thus determining which sentencing grid a defendant ultimately wound up on (Espeland and Vannebo 2007; Schauer 2003).

When we view algorithms in a moment of assessment—at the point when a score or recommendation issues forth—it may seem that decisions are automatic and devoid of human influence. Front-line employees are just following the rules, doing what the output says. Yet as Seaver (2018:378) reminds us, "If you cannot see a human in the loop, you just need to look for a bigger loop." Behind algorithms sit people who decide which data to include and what rules to codify in code—processes packed with judgment calls (Bowker and Star 1994; Hannah-Moffat et al. 2009; Stuart 2003). Whether it's computer programmers, product managers, or another system designer, someone is still shaping algorithms according to taken-for-granted understandings about how the world does and should work (boyd and Crawford 2012; Burrell and Foucade 2021; Zuboff 2019). Algorithms don't get rid of human reasoning; they relocate it.

The algorithms literature is good at pointing this out, but what has gone less explored is what this relocation means for the process of categorizing a seemingly risky person as unproblematic. When organizations process records with algorithms rather than experts reading individual files, judgment is exercised by different people in different places at different times, and this, we argue, carries significant downstream implications for how exceptions are made and who benefits from them. Below, we explain why tenant screening is a good case for revealing these differences, but first we turn to another body of scholarship that helps establish expectations for how and why organizational actors would go against the record.

LESSONS FROM THE STUDY OF BUREAUCRACY AND RULES-BOUND ORGANIZATIONS

Why have rules-based risk assessment in the first place? The answer to that question proves useful for making sense of how individuals and organizations later selectively ignore negative credentials.

To start, rules might lead to better predictions about which individuals will be problematic. This could be especially true if rules are statistically validated (Rona-Tas 2020). But even absent evidence that rules boost the efficacy of record use, there are strong forces pushing organizations, especially larger ones, in the direction of pre-articulated, codified rules. Organizations are attentive to external audiences as well as to internal operations, and to the extent that regulators, investors, insurers, and other stakeholders expect rules-based procedures, organizations will be likely to use them (Meyer and Rowan 1977; DiMaggio and Powell 1983; Power 1999). Indeed, signaling legitimacy through a commitment to rules and standards has accelerated in recent decades (Merry 2011; Timmermans and Epstein 2010).

This is nowhere more apparent than in how organizations deal with risk. As scholars from diverse quarters have noted, we now live in a “risk society,” where organizations are expected to be attentive to future dangers and deal with them in instrumentally rational ways (Beck 1992; Clarke and Short 1993; Garland 2003). Rules-based systems also comport with contemporary notions of fair decision-making—of evaluating each individual in the same way, irrespective especially of ascriptive traits. This is a major reason why, for instance, in the 1990s the U.S. consumer lending industry shifted from judgmental underwriting to rules-based credit scores (Hyman 2011). As Carruthers (2013) observes, the adoption of such practices can run far ahead of evidence that they lead to more accurate predictions.[7] There is value in moving from judgment to rules, given their aura of objectivity, whether or not they statistically predict outcomes.

Yet it is precisely because organizations often stake out positions motivated by what others think that they then diverge from those positions in day-to-day practice. The literature on loose coupling shows how organizations frequently present one image to the outside world—e.g., we never rent to risky tenants—while internally doing something different (March and Olsen 1976; Meyer and Rowan 1977; Weick 1976). This divergence can arise from the practical realities of what it takes to run a business, as well as the fact that organizations, and individuals within them, often face conflicting values, goals, and motivations (Canales 2014; March 1994).

How, then, do exceptions come about? One major mechanism is through the exercise of discretion. In his classic study of “street-level” bureaucracy, Lipsky (1980) shows that front-line employees charged with allocating resources often bend or ignore an organization’s formal directives, either because the person being evaluated doesn’t neatly fall into the categories rules depend on, or because notions of fairness beyond equal treatment entail taking into account other aspects of a person’s life (see also, Prottas 1979). As organizations automate decision-making and technologically constrain ground-level workers, this discretion may seem to disappear. But just as in the literature on algorithms, scholars of bureaucracy demonstrate that judgment simply moves elsewhere, to locations where rules don’t (yet) reach (Bovens and Zouridis 2002; Crozier 1964; Zouridis, van Eck, and Bovens 2020). Indeed, as we show below, when risk assessment is

[7] In the U.S., this is the history of decision-making in both consumer credit and property insurance. Credit grantors and insurance underwriters made decisions according to scorecards and schedules of rules long before these systems were statistically validated (Hexamer 1905; Lauer 2017; see also, Rosenberger, Nash, and Graham 2009:80-81 on the value of rules-based decision-making even absent mathematical prediction).

algorithmic, upper-level managers become the ones with the power to deem certain situations special and whose intuitions get baked into decision-making systems.

Accordingly, in this article we conceptualize two varieties of exceptions, which we define as deviations from an ideal action (e.g., for risk-avoidant organizations, simply excluding all individuals whose records are marred). *Ad hoc* exceptions are case-specific and one-off, the classic scenario of frontline workers making decisions based on the details in front of them rather than broader organizational goals. *Systematic* exceptions, by contrast, are for entire groups of people. They are still exceptions in that they contravene the primary rule driving decision-making—e.g., reject people with negative credentials—but they do so in ways that transcend individual cases.

While the extant literature hints at this distinction, our empirical findings present a novel documentation of it. To date, scholars have largely left unanswered the question of how shifts in who makes exceptions and when such judgment occurs carry implications for how exception-making unfolds and the consequences for which sorts of blemished records are more or less likely to be overlooked.

CREDIT REPORTS, CRIMINAL RECORDS, AND EVICTION HISTORIES IN TENANT SCREENING

In this section, we turn to the details of our case: tenant background screening. In the U.S., most landlords and property managers procure information about would-be tenants from background check companies, which gather and sell records from credit bureaus and criminal and civil courts (Dunn and Grabchuk 2010; Hiner 2020; Consumer Financial Protection Bureau 2022). Screening companies tend to package credit reports, criminal records, and eviction histories together, which means landlords generally do not select into knowledge of particular information types. This case is therefore useful for teasing apart differences in exception-making between algorithmic and judgmental users of data, since the underlying information that landlords receive is broadly the same.[8] Any differences observed can be attributed to the mode of analysis and not variation in the underlying data itself, a distinction Christin (2020b) underscores as important yet often ignored.

Landlords have long had an interest in anticipating how individuals will behave (e.g., who will pay rent on time, maintain a property, make an unobtrusive neighbor). Traditionally, landlords' knowledge of tenants was interpersonally gleaned—gathered from interactions with would-be renters and those who knew them, such as past landlords (Thacher 2008). Information from background screening companies is different in two ways. First, it represents knowing "at a distance," a socially disembedded rendering of a person in a paper-bound, rationalized, and stripped-down form (Leyshon and Thrift 1999; Miller and Rose 1990). Second, background checks carry the imprimatur of credit bureaus and courts. The information is official, authoritative, and legible to other organizations (Pager 2003; Wheeler 1969). Landlords first gained access to such information in the late 19th century, with the emergence of consumer credit bureaus (Lauer 2017).

Yet it wasn't until the 1980s, and really the 1990s, that using background check records to screen out ostensibly undesirable tenants became widespread. In that era, background screening of all sorts grew common, as the internet and advances in computer processing allowed for the faster and cheaper aggregation, storage, and circulation of personal data (Hiner 2020; Pasley, Oostrom-Shah, and Sirota 2021). Alongside this technological shift came a growing belief that it was important for organizations to protect against the dangers individuals

[8] There may be minor differences based on which credit bureau the screening company contracts with and which courts are included (e.g., in-state vs. out-of-state jurisdictions).

posed, and that consulting records of past behavior could do so (Thacher 2008). While landlords and property managers continued to care about other sorts of information—an applicant's income, for example, to gauge ability to pay—records of behavioral infractions, from unpaid debts to criminal convictions, became customary markers for whether a tenant would prove problematic and ought to be avoided. Landlords and property managers thus use personal records to *avoid risk*.[9] (In recent decades, some industries have also begun using personal data to deliberately take on *more risk* at a higher price—subprime lending is a classic example—but that is not the business model employed here (Baker and Simon 2002; Mays 2004).)

Today, tenant screening outfits sell landlords raw data—the verbatim contents of credit reports and court records—as well as scores and other quantitative tools designed to summarize data and simplify decision-making (Dunn and Grabchuk 2010; Consumer Financial Protection Bureau 2022). These may or may not be statistically validated against outcomes, such as the likelihood of a person ending a lease with rent in arrears. While the statistical use of credit data is common in other industries, property managers have been slower to embrace predictive scoring.[10] One tenant screening company executive we spoke to for this research painted the real estate industry as old-fashioned. Some of our respondents described another dynamic: the financial upside to better predicting tenant risk was simply not that great compared to other decisions firms routinely make, such as setting rents and picking properties to buy and sell.

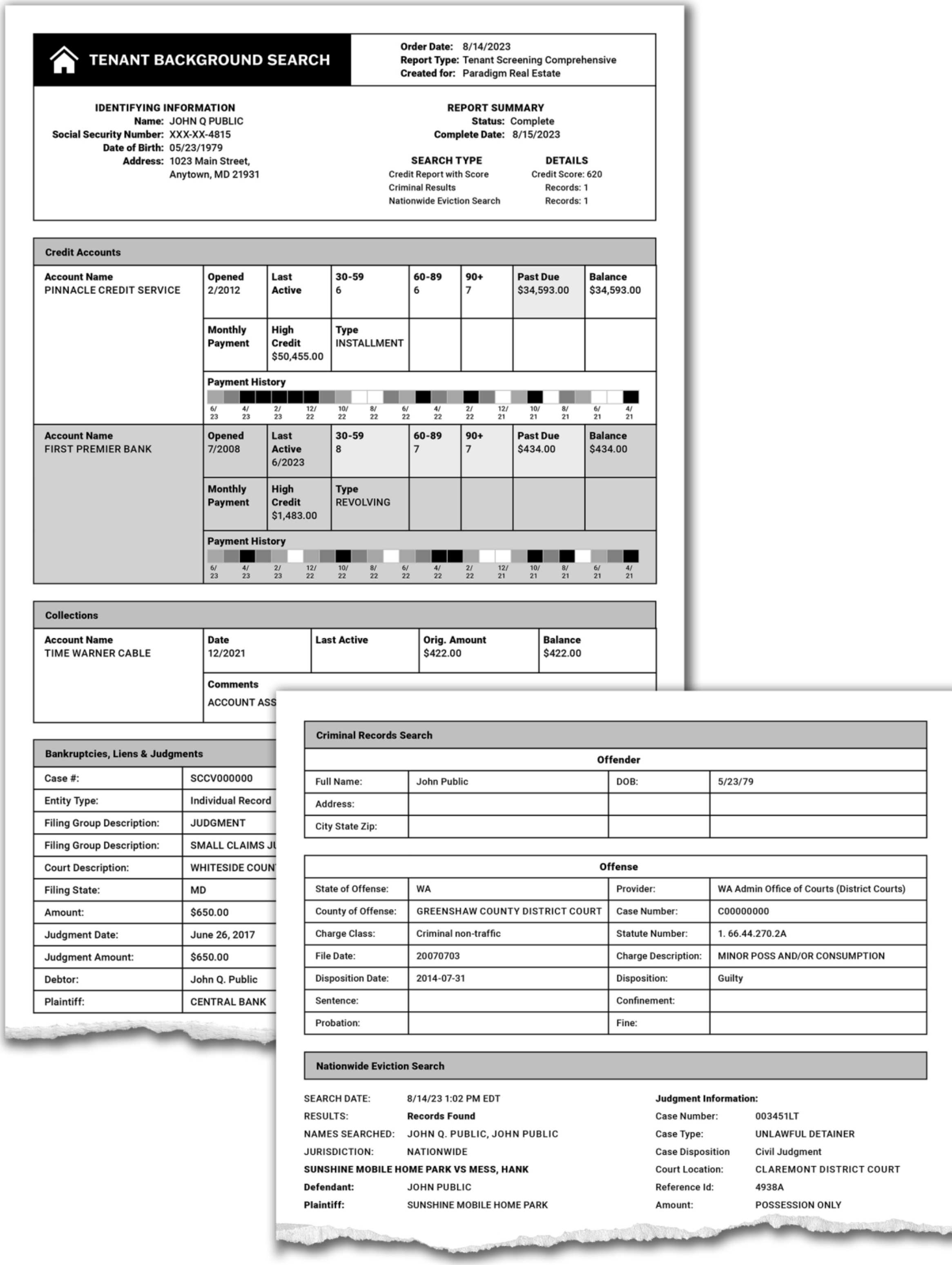
---

[9] In recent decades, some industries have also begun using personal data to deliberately take on *more risk* at a higher price (e.g., subprime lending), but that is not the business model employed here (Baker and Simon 2002; Mays 2004).

[10] Statistically validated scores have existed since at least the 1990s (Rich 2001) yet many respondents, even at larger firms, did not highlight their use. To the best of our knowledge, predictive scores only exist for financial risk and do not include the contents of criminal records. This could change with advances in predictive analytics.

Crucially for us, some landlords and property managers process the information supplied by tenant screening companies with algorithms and others do not (Reosti 2018, 2020; Rosen, Garboden, and Cossyleon 2021). This dichotomy makes the case a compelling one for answering our theoretical question of how exception-making takes shape differently when risk assessment transpires algorithmically, since our case contains built-in comparison.[11] Algorithm use roughly maps onto organization size, with larger firms more likely to employ rules-based assessment (Crowder 2018). In these larger firms, cognition is distributed: senior managers and executives create the screening rules that constitute algorithms, while ground-level employees (e.g., those fielding applications on-site at apartment complexes) apply them. At smaller firms and among sole proprietors, the process generally unfolds from start to finish with just one person. These differences go hand-in-hand with variation in the form information takes. Small and mid-sized organizations typically buy comprehensive tenant screening reports, long documents with fine-grained details about specific individuals. Figure 1 provides a demonstration of such a report. In larger firms, executives create rules by going through lengthy lists of possible infractions—Figure 2 provides a demonstration of such a list—while front-line workers only see the final disposition, as represented by Figure 3. No matter what form the information takes, the underlying content is the same, drawn from the same credit bureaus and courthouses.

[11] It is possible that this divide is related to the historical moment of this study, and that longer term, rental housing will broadly move to algorithmic methods, as other industries, such as credit and insurance, have in the past.



TENANT BACKGROUND SEARCH

Order Date: 8/14/2023
Report Type: Tenant Screening Comprehensive
Created for: Paradigm Real Estate

IDENTIFYING INFORMATION
Name: JOHN Q PUBLIC
Social Security Number: XXX-XX-4815
Date of Birth: 05/23/1979
Address: 1023 Main Street, Anytown, MD 21931

REPORT SUMMARY
Status: Complete
Complete Date: 8/15/2023

SEARCH TYPE	DETAILS
Credit Report with Score	Credit Score: 620
Criminal Results	Records: 1
Nationwide Eviction Search	Records: 1

Credit Accounts

Account Name	Opened	Last Active	30-59	60-89	90+	Past Due	Balance
PINNACLE CREDIT SERVICE	2/2012		6	6	7	$34,593.00	$34,593.00
	Monthly Payment	**High Credit** $50,455.00	**Type** INSTALLMENT				

Payment History
6/23 4/23 2/23 12/22 10/22 8/22 6/22 4/22 2/22 12/21 10/21 8/21 6/21 4/21

Account Name	Opened	Last Active	30-59	60-89	90+	Past Due	Balance
FIRST PREMIER BANK	7/2008	6/2023	8	7	7	$434.00	$434.00
	Monthly Payment	**High Credit** $1,483.00	**Type** REVOLVING				

Payment History
6/23 4/23 2/23 12/22 10/22 8/22 6/22 4/22 2/22 12/21 10/21 8/21 6/21 4/21

Collections

Account Name	Date	Last Active	Orig. Amount	Balance
TIME WARNER CABLE	12/2021		$422.00	$422.00

Comments
ACCOUNT ASS

Bankruptcies, Liens & Judgments

Case #:	SCCV000000
Entity Type:	Individual Record
Filing Group Description:	JUDGMENT
Filing Group Description:	SMALL CLAIMS JU
Court Description:	WHITESIDE COUN
Filing State:	MD
Amount:	$650.00
Judgment Date:	June 26, 2017
Judgment Amount:	$650.00
Debtor:	John Q. Public
Plaintiff:	CENTRAL BANK

Criminal Records Search

Offender

Full Name:	John Public	DOB:	5/23/79
Address:			
City State Zip:			

Offense

State of Offense:	WA	Provider:	WA Admin Office of Courts (District Courts)
County of Offense:	GREENSHAW COUNTY DISTRICT COURT	Case Number:	C00000000
Charge Class:	Criminal non-traffic	Statute Number:	1. 66.44.270.2A
File Date:	20070703	Charge Description:	MINOR POSS AND/OR CONSUMPTION
Disposition Date:	2014-07-31	Disposition:	Guilty
Sentence:		Confinement:	
Probation:		Fine:	

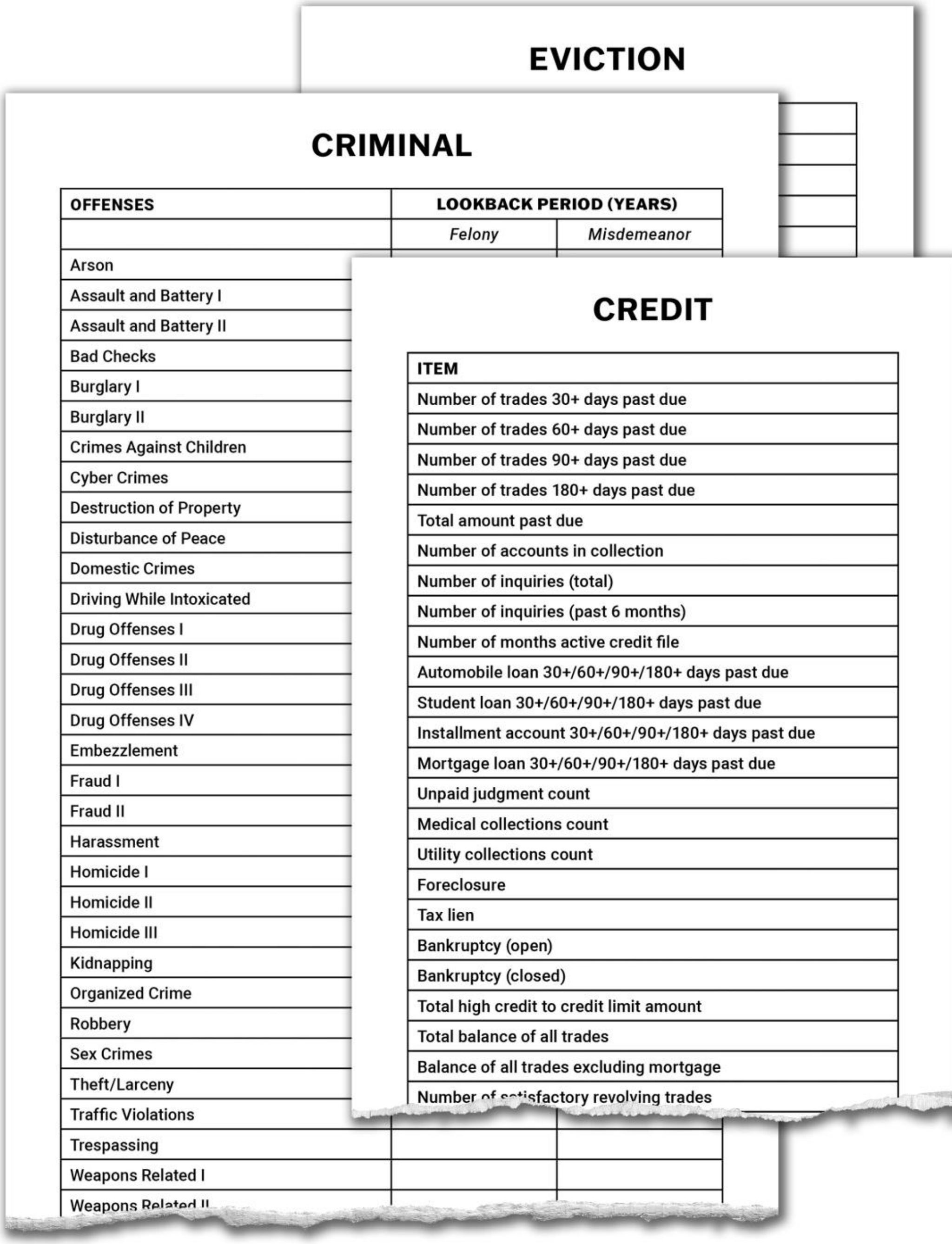
Nationwide Eviction Search

SEARCH DATE:	8/14/23 1:02 PM EDT
RESULTS:	**Records Found**
NAMES SEARCHED:	JOHN Q. PUBLIC, JOHN PUBLIC
JURISDICTION:	NATIONWIDE
SUNSHINE MOBILE HOME PARK VS MESS, HANK	
Defendant:	JOHN PUBLIC
Plaintiff:	SUNSHINE MOBILE HOME PARK

Judgment Information:

Case Number:	003451LT
Case Type:	UNLAWFUL DETAINER
Case Disposition	Civil Judgment
Court Location:	CLAREMONT DISTRICT COURT
Reference Id:	4938A
Amount:	POSSESSION ONLY

Figure 1. Demonstration of a tenant screening report



EVICTION

CRIMINAL

OFFENSES	LOOKBACK PERIOD (YEARS)	
	Felony	*Misdemeanor*
Arson		
Assault and Battery I		
Assault and Battery II		
Bad Checks		
Burglary I		
Burglary II		
Crimes Against Children		
Cyber Crimes		
Destruction of Property		
Disturbance of Peace		
Domestic Crimes		
Driving While Intoxicated		
Drug Offenses I		
Drug Offenses II		
Drug Offenses III		
Drug Offenses IV		
Embezzlement		
Fraud I		
Fraud II		
Harassment		
Homicide I		
Homicide II		
Homicide III		
Kidnapping		
Organized Crime		
Robbery		
Sex Crimes		
Theft/Larceny		
Traffic Violations		
Trespassing		
Weapons Related I		
Weapons Related II		

CREDIT

ITEM
Number of trades 30+ days past due
Number of trades 60+ days past due
Number of trades 90+ days past due
Number of trades 180+ days past due
Total amount past due
Number of accounts in collection
Number of inquiries (total)
Number of inquiries (past 6 months)
Number of months active credit file
Automobile loan 30+/60+/90+/180+ days past due
Student loan 30+/60+/90+/180+ days past due
Installment account 30+/60+/90+/180+ days past due
Mortgage loan 30+/60+/90+/180+ days past due
Unpaid judgment count
Medical collections count
Utility collections count
Foreclosure
Tax lien
Bankruptcy (open)
Bankruptcy (closed)
Total high credit to credit limit amount
Total balance of all trades
Balance of all trades excluding mortgage
Number of satisfactory revolving trades

Figure 2. Demonstration of a list considered by executives while creating tenant screening rules

Figure 3. Demonstration of decision made by a screening algorithm

The Role of Economic Forces

Importantly, housing rental and tenant screening occur in the context of a market, where profit consideration drives decisions, at least to a large extent.[12] A key reason to go against the record, then, might be because a stricter risk mitigation strategy would be less profitable or money-losing. Indeed, scholars show that landlords lower background check standards when they encounter less demand for their units (Clark 2007; Reosti 2020), and, we would surmise, when the applicant pool makes finding unblemished records less likely.[13] In the context of tenant screening, there are two ways to lose money: fail to screen out tenants who later default on the

[12] This reflects that rental housing in the contemporary U.S. is institutionalized as a commodity (Pattillo 2013). While public housing authorities also use background checks, such landlords fall outside the scope of our sample.
[13] Landlords and property managers are also more likely to be lax on background checks when they have other ways to offset risk. For example, landlords care less about pristine credit records when they can mitigate financial loss by collecting an extra security deposit or government-provided rent subsidy (Rosen 2014; Rosen et al. 2021).

rent or otherwise cause problems, or screen out so many tenants that units go unfilled and not enough rent is collected to cover costs in the first place.

Still, invoking an economic concept like supply and demand does little to suggest *how* landlords and property managers come to overlook some background check blemishes but not others. As economic sociologists show time and again, profit-seeking actors do not automatically react to financial pressures, but rather construe their interests and possible courses of action through culturally mediated understandings (e.g., Beckert 2011; Elliott 2021; Livne 2014; Turco 2012). Market forces may push landlords to rent to individuals with marred records, but under such conditions, how do landlords decide which problems to overlook, and when to hold the line? Moreover, how does that process differ according to whether record use is judgmental or algorithmic? These are the questions to which we now turn.

DATA AND METHODS

To understand how landlords and property managers make exceptions for people with blemished background checks, we conducted in-depth interviews with individuals who play a role in leasing decisions. This included individuals who rent housing units they personally own, as well as individuals who work at companies that own and/or manage rental properties.[14] Interviews are well-suited for learning how people understand the world around them and how those understandings guide action (Lamont and Swidler 2014; Weiss 1994). Extant research

[14] The U.S. rental market includes owners of housing who manage it themselves (i.e., "landlords") and those that pay property management companies to so do. We include both in our sample. There are many types of property managers, including real estate agents who manage rental properties on the side, property management firms that cater to individual owners, and property management firms that cater to corporate owners (Gomory 2021; Korver-Glenn 2020).

based on interviews with landlords and property managers shows that how these individuals assign meaning to information shapes leasing decisions (Greif 2022; Reosti 2020; Rosen 2020).

We created a list of landlords and property managers to approach for interviews through a mix of random and purposive sampling. The random element helped make sure our sample was not systematically biased, while the purposive element helped ensure we included hard-to-reach and theoretically significant categories of respondents (Small 2009).

In line with prior studies, we drew an initial sample from rental housing web sites (Boeing and Waddell 2017; Garboden et al. 2018; Garboden and Rosen 2018), focusing on the Durham, N.C. and San Jose, Calif. metropolitan areas. We selected these locations to capture variation in vacancy rate, median rent, and other key metrics that speak to how easy it is for landlords to fill units (Joint Center for Housing Studies of Harvard University 2020). In the findings section below, we discuss the role of economic forces in exception-making processes.[15] We sought to sample properties catering to all segments of the rental housing market: high-end, middle-tier, and low-income. To do this, we used three web sites, including one that showcases more affordable (i.e., low-end) units, and one that includes luxury apartments and other pricey properties. In this way, our study significantly departs from most prior sociological work on rental housing, which generally focuses on low-income and government-subsidized units and excludes the majority of U.S. renters who are not poor or near-poor (Aurand et al. 2022; e.g., DeLuca and Rosen 2022; Desmond 2016; Greif 2018). For seven days in October 2020, we used a random number generator to select 10 listings a day from each web site in each metropolitan area.

[15] In this article, we pool data from across our field sites; in other work, we more systematically compare aspects of the two locations. San Jose became a softer rental market during our study, given the COVID pandemic, but we still had enough variation, both across and within field sites, to identify the role of economic context in exception-making.

PhD students at Duke and Stanford universities contacted individuals associated with each listing to ask if they would participate in our study. To this sample, we added referrals obtained from the initial respondents. Many referrals were small-time owner-operators who we asked to be introduced to, since such landlords are more likely to find tenants through word of mouth and thus be underrepresented in the original sample. When recruiting respondents, we presented the study as about how landlords find good tenants and make other decisions. The interview guide covered multiple aspects of property management but focused on tenant screening. Throughout the interview, we asked respondents for concrete examples to back up any general claims they made. For example, if a respondent said she went easy on applicants with misdemeanors, we asked to hear about the last time she had done so. Given the COVID pandemic, we conducted interviews by video-chat software or telephone. Our respondents seemed comfortable being interviewed by video software, with many using such tools in their own professional endeavors, and we do not believe this mode of interviewing meaningfully influenced our data collection.

The individuals listed in rental ads may or may not be in charge of background screening, and at larger companies, they almost certainly are not. Given that novel information about record use can sit at more senior levels, we also recruited executives at the larger firms captured in our random sample. Kiviat used a business intelligence database to pinpoint who in each organization might best speak to background screening. This author then sought to make contact by email, phone, social media message, and personal introduction. In our final sample, we therefore have respondents from large companies who work directly with tenants (e.g., leasing agents and property managers), as well as respondents whose actions affect would-be tenants from afar, often multiple states away. Respondents in this second group have titles such as regional manager, regional vice president, senior vice president, senior director, vice president of operations, president, and chief executive officer. We refer to these individuals as "executives."[16] This is a second way our study is distinct from prior research on landlords and screening decisions. We offer a line of sight into the decision-making processes of individuals high up in major real estate and property management companies. This is crucial for understanding exception-making because ground-level employees often have reduced information and limited discretion.

As we conducted interviews, we came to appreciate the major role that tenant screening companies play in how landlords and property managers use personal records. Tenant screening companies not only sell data, but also implement standards established at large companies, and even help craft standards. Given this influence, we set out to recruit executives from such firms into our sample. Kiviat attempted to contact individuals at all tenant screening companies used by respondents, and others mentioned in the news. In recent years, the tenant screening industry has come under significant scrutiny, and these were difficult interviews to land. Kiviat aggressively sought to make contact by email, phone, social media message, and personal introduction. This author also pursued individuals who had recently left screening companies, as former executives might feel freer to discuss their work. This author conducted all of these interviews. These interviews represent the third way our study contains data and perspectives absent from prior research on tenant screening.

Our final sample includes 78 respondents who are landlords or property managers, and 10 current and former executives from tenant screening companies. Kiviat and Greene read transcripts of interviews as they were conducted and stopped data collection once new interviews

[16] We do this in part to make research participants less identifiable.

yielded little additional insight (Lamont and White 2008; Small 2009). The research team conducted interviews between October 2020 and April 2021.

Table 1 shows the distribution of respondents by geography, organization type, and organizational role. The landlord and property manager portion of the sample represents 64 distinct entities, since we interviewed more than one person at multiple companies (e.g., a property manager and an executive). Table 1 also shows the percentage of respondents that use credit, criminal, and eviction records in tenant screening. California respondents largely drive the lower frequency of criminal record use. Respondents explained that it was harder to compile criminal records in California and there were legal prohibitions on their use (e.g., bans in the cities of Berkeley, Oakland, and Richmond).

We analyzed our data abductively, toggling between interviews and existing literature (Tavory and Timmermans 2014). To detect empirical patterns, we followed a three-step process that relied on memo-writing and coding of transcript excerpts (Miles and Huberman 1994; Lofland et al. 2006). In the first step, we read interview transcripts, wrote memos to identify processes, themes, similarities, and differences, and met to discuss these observations. In the second step, we developed a set of qualitative codes and then applied these codes to each transcript, using the software Dedoose. In the third step, we read within code across transcript, and wrote another series of memos to capture additional patterns.

As the importance of algorithmic and judgmental analysis emerged, we independently coded which sort of analysis landlords and property managers engaged in and had an outside research assistant do so, as well. This revealed that of the 64 organizations (or sole proprietors) in the landlords portion of our sample, 20 processed information from records algorithmically.[17]

[17] From these organizations, we interviewed 33 different respondents, representing both front-line employees and executives.

Since our sample is not designed to be statistically representative of a larger population, this figure should be understood as a feature of our sample and not as a frequency in the broader U.S. rental market.

Table 1. Sample description

Number of respondents			
Landords and property managers		78	
Current and former executives of tenant screening companies		10	
		Percent of landlords/property managers (N=78)	
Location of enterprise			
CA-only		35%	
NC-only		37%	
Multiple states		28%	
Type of organization			
Individual owner-operator		26%	
Real estate agency with property management services		12%	
Property management company catering to individual owners		19%	
Mid-market owner-operator		3%	
Property management company catering to mid-market owners		8%	
Large corporate owner-operator		24%	
Property management company catering to large corporate owners		9%	
Respondent role			
Property-level/direct tenant interaction		78%	
Executive-level		22%	
Personal data use	*Yes*	*No*	*Don't know*
Credit report	96%	4%	n/a
Criminal record	73%	17%	10%
Eviction history	88%	6%	5%

FINDINGS

Two Worlds of Record Use

Respondents in our sample overwhelmingly understood background screening as a way to avoid undesirable events. The events respondents most cared about avoiding were tenants not paying the rent, damaging the unit or property, and being disruptive or dangerous neighbors. Respondents primarily viewed personal records as tools for deciphering whether would-be tenants posed any of these risks, because they believed that people, to a first approximation, would behave in the future as they had in the past. When we asked respondents to describe their ideal, their answers were strikingly consistent: a credit report without large debts and no late payments or accounts in collection; a clean criminal record; and a lack of eviction history. Across the board, respondents desired tenants with unblemished records.[18]

The reality, however, was that respondents routinely faced records marred in all sorts of ways. Respondents described credit reports showing late payments on credit cards and loans, delinquent debts including money owed to past landlords, utility bills in collection, large amounts of (sometimes unpaid) medical and student loan debt, bankruptcies, foreclosures, judgments for unpaid child support, tax liens, low credit scores, and so on. When it came to criminal records, respondents described seeing charges and convictions for intoxicated driving, assault, drug possession and distribution, fraud, larceny, illegal firearms possession, traffic violations, arson, disturbing the peace, shoplifting, burglary, prostitution, manslaughter, and more. For eviction records, respondents reported seeing both completed and in-process evictions, as well as court judgments for money owed to past landlords.

[18] None of our respondents sought out tenants with compromised records, although that is a possible business model (see Rosen (2014) for an example).

For our respondents, moving from the data in these records to leasing decisions posed an evaluative challenge. Respondents rarely thought that holding out for perfect records was an economic possibility—too many units would go unfilled—and so they had to decide which blemishes should be disqualifying, and which could be overlooked. As one respondent explained, "There's always risk involved, it's just what can we do to minimize the risk." To solve this problem, respondents took two distinct paths, presaged by the literature above.

In *judgmental analysis*, respondents focused on raw data and their interpretation of it. This mode of analysis went hand-in-hand with respondents using full tenant screening reports, as portrayed in Figure 1. Such reports often include scores—whether pure credit scores or composite metrics that also take into account information such as rent-to-income ratio—but respondents frequently downplayed these numbers. Instead, they prioritized the fine-grained details of an applicant's record and how they compared to those of other applicants the respondent had seen. Applicants with extremely bad records relative to what a respondent was used to were quickly rejected. To decide marginal cases, respondents typically asked the applicant for an explanation of what had happened. As an owner-operator with about 120 units explained: "I happily call and say, 'Hey, I see you have a car repossessed, what was the situation there?'... And if they justify it in a way that makes sense, then maybe that's forgivable." The particulars of an applicant's situation, as well as their affective response to it, helped respondents decide whether the infraction suggested the applicant would pose a risk going forward.

In *algorithmic analysis*, by contrast, respondents relied on codified sets of rules. In some cases, these rules were programmed into a computer for automated screening; in other cases, they were manually applied by a respondent consulting a table or matrix of disqualifying infractions. Algorithmic analysis was largely rooted in quantitative measures, from simple counts to composite scores, which had sometimes (though far from always) been shown to correlate with tenant outcomes, such as ending a lease with rent in arrears. Applicants were evaluated by comparing metrics derived from their records to pre-set thresholds. In larger companies, the respondents who applied these rules often knew little about them—at one extreme only receiving information that an applicant had been approved or denied (as demonstrated by Figure 3) — while other, higher-ranking respondents knew about the rules in detail, and in some cases helped develop them.[19]

Broadly speaking, respondents stuck to one mode or the other, even though many were aware of landlords and property managers who did things differently. In drawing comparisons between themselves and others, respondents were often dismissive, describing how automated, algorithmic decisions opened the door to heartlessness, or personal judgment begat bias. As one former tenant screening company executive put it, the industry was made up of two types: those using brain power and judgment, and those with scoring models and standardization.

Which respondents engaged in judgmental analysis and which used algorithms shook out largely as scholars of organizations might expect: Algorithmic analysis corresponded with respondents working in larger, more bureaucratic (rather than organizationally flat) settings. In these firms, algorithmic analysis served multiple purposes, including exercising control over front-line workers and satisfying the demands of third parties, such as investors and fair housing regulators.[20] Indeed, respondents in these organizations often described another sort of risk: the

[19] A number of respondents engaging in algorithmic analysis used the word algorithm.
[20] Or other tenants. One executive told us that running criminal checks was important for marketing purposes—to be able to tell potential applicants that current residents had been criminally vetted. Respondents at large companies also liked how fast decisions could be made algorithmically. As one executive explained: "Just about every big company now can make a decision in two hours. We're all relying on these databases, and I don't know if they're overly reliable or not, but everybody wants a quick decision. Everybody needs a database in order to get that quick decision."

possibility of being sued by the government for treating applicants unequally. In this way, institutional environment factored into respondents' mode of moving from data to decision—as well as their reflexive orientation to it. Algorithm users often denied that they were even making decisions, but rather only doing as the data commanded. As an executive at a national real estate investment trust put it: "There isn't a lot of decision-making in the process, which is exactly what we want."

If one only paid attention to low-level employees at large firms, it might in fact look like algorithmic analysis involved little in the way of judgment and discretion. As an on-site leasing manager for one of the nation's largest property management companies described the process: "The system really does all of the work. We just press a button… [The computer] does the screening and then it shoots out a decision: approved, approved with conditions [e.g., a larger security deposit], or denied… There's not really much that we have to go in and do." Other property-level respondents—i.e., those dealing directly with applicants and tenants—described similar systems, including some that simply produced colors: green for approve, red for deny, and yellow for approve with an extra deposit. In day-to-day implementation, the algorithmic processing of personal records can indeed appear decision-less, as a way of arriving at outcomes that is automatic, impartial, and instantaneous.

Yet, in reality, whether organizations used judgmental or algorithmic methods, someone, somewhere was making—or in the past had made—decisions. And this included decisions about when a record revealing a problematic past could be overlooked.

Exceptions as Counter-Rules

What varied between judgmental and algorithmic analysis was not whether exceptions were made, but how they took shape. While going against the record in judgmental analysis often involved contextualizing the events in a specific applicant's life, exceptions in algorithmic analysis were codified in writing long before any particular applicant came along. Respondents who had a line of sight into how algorithms were created frequently pointed to examples of infractions that were specifically excluded from consideration—medical debt, for example, or unpaid loans below a certain dollar threshold, or misdemeanors, or non-violent felonies more than a certain number of years old. These exceptions were themselves written into the algorithms, as counter-rules capturing the circumstances under which the primary rule of tenant screening—don't rent to individuals with problematic pasts—could be contravened.

Typically, these counter-rules were developed by executives, or teams of executives, and often in conjunction with tenant screening companies.[21] Multiple executive-level respondents recounted the experience of sitting down with someone from a screening company and going through a long (e.g., 12-page) list of infractions, deciding whether or not each would count against applicants, and if so, for how long. As an executive at a property management company described the process: "When you sign up for the service, there's a spreadsheet with criteria that you go through with them… How many late payments do you have on your credit report? How many do you have in collections? What's the dollar amount, all those types of things." (Figure 2 demonstrates what such a spreadsheet might look like.) Or, as another respondent explained: "You've got the ability to look at different felonies and misdemeanor classes and go through and [decide]… [if] someone's been convicted of a murder, it's going to trigger a fail. If they've got a DUI [driving under the influence of alcohol], it's not."

That is to say, executives creating algorithms engaged in the same sort of fine-grained assessment as judgmental users of data, just removed in time and place from decisions about

[21] "Counter-rule" is an etic term, not an emic one.

particular tenants. Nonetheless, exception-making in both judgmental and algorithmic data use depended on the mobilization of commonsense cultural understanding. As an executive at a national owner-operator described the rule-creation process: “A lot of it is just based on how long I’ve been in the industry and what I know works and doesn’t work from my experience. [And] a lot of it [is] my attorney, where my attorney says to me, ‘You know what? I don’t like that a person was driving drunk, but how does that affect them living at your community?’... Kind of the same with credit. We just go through and try to determine, is it a... risk?”[22]

At times, tenant screening companies provided executives with statistical evidence about the connection between past and future behavior (at least for financial outcomes such as ending a lease with rent in arrears), but even then, lay intuitions could break through.[23] Respondents from multiple tenant screening companies discussed chipping away at known correlations at clients’ insistence. For example, landlords and property managers sometimes demanded algorithms exclude certain types of debt, such as those tied to medical bills, even if the data were predictive of tenant outcomes. Clients were also known to demand certain factors remain in, despite the absence of strong correlations. One tenant screening company executive had data showing that evictions more than a few years old no longer really mattered. And yet, as he explained, certain landlords and property managers insisted on excluding applicants with evictions of any age, a reaction he observed as “emotional.”

Despite what the algorithmic use of personal records might look like on the ground—a mechanical application of dispassionate rules—it baked in many of the same interpretive and

[22] Landlords and property managers sometimes ask for advice at tenant screening companies, at which point employees discuss how other executives have wrangled with decisions.
[23] None of our respondents described statistical predictions derived from criminal records. An executive at a leading tenant screening company told us that criminal record data are harder to work with in a statistical framework, given variability in how crimes are categorized across jurisdictions.

discretionary features as judgmental analysis. In the next section, we describe the main process by which this transpired: situational and temporal re-embedding. This cultural process was common across judgmental and algorithmic decision-making. Yet it did not play out identically, which we explore in the following section.

Situational and Temporal Re-Embedding

Administrative records render events in people's lives—defaulting on a loan, being convicted of a crime, getting evicted—as dis-embedded from situational and temporal context. Records, and the databases they feed into, rely on standardized categories that abstract away from the contingency and complication of lived experience (Espeland 1993). This rationalization is not incidental, but part of what makes records useful; it allows them to be compiled at scale and circulated across organizations (Beniger 1986; Gandy 1993). Yet this reduction in information about circumstance and how events fit into life trajectories can later prove problematic for decision-makers trying to parse which events can be safely discounted (Kiviat 2019a). Indeed, our respondents consistently sought to re-embed records in situational and temporal context.

In deciding which infractions to ignore, respondents perennially returned to questions about whether applicants had been the ultimate cause of their background check blemishes; if they were, then whether they had since sufficiently changed; and how logically similar a particular sort of background check blemish was to the events landlords were trying to avoid. To answer these questions, respondents deployed both narrative and analogical reasoning, and in the process often reached for information that sat beyond background check records—such as would-be tenants' motivations, what had (or hadn't) transpired since, the role played by others, and the constraints people in various situations face.

Judgmental users of data typically filled in these gaps by talking to applicants. As an assistant property manager at an apartment complex explained: "We really try to get into detail about what exactly happened, why did it happen, and what was the aftermath? Basically, what kind of a person are you now? Are you most likely going to slip up again?" Most respondents at least partly understood people as variable over time. Respondents recalled applicants with criminal records who had pulled their lives together, and those with financial infractions who now had good-paying jobs and took bills seriously. Through stories, respondents placed background check blemishes into the context of an individual's unfolding life course in order to decipher whether a person was sufficiently different than they had been to be deemed no longer a risk.

Stories also played a key role in how algorithmic users of data constructed counter-rules, although they did not start with specific tenants. Rather, executives drew on cultural narratives about broad classes of people and situations in order to parse whether a blemish ought to be disqualifying. For example, many algorithms were programmed to downplay or ignore medical debt, and, to a lesser extent, student loans. As an executive at a company that manages thousands of units explained the decision: "The theory is that some of those events came about beyond [people's] control. They made a commitment to get their education but haven't been able to find the right job to pay off all of the debt. [Or] they had a catastrophic medical event… If we think that good credit and payment histories are predictors of your behavior as a renter, it make[s] sense to remove some of those things that are one-off in nature." With narrative, respondents reasoned through whether a particular type of blemished record indicated a personal (and ostensibly repeatable) failing, or forces that transcended the individual.[24]

[24] Beliefs about the moral standing of certain debts also likely played a role given that people tend to view morally legitimate actions as less risky (Douglas 1985; Douglas and Wildavsky 1982).

Respondents also invoked temporal arcs more broadly. Many described time limits for particular offenses—overlooking debts in collection more than five years old, non-violent crimes more than two, and so on. A blemish with a subsequent infraction-free period signaled changed ways. For example, the president of one property management firm justified creating a rule to ignore bankruptcies more than three years old by explaining: "If you've shown responsibility to clean up the mess that you left behind, that tells [me] a lot about the person."

Yet time passing meant more for some infractions than others. Blemishes that respondents considered to be most situationally similar (or analogous) to the events they were hoping to avoid were less likely to be overlooked. Many respondents, for example, discussed ignoring some number of missed payments on credit reports, especially when they were small in value or distant in time—but that flexibility nearly always disappeared if the creditor was a former landlord, or even just a provider of housing-related services, such as a utility company. When respondents construed a debt as adjacent to the act of renting, then exceptions were less likely.

This was nowhere more apparent than in how respondents talked about eviction records. These were the infractions for which respondents had the least tolerance, using phrases such as "deal breaker" and "showstopper." Evictions certainly represented an extreme risk in that they can be very costly for landlords, but the possible money at stake was not the only factor driving respondents' reaction. Many respondents also sympathized with landlords who had gone through evictions, at times imagining themselves in a prior landlord's place, dealing with missed rent or a unit left in bad condition.[25]

---

[25] Some respondents did distinguish between eviction *filings* and eviction *judgments*, since in the former case, a court had yet to render its verdict.

Indeed, for many respondents, owing any amount of money to a past landlord, eviction or not, was an "automatic fail." The connection between past and future behavior was logically tight, given that the record portrayed the exact situation respondents sought to avoid. Respondents saw little room for extenuating circumstance.[26] As one property manager said: "A leopard don't change his spots." Respondents typically understood applicants who had done wrong by past landlords as all of the same type—ones who would do so again. Now, that doesn't mean landlords never made exceptions for eviction records. Indeed, some occasionally did, which we detail below, but the path overall was narrow.

Notably, we observed more wiggle room for applicants with criminal records.[27] While a good number of respondents did automatically eliminate applicants with felony records (the more serious category of crime indicating too extreme a risk), most respondents described carefully sorting through misdemeanors, parsing which were related to being a tenant and which were not. Respondents did not always come to the same conclusions. For example, some turned down applicants with drug offenses, while others ignored such charges. Yet the method of narrative and analogical reasoning remained consistent. Those who took a hard stance on drug offenses explained their position by describing how past involvement with drugs would logically translate into a bad tenancy—citing, for instance, the chances of unsavory individuals visiting the property, or the risk posed to other tenants' children. Those who exempted drug offenses simply saw them as unrelated.

[26] Scholars of eviction document potentially extenuating circumstances, including landlord-tenant disputes over property repair and landlords filing for eviction to empty a property of residents (Consumer Financial Protection Bureau 2022; Desmond 2016; Leung, Hepburn, and Desmond 2021).
[27] That eviction history is more meaningful than criminal history comports with Clark (2007)'s survey data and So (2022)'s experimental results.

In sum, whether using records judgmentally or algorithmically, respondents engaged in a process of temporal and situational re-embedding, since background check records on their own often lacked important context. Yet, as we explore next, when respondents sought out such context and where they turned to retrieve it systematically varied, with consequences for which sorts of exceptions were more or less likely to be made.

Differences in Algorithmic and Judgmental Exception-Making

Respondents who used personal records algorithmically often said they did not make exceptions. Many cited fair housing law and the specter of discrimination as reasons all applicants must be treated the same, even when there was reason to do otherwise. As an executive at a real estate investment trust explained: "It really weighs on you if someone comes to you and says, 'I left an abusive relationship... I have all of this debt. I have two kids. I don't know what to do.' It's so hard. I have been in the position where I've had to tell them, 'You know, as much as I feel for you and your circumstance... I have to screen you the same as everyone else.'"

Yet as we've seen, even if algorithmic users of data steered clear of ad hoc exceptions, they nonetheless made more systemic ones through the carve-outs they wrote into algorithms, allowing some but not other marred records to be disregarded. This shift from one-off exception-making to counter-rules was consequential for two reasons. First, it meant that algorithm users made exceptions not for particular people, but for particular *categories* of people. Second, it meant that deciding what constituted permissible exceptions no longer occurred at the same time as tenants applying for units. These distinctions mattered in multiple ways (summarized in Table 2).

Table 2. Differences in judgmental and algorithmic exception-making

	Judgmental	*Algorithmic*
Unit of analysis	Individual applicant	Category of applicant
Moment of exception	Contemporaneous	In advance
Style of exception	Ad hoc	Systematic counter-rule
Stories called upon	Individual life histories	Cultural narratives
Meaning-making	Co-constituted	Organizationally determined
Effect of record design	Influence	Constraint
Variety of exceptions	Broad but inconsistent	Narrow but consistent

Consider one facet described above: that respondents at times went against the record because they attributed the cause of a background check blemish to forces beyond an applicant's control or because they felt a would-be tenant had changed her ways. Respondents using records judgmentally drew these conclusions by scouring records for telling details and interacting with applicants. As one landlord explained: "If somebody has a bad collections on their credit report, I ask them directly, 'What happened?'" Delving into specific applicants' situations was not an option for executives creating the rules that powered algorithms, because such rules were created long before specific applicants came along. Executives therefore relied on assumptions about *kinds* of applicants, and what the stories behind their background check blemishes *would likely be*. Sitting in offices, deciding which infractions could be overlooked, executives drew on cultural archetypes—the student overwhelmed by the debt that had paid for her education, the one-time drug dealer who had turned his life around, and so on.

This was consequential because some situations were easier to imagine in advance than others. Only the most common and culturally salient scenarios made it into the discussion. While some of the exception-worthy situations recounted by respondents using records judgmentally were idiosyncratic and nuanced—a couple, for instance, whose bad credit originated with being in an airplane crash—the exceptions described by respondents using algorithms were more formulaic. In this way, judgmental users of records were able to entertain a broader range of exceptions.

Judgmental use of records also allowed for more serious infractions to be granted exceptions. For example, nearly all respondents took a hard stance against renting to applicants with sex offenses on their criminal records. Yet one judgmental user of data, a property manager who normally felt that way, discussed renting to one such person because of the particulars of the situation, gleaned from interactions with the applicant and extra documents he provided. As she explained: "The story was, he was [an] 18-year-old kid in high school with a 17-year-old [girlfriend], and the parents went after him... He actually had the documentation to show this was a genuine relationship in high school… So, you hear the story, and it's like, well gosh. I can't just look at your criminal history and take it for what it's worth." Judgmental record users were also more likely to make exceptions for applicants with evictions, a process that unfailingly involved digging into the specifics a person's situation and probing for extreme circumstances—a history of domestic violence was repeatedly held up as the quintessential example. As one landlord explained, "The more research I can do, the better."

What it all added up to: In our interviews, both judgmental and algorithmic users of data described offenses they thought might occasionally deserve an exception, but only judgmental users of data could act on those occasions. For algorithmic users of records, including an exception as a counter-rule meant *consistently* overlooking an infraction—and so if, *in most cases*, the infraction suggested risk, the counter-rule was not included and no exceptions were made. That is to say, a type of infraction that respondents thought could go either way—one that could indicate continued risk or not—was hard to write into a counter-rule, but easy to grapple with judgmentally, since respondents could gather more information about the particular case at hand.

The flip side of this was that if an infraction did come to be associated with an exculpatory cultural narrative, then everyone whose record contained that infraction benefited. One executive, for example, reported that in the wake of the 2007-2008 financial crisis, her company created a rule to ignore foreclosures on credit reports because of all of the "bad loans" people were experiencing during "that trying period." This understanding of the situation—of borrowers sold substandard mortgages and pummeled by dropping property values—applied equally to everyone with a foreclosure on their record, not just to applicants who offered up a personal story of misfortune. Going against the record with counter-rules meant that a smaller set of exceptions made it through, but those that did were broadly applied.

Algorithmic users of data were constrained by another reality, as well: administrative records reduce lived experience to a particular set of categories, which only partially capture the circumstances of people's lives. Both algorithmic and judgmental users of data described making exceptions for people who had been overwhelmed by medical debt, fallen behind on student loans, or lost a house to foreclosure. These events in people's lives were easy to carve out of an algorithm because credit reports come with categories capturing each sort of debt and whether borrowers are paying it off on time. By contrast, credit reports do not include checkboxes for when bad credit is caused by divorce, involuntary job loss, or domestic abuse. These were all circumstances that judgmental, but not algorithmic, users of records at times made exceptions for. Since algorithmic counter-rules had to be written in the language of records—a language created by credit bureaus and courts for their own purposes—some potentially extenuating circumstances were impossible to operationalize.

These dynamics also took hold in how record users accounted for the passage of time and a person's potential for change. Nearly all respondents using data algorithmically described look-back periods that varied based on the seriousness of the infraction. These counter-rules were easy to implement because administrative records include a surfeit of dates—when a payment was missed, a court judgment was handed down, and so on. Yet limiting the influence of a background check blemish to a set number of years was a blunt tool, one that assumed journeys of self-improvement occurred at a single speed. By contrast, judgmental users of data, who were focused on distinct individuals, described assigning weight to other sorts of information, as well, such as applicants' expressions of contrition and evidence that they now led a better life (e.g., being in Alcoholics Anonymous, completing a college degree, or holding down a steady job).

This ability to consider other aspects of an applicant's life also helped respondents using data judgmentally deal with the absence of information—in particular, applicants without credit history. Many respondents considered no credit record to be a red flag, unless the applicant was just out of school or new to the U.S. Judgmental users of data often took these life trajectories into account. One respondent, for example, described renting to a recently arrived Iranian family, while saying he would not have done so had the family been in the country a long time. "This is a country of immigra[nts]... so you never want to punish anybody for that," he said, "[but] if they've been in the country for five [or] ten years, and they haven't established credit history, that's [bad]." Some respondents using data algorithmically accepted applicants with no credit record with a larger security deposit, but they lacked a way to encode immigrant status into a counter-rule, since that information did not exist in background check records.

In a way, it might seem that the main difference between the two modes of exception-making was that judgment left room for storytelling, while algorithms necessitated placing applicants into (at times ill-fitting) categories. Yet stories were also part of the creation of counter-rules, just as generalized cultural narratives. What judgmental analysis uniquely allowed for were *individual-level* stories, and for those stories to be emergent, not pre-ordained. Whether reading records interpretively to piece together the arc of an individual's life or calling up the applicant to let them offer a story of their own, judgmental users of records were able to take into account the "whole" person. This, in effect, was recognition of the fact that the complexity of life was often difficult to demarcate in the abstract in advance, as algorithms necessarily do.

One implication of this was that with judgmental, but not algorithmic, data use, would-be tenants could participate in the process of situational and temporal re-embedding. When respondents asked applicants for their stories, the significance attached to the record was co-created, with applicants playing an active role in shaping interpretations about what particular infractions meant, and whether they indicated future risk. Applicants' self-narrations provided lenses through which respondents read records. By contrast, the meaning-making phase of algorithmic data use transpired far in advance, and the meanings executives assigned to blemishes were already locked in.

That is not to say that meaning could never be changed at companies using data algorithmically. Applicants could in some cases still contest records—claiming inaccuracy, if not always extenuating circumstance—but this necessarily happened after the algorithm rendered its verdict.[28] Applicants might be able to dispute a marred record having excluded them from

[28] Most algorithm users described a process for contesting inaccurate records at the background screening company. The results of such appeals are beyond our scope, but other scholars show that correcting mistakes in records can be a byzantine process (Consumer Financial Protection Bureau 2022; Lageson 2020; Kleysteuber 2007). Some respondents also described appeals for extenuating circumstances. These typically involved off-site managers reviewing cases. An applicant's pathway to an exception here was narrower—many companies did not allow appeals at all, and among those that did, the process meant scrutiny by people removed from local context considering written rather than interactional accounts.

housing, but the task was to argue against an established meaning—to change a determination of risk—more of an uphill battle than helping to create meaning in the first place.

Moreover, only with judgmental data use could applicants offer their version of events first, pre-empting what records had to say. In fact, a number of respondents using data judgmentally assigned importance to applicants with blemished records mentioning those problems before the background check was even conducted. Voluntary disclosure was seen as the mark of a transparent, less risky tenant.[29] As one individual owner-operator said: "I tend to really value people that are upfront and honest… They'll tell you before they apply to give you a forewarning." This opportunity, to set the stage for what was to be revealed in one's records, was denied to applicants at companies using data algorithmically. Multiple property-level respondents told us that applicants often tried to pre-emptively offer explanations for bad records, but there was simply nothing for them to do with the information.

The Role of Economic Forces Redux

The dynamics of going against the record that we've described so far largely reflect the importance of both cultural understanding and the constraints imposed by the structure of administrative records. In this final findings section, we return to an earlier issue: the role of economic forces, given the market context of our case.

Respondents in our sample overwhelmingly felt that holding out for tenants with perfect records would prove too costly in terms of units sitting vacant, which is what set them down the path of exception-making. Yet how fast they went down that path at times depended on other economic factors. As an owner of a property management company using records judgmentally explained: "It is a very strong market for rentals right now... so if I've got to wait another few

[29] This aligns with advice tenants receive from housing experts (McCabe 2022).

days for a better applicant, I'm going to do that." Respondents using records algorithmically broadly shunned such picking and choosing, often emphasizing that fairness meant holding all applicants to the same standards. But standards themselves could change in response to economic pressures. Algorithm-using respondents described across-the-board cuts when seasonal demand was low, when a new building first opened and managers were under pressure to quickly fill it, and when a property was up for sale and executives wanted potential buyers to see it at capacity.

Respondents also recounted leniency in certain market segments, if a property was in a less affluent building or part of town. Phrases respondents used to describe such buildings and areas included "working class," "blue collar," "affordable," and "troubled." For algorithmic users of data, this again meant that a different set of rules might apply. Some respondents described thresholds as variable at the level of the metro area, or even particular apartment buildings. These respondents often indicated being more forgiving of background check problems at "class C" (vs. "A" and "B") buildings, referring to a lettering system used by investors to indicate a building's age, location, and amenities. As a broker at one real estate agency explained: "When you go to a property where it's going to be renting for a lower amount, you do become more flexible in what you can deal with... You're not going to find too many 800 credit score people who are looking to live in a 333 square foot studio."

The practices of going against the record that we've documented in this article were nested within these more generalized economic concerns. Market forces at times led landlords and property managers to relax their standards, but to understand how they did so—to make sense of how they parsed which infractions could be overlooked and which could not—our insights about situational and temporal re-embedding and the differences between judgmental and algorithmic exception-making remain crucial. No matter the economic conditions, the processes we identify remained markedly consistent. Market forces did not supplant cultural understandings and the constraints imposed by record structure, but rather worked *through* them.

DISCUSSION

As organizations increasingly use algorithmic rather than judgmental methods to evaluate the risks individuals pose, how does exception-making change? In this article, we've shown that in the case of tenant screening, going against the record to rent to a tenant with a blemished past is still permeated with the sorts of interpretation, intuition, and discretion that is the hallmark of judgmental evaluation. In line with extant literature (e.g., Brayne and Christin 2021; Gillespie 2018; Gray and Suri 2019; Seaver 2018), human reasoning does not disappear, but is instead relocated. While algorithms may come off as dispassionate and mechanical, behind that façade is a history of judgment calls about which infractions should be ignored, and when people ought to have their pasts overlooked. Records are thin versions of reality, and decision-makers of all kinds turn to situational and temporal re-embedding to re-inflate them with social meaning.

The difference, as we've shown, is that with algorithms, exceptions get codified into counter-rules, which means that exception-worthy circumstances are not constructed in real time, but articulated far in advance, and necessarily in ways that are interoperable with records' classification systems. Those determining exceptions contemplate would-be tenants not as individuals, but as categories, and not just any categories, but ones that are both culturally accessible to the executives making decisions and legible to the institutions producing databases. Cultural understanding still helps gatekeepers move from data to decision, but generic narratives replace life histories, record design becomes a hard constraint rather than a suggestive influence, and the people about whom decisions are made get boxed out of the meaning-making process.

Taken together, these findings document some of the downstream consequences of algorithmic systems relocating discretion. For individuals with background check blemishes, the use of algorithms in risk-assessment decisions does not preclude the possibility of leniency but does change the nature of it—even when gatekeepers' intuitions about who deserves a break are broadly the same. As Christin (2020a:898) notes, algorithms are "complex sociotechnical assemblages involving long chains of actors, technologies, and meanings" (see also, Gillespie 2016). Algorithms stretch the process of decision-making across time and place, and here we see how that shapes which decisions are possible.

What does this mean for the sorts of exceptions made? While the judgmental use of records allows for a broad range of exceptions, algorithms narrow the field. Reasons for going against the record must be imaginable (and programmable) in advance, and by executives whose social location undoubtedly shapes the examples of forgivable infractions that come to mind. Lay assessments of risk depend on events being cognitively available (Heimer 1988; March 1994:36), which means that with algorithms, rare situations are unlikely to garner exceptions, as are those uncommon to higher-ups at real estate companies—typically educated and class-advantaged individuals. By contrast, with judgmental data use, opportunities for applicants to co-construct meaning provide pathways for landlords to consider situations they never would have thought about on their own, or which, on first pass, seem to justify exclusion.

At the same time, there is a trade-off to the breadth of exception-making characteristic of judgmental data use. Judgmental users of data are quicker to adapt to the particulars of the applicant in front of them, which means that an infraction granted an exception one day may not be the next. With algorithms, exceptions do not depend on how landlords feel about an applicant, who else is in the applicant pool, or a would-be tenant's ability to tell a culturally resonant story about their past. This may block moments of much-deserved compassion and understanding, but also the sorts of bias routinely documented in decision-making (Evans and Porter 2015; Lempert and Monsma 1994; O'Brien and Kiviat 2018). Indeed, that is a big part of the appeal. Algorithms restrict the discretion of employees dealing directly with tenants, which helps companies claim that proscribed traits, such as race and sex, do not factor into decisions.

Implications for Stratification, Bias, and Discrimination

Of course, there is now a robust literature on how algorithms nonetheless *indirectly* reproduce social patterns, including those tied to systemic disadvantage (Barocas and Selbst 2016; Benjamin 2019; Gandy 2009; Noble 2018). That will certainly be the case here. Black Americans, for example, are more likely to have bad credit, criminal convictions, and a history of eviction, in no small part because of practices such as redlining, predatory lending, and mass incarceration (Federal Reserve 2007; Hepburn, Louis, Desmond 2020; Shannon et al. 2017). Algorithmically using records without accounting for these inequities reproduces those patterns.

Yet what our study suggests is that the original pathway—the one algorithms supposedly block—never fully goes away, either. Since algorithms don't get rid of judgment, intuition, and discretion, but only relocate these interpretive aspects of decision-making, algorithms also don't get rid of the potential for bias and stereotype. That, too, is simply relocated. As we've shown, the construction of counter-rules involves calling upon cultural archetypes and narrative tropes. As executives consider which records deserve forgiveness and which don't there is still space for racialized, gendered, and class-based assumptions to influence rule creation. One might assume that using statistically validated correlations averts the problem. But building models divorced from intuitive understanding is often easier said than done, especially when multiple stakeholders are involved (Kiviat 2019b). Cultural mechanisms persist, and therefore so do openings for culturally derived bias.

More broadly, our study carries implications for scholars attentive to the influence of records on life chances. Many Americans carry negative credentials: between 70 and 100 million Americans have a criminal record (Leasure and Andersen 2016); nearly a third of credit reports show at least one debt in collections (Ratcliffe et al., 2014); and nearly 3 million households receive an eviction notice each year (Gromis et al. 2022). When organizations use records of individuals' pasts to allocate resources, these blemishes bring the potential for cumulative disadvantage. Cycles of disadvantage can be disrupted: landlords' willingness to make exceptions is a testament to that. Yet the notion that algorithms do this unproblematically by treating all applicants equally is, as we've seen, misleading. Algorithms may make exceptions consistently, but the content of those exceptions still sets apart some people from others—and in ways that are constrained by the decision to process information algorithmically. At times, executives making counter-rules were amenable to extenuating circumstances that they simply weren't able to operationalize algorithmically.

Lessons for Making Decisions with Rules and Records

To return, then, to Weber's iron cage, we might ask why the strong version of that vision doesn't come to pass—why do judgment and discretion perennially find a new home? One way of understanding what we have witnessed in this article is as what happens when decision-makers insist that rules be "thin" rather than "thick." As the historian Lorraine Daston (2022) explains, reliance on thin rules—those abstracted away from context and decision-making authorities—is largely a modern feat. In earlier periods, rule systems often went hand-in-hand with what we call exceptions, but which were then simply seen as part of an authority applying the rules. Thin rules have rhetorical appeal—they lend an aura of objectivity and let people to say things like "there isn't a lot of decision-making in the process." Yet for individuals in organizations to actually make decisions, or at least ones they're satisfied with, thickness may be necessary. People try to enact the Weberian ideal of efficiency and fairness via thin, algorithmic rules, but in practice this is insufficient, so actors return to other forms of (cultural) understanding.

Yet it's not just rules that are thin, but also the information fed into them. Reducing people in ways that they can be recorded in the databases of credit bureaus and courts necessarily leaves out substantial information about individuals' lives (Beniger 1986; Espeland 1993; Kiviat 2023). At times, executives making counter-rules were sympathetic to contingencies that weren't visible in the data they had to work with. While some sorts of information are harder to record in databases, what is also true is that the records landlords and property managers use are not created with them in mind. As personal data increasingly circulate from one domain of life to another, certain organizations wield power by virtue of their ability to decide what information will—and won't—be recorded. Credit bureaus and courts make decisions with certain constituencies in mind, and when other organizations come along and use the data in novel settings, gaps arise, including ones that restrict the ability to make desired exceptions.

Scope Conditions and Future Research

One feature of the case presented here is its market context. This raises the question of whether we would expect to see similar dynamics when records are used by non-market actors to assess the chances of recidivism, child endangerment, and the like. We think we would—that our high-level take-aways about situational and temporal re-embedding and the limitations imposed by articulating exceptions as counter-rules would still apply. What we would expect to be different is the reason for exception-making in the first place. In our case, profit consideration led gatekeepers to consider individuals with blemished records. In other contexts, the impetus might be political pressure, moral concern, or something else. That is, given a different institutional field, we might observe a different set of imperatives leading gatekeepers to want to be more or less forgiving of checkered pasts. Nonetheless, we believe the theoretical processes we've outlined would still transpire to dictate how some, but not other, exceptions came to be made.

Another scope condition of our case is that, even though tenant screening algorithms are deployed in markets, tenant selection is not a core profit center for most landlords. The literature on algorithms in markets (e.g., Fourcade and Healy 2017; Zuboff 2019) tends to assume that algorithms are valuable for how they boost internal efficiencies and increase profit. Yet in the case of rental housing, many actors seem content in managing downside risk to a first approximation. Especially for larger companies, algorithms accomplish other important tasks such as signaling compliance with fair housing law. A skeptic might say that this is what allows our algorithm-using respondents to go against the record so easily: that there is space for cultural understanding to play a formative role precisely because landlords and property managers are not scrambling to extract incremental gain from these algorithms.

Yet this, we surmise, is not so much an anomaly as a good reminder. Our suspicion is that the multi-faceted drive toward algorithm use that we observe in our setting is not unusual. There are plenty of reasons for organizations to adopt rules-based decision-making, including many that leave room for selectively ignoring individuals' problematic pasts—whether that means going against the record one person at a time or more systematically.

REFERENCES

Ajunwa, Ifeoma. 2019. "The Paradox of Automation as Anti-Bias Intervention." *Cardozo Law Review* 41(5):1671-1742.

Albright, Alex. 2019. "If You Give a Judge a Risk Score: Evidence from Kentucky Bail Decisions." Unpublished manuscript.

Aurand, Andrew, Dan Emmanuel, Matthew Clarke, Ikra Rafi, and Diane Yentel. 2022. *The Gap: A Shortage of Affordable Homes*. National Low Income Housing Coalition. Accessed Jan. 16, 2022 (https://nlihc.org/sites/default/files/gap/Gap-Report_2022.pdf).

Baker, Tom and Jonathan Simon. 2002. "Embracing Risk." Pp. 1-26 in *Embracing Risk: The Changing Culture of Insurance and Responsibility*, Tom Baker and Jonathan Simon, eds. Chicago: University of Chicago Press.

Barocas, Solon and Andrew D. Selbst. 2016. "Big Data's Disparate Impact." *California Law Review* 104:671-732.

Beck, Ulrich. 1992. *Risk Society: Towards a New Modernity*. Translated by Ritter, Mark. London: Sage Publications.

Beckert, Jens. 2011. "Where Do Prices Come From? Sociological Approaches to Price Formation." *Socio-Economic Review* 9(4):757-786.

Beniger, James R. 1986. *The Control Revolution: Technological and Economic Origins of the Information Society*. Cambridge, MA: Harvard University Press.

Benjamin, Ruha. 2019. *Race After Technology: Abolitionist Tools for the New Jim Code*. Cambridge, UK: Polity Press.

Bielby, William T. 2000. "Minimizing Workplace Gender and Racial Bias." *Contemporary Sociology* 29(1):120-29.

Boeing, Geoff, and Paul Waddell. 2017. "New Insights into Rental Housing Markets across the United States: Web Scraping and Analyzing Craigslist Rental Listings." *Journal of Planning Education and Research* 37(4):457-76.

Bosk, Emily Adlin. 2018. "What Counts? Quantification, Worker Judgment, and Divergence in Child Welfare Decision Making." *Human Service Organizations: Management, Leadership & Governance* 42(2):205-224.

Bosk, Emily A. 2020. "Iron Cage or Paper Cage? The Interplay of Worker Characteristics and Organizational Policy in Shaping Unequal Responses to a Standardized Decision-Making Tool." *Social Problems* 67:654-676.

Bovens, Mark and Stavros Zouridis. 2002. "From Street-Level to System-Level Bureaucracies: How Information and Communication Technology Is Transforming Administrative Discretion and Constitutional Control." *Public Administration Review* 62(2):174-184.

Bowker, Geoffrey C. and Susan Leigh Star. 1994. "Knowledge and Infrastructure in International Information Management." Pp. 187-213 in *Information Acumen: The Understanding and Use of Knowledge in Modern Business*. London: Routledge.

boyd, danah and Kate Crawford. 2012. "Critical Questions for Big Data." *Information, Communication & Society* 15(5):662-679.

Brayne, Sarah, and Angèle Christin. 2021. "Technologies of Crime Prediction: The Reception of Algorithms in Policing and Criminal Courts." *Social Problems* 68(3):608-624.

Brayne, Sarah. 2021. *Predict and Surveil: Data, Discretion, and the Future of Policing*. New York: Oxford University Press.

Burrell, Jenna and Marion Fourcade. 2021. "The Society of Algorithms." *Annual Review of Sociology* 47:213-37.

Canales, Rodrigo. 2014. "Weaving Straw into Gold: Managing Organizational Tensions Between Standardization and Flexibility in Microfinance." *Organization Science* 25(1):1-28.

Carruthers, Bruce. 2013. "From Uncertainty Toward Risk: The Case of Credit Ratings." *Socio-Economic Review* 11(3):525-55.

Christin, Angèle. 2017. "Algorithms in Practice: Comparing Web Journalism and Criminal Justice." *Big Data & Society* 2:1-14.

Christin, Angèle. 2020a. "The Ethnographer and the Algorithm: Beyond the Black Box." *Theory and Society* 49:897-918.

Christin, Angèle. 2020b. "What Data Can Do: A Typology of Mechanisms." *International Journal of Communication* 14:1115-1134.

Clark, Lynn M. 2007. "Landlord Attitudes toward Renting to Released Offenders." *Federal Probation* 71(3):20-30.

Clarke, Lee and James F. Short. 1993. "Social Organization and Risk: Some Current Controversies." *Annual Review of Sociology* 19:375-399.

Consumer Financial Protection Bureau. 2022. *Tenant Background Checks Market*. Washington DC: Consumer Financial Protection Bureau.

Crowder, Kyle. 2018. *Seattle Rental Housing Study*. Center for Studies in Demography and Ecology. Seattle, WA: University of Washington.

Crozier, Michel. 1964. *The Bureaucratic Phenomenon*. Chicago, IL: University of Chicago Press.

Daston, Lorraine. 2022. *Rules: A Short History of What We Live By*. Princeton, NJ: Princeton University Press.

De-Arteaga, Maria, Riccardo Fogliato, and Alexandra Chouldechova. 2020. "A Case for Humans-in-the-Loop: Decisions in the Presence of Erroneous Algorithmic Scores." ACM Conference on Human Factors in Computing Systems (ACM CHI).

DeLuca, Stefanie, and Eva Rosen. 2022. "Housing Insecurity Among the Poor Today." *Annual Review of Sociology* 48(1):343-71.

Desmond, Matthew. 2016. *Evicted: Poverty and Profit in the American City*. New York: Crown.

DiMaggio, Paul J. and Walter W. Powell. 1983. "The Iron Cage Revisited: Institutional Isomorphism and Collective Rationality in Organizational Fields." *American Sociological Review* 48:147-160.

Dobbin, Frank, Daniel Schrage, and Alexandra Kalev. 2015. "Rage against the Iron Cage: The Varied Effects of Bureaucratic Personnel Reforms on Diversity." *American Sociological Review* 80(5):1014-1044.

Douglas, Mary. 1985. *Risk Acceptability According to the Social Sciences*. New York: Russell Sage Foundation.

Douglas, Mary and Aaron Wildavsky. 1982. *Risk and Culture: An Essay on the Selection of Technical and Environmental Dangers*. Berkeley, CA: University of California Press.

Dunn, Eric, and Marina Grabchuk. 2010. "Background Checks and Social Effects: Contemporary Residential Tenant-Screening Problems in Washington State Residential Tenant-Screening." *Seattle Journal for Social Justice* 9(1):319-400.

Elliott, Rebecca. 2021. *Underwater: Loss, Flood Insurance, and the Moral Economy of Climate Change in the United States*. New York: Columbia University Press.

Espeland, Wendy. 1993. "Power, Policy and Paperwork: The Bureaucratic Representation of Interests." *Qualitative Sociology* 16(3):297-317.

Espeland, Wendy Nelson and Berit Irene Vannebo. 2007. "Accountability, Quantification, and Law." *Annual Review of Law and Social Science* 3:21-43.

Eubanks, Virginia. 2017. *Automating Inequality: How High-Tech Tools Profile, Police, and Punish the Poor*. New York: St. Martin's Press.

Evans, Douglas N., and Jeremy R. Porter. 2015. "Criminal History and Landlord Rental Decisions: A New York Quasi-Experimental Study." *Journal of Experimental Criminology* 11(1):21-42.

Federal Reserve System, Board of Governors. 2007. *Report to the Congress on Credit Scoring and Its Effects on the Availability and Affordability of Credit*. Washington DC: Federal Reserve System.

Fourcade, Marion and Kieran Healy. 2013. "Classification situations: Life-chances in the Neoliberal Era." *Accounting, Organizations and Society* 38:559-572.

Fourcade, Marion and Kieran Healy. 2017. "Seeing Like a Market." *Socio-Economic Review* 15(1):9-29.

Gandy, Oscar H. 1993. *The Panoptic Sort: A Political Economy of Personal Information.* Boulder, CO: Westview Press.

Gandy, Oscar H., Jr. 2009. *Coming to Terms with Chance: Engaging Rational Discrimination and Cumulative Disadvantage*. Burlington, VT: Ashgate Publishing Company.

Garboden, Philip M. E., and Eva Rosen. 2018. "Talking to Landlords." *Cityscape* 20(3):281-91.

Garboden, Philip M. E., Eva Rosen, Stefanie DeLuca, and Kathryn Edin. 2018. "Taking Stock: What Drives Landlord Participation in the Housing Choice Voucher Program." *Housing Policy Debate* 28(6):979-1003.

Garland, David. 2003. "The Rise of Risk." Pp. 48-86 in *Risk and Morality*, edited by Richard V. Ericson and Aaron Doyle. Toronto: University of Toronto Press.

Gillespie, Tarleton. 2016. "Algorithm." Pp. 18-30 in *Digital Keywords: A Vocabulary of Information Society and Culture*, edited by Benjamin Peters. Princeton, NJ: Princeton University Press.

Gillespie, Tarleton. 2018. *Custodians of the Internet: Platforms, Content Moderation, and the Hidden Decisions that Shape Social Media*. New Haven, CT: Yale University Press.

Gomory, Henry. 2021. "The Social and Institutional Contexts Underlying Landlords' Eviction Practices." *Social Forces* (soab063).

Gray, Mary L. and Siddharth Suri. 2019. *Ghost Work: How to Stop Silicon Valley from Building a New Global Underclass*. Boston, MA: Houghton Mifflin Harcourt.

Greif, Meredith. 2018. "Regulating Landlords: Unintended Consequences for Poor Tenants." *City & Community* 17(3):658-74.

Greif, Meredith. 2022. *Collateral Damages: Landlords and the Urban Housing Crisis*. New York: Russell Sage Foundation.

Gromis, Ashley, Ian Fellows, James R. Hendrickson, Lavar Edmonds, Lillian Leung, Adam Porton, and Matthew Desmond. 2022. "Estimating Eviction Prevalence across the United States." *Proceedings of the National Academy of Sciences* 119(21).

Grove, William M., David H. Zald, Boyd S. Lebow, Beth E. Snitz, and Chad Nelson. 2000. "Clinical Versus Mechanical Prediction: A Meta-Analysis." *Psychological Assessment* 12(1):19-30.

Guseva, Alya. 2008. *Into the Red: The Birth of the Credit Card Market in Postcommunist Russia*. Stanford, CA: Stanford University Press.

Hannah-Moffat, Kelly, Paula Maurutto, and Sarah Turnbull. 2009. "Negotiated Risk: Actuarial Illusions and Discretion in Probation." *Canadian Journal of Law and Society*, 24(3):391-409.

Harcourt, Bernard E. 2007. *Against Prediction: Profiling, Policing, and Punishing in an Actuarial Age.* Chicago: University of Chicago Press.

Heimer, Carol A. 1988. "Social Structure, Psychology, and the Estimation of Risk." *Annual Review of Sociology* 14:491-517.

Hepburn, Peter, Renee Louis, and Matthew Desmond. 2020. "Racial and Gender Disparities among Evicted Americans." *Sociological Science* 7:649-662.

Hexamer, Charles A. 1905. "Fire Insurance—Rates and Schedule Rating." *The Annals of the American Academy of Political and Social Science* 26(2):211-223.

Hiner, Jacqueline. 2020. *Background Check Services*. IBISWorld. Accessed Jan. 28. 2021 (https://my.ibisworld.com/).

Hyman, Louis R. 2011. "Ending Discrimination, Legitimating Debt: The Political Economy of Race, Gender, and Credit Access in the 1960s and 1970s." *Enterprise & Society* 12(1):200-232.

Issar, Shiv and Aneesh Aneesh. 2022. "What Is Algorithmic Governance?" *Sociology Compass* 16(1):e12955.

Joint Center for Housing Studies of Harvard University. 2020. *America's Rental Housing 2020*. Cambridge, MA: Joint Center for Housing Studies of Harvard University.

Kiviat, Barbara. 2019a. "The Art of Deciding with Data: Evidence from How Employers Translate Credit Reports into Hiring Decisions." *Socio-Economic Review* 17(2):283-309.

Kiviat, Barbara. 2019b. "The Moral Limits of Predictive Practices: The Case of Credit-Based Insurance Scores." *American Sociological Review* 84(6):1134-1158.

Kiviat, Barbara. 2023 (forthcoming). "The Moral Affordances of Construing People as Cases: How Algorithms and the Data They Depend on Obscure Narrative and Noncomparative Justice." *Sociological Theory*. https://journals.sagepub.com/doi/10.1177/07352751231186797

Kleysteuber, Rudy. 2007. "Tenant Screening Thirty Years Later: A Statutory Proposal to Protect Public Records Note." *Yale Law Journal* 116(6):1344-88.

Knight, Frank H. 1921. *Risk, Uncertainty and Profit*. Chicago, IL: University of Chicago Press.

Korver-Glenn, Elizabeth. 2020. "Property Manager-Produced Precarity in U.S. Rental Markets." Virtual presentation given at the Annual Meetings of the American Sociological Association, August 8-11, 2020.

Krippner, Greta R. 2017. "Democracy of Credit: Ownership and Politics of Credit Access in Late Twentieth-Century America." *American Journal of Sociology* 123(1):1-47.

Krippner, Greta R. and Daniel Hirschman. 2022. "The Person of the Category: The Pricing of Risk and the Politics of Classification in Insurance and Credit." *Theory and Society* 51(5):685- 727.

Lageson, Sarah Esther. 2020. *Digital Punishment: Privacy, Stigma, and the Harms of Data-Driven Criminal Justice*. New York: Oxford University Press.

Lamont, Michèle, and Ann Swidler. 2014. "Methodological Pluralism and the Possibilities and Limits of Interviewing." *Qualitative Sociology* 37(2):153-71.

Lamont, Michèle and Patricia White. 2008. *The Evaluation of Systematic Qualitative Research in the Social Sciences*. National Science Foundation.

Lauer, Josh. 2017. *Creditworthy: A History of Consumer Surveillance and Financial Identity in America.* New York: Columbia University Press.

Leasure, Peter and Tia Stevens Andersen. 2016. "The Effectiveness of Certificates of Relief as Collateral Consequence Relief Mechanisms: An Experimental Study." *Yale Law and Policy Review* 35:11-22.

Lempert, Richard, and Karl Monsma. 1994. "Cultural Differences and Discrimination: Samoans Before a Public Housing Eviction Board." *American Sociological Review* 59(6):890-910.

Leung, Lillian, Peter Hepburn, and Matthew Desmond. 2021. "Serial Eviction Filing: Civil Courts, Property Management, and the Threat of Displacement." *Social Forces* 100(1):316-44.

Levy, Karen, Kyla E. Chasalow, and Sarah Riley. 2021. "Algorithms and Decision-Making in the Public Sector." *Annual Review of Law and Social Science* 17:309-334.

Leyshon, Andrew and Nigel Thrift. 1999. "Lists Come Alive: Electronic Systems of Knowledge and the Rise of Credit-Scoring in Retail Banking." *Economy and Society* 28(3):434-466.

Lipsky, Michael. 1980. *Street-Level Bureaucracy: The Dilemmas of the Individual in Public Service*. New York: Russell Sage Foundation.

Livne, Roi. 2015. "Economies of Dying: The Moralization of Economic Scarcity in U.S. Hospice Care." *American Sociological Review* 79(5):888-911.

Lofland, David, David A. Snow, Leon Anderson, and Lyn H. Lofland. 2006. *Analyzing Social Settings: A Guide to Qualitative Observation and Analysis, 4th Ed*. Belmont, CA: Wadsworth/Thomson Learning.

March, James G. 1994. *A Primer on Decision-Making: How Decisions Happen*. New York: The Free Press.

March, James G. and Johan P. Olsen. 1976. *Ambiguity and Choice in Organizations*. Bergen, Norway: Universitetsforlaget.

Maroto, Michelle. 2012. "The Scarring Effects of Bankruptcy: Cumulative Disadvantage Across Credit and Labor Markets." *Social Forces* 91(1):99-130.

Mays, Elizabeth, editor. 2004. *Credit Scoring for Risk Managers: The Handbook for Lenders*. Mason, OH: Thomson South-Western.

McCabe, Brian. 2022. "Ready to Rent: Administrative Decisions and Poverty Governance in the Housing Choice Voucher Program." *American Sociological Review*.

Meehl, Paul. 1954. *Clinical Versus Statistical Prediction: A Theoretical Analysis and a Review of the Evidence*. Minneapolis, MN: University of Minnesota Press.

Merry, Sally Engle. 2011. "Measuring the World: Indicators, Human Rights, and Global Governance." *Current Anthropology* 52(S3):S83-S95.

Meyer, John W. and Brian Rowan. 1977. "Institutionalized Organizations: Formal Structure as Myth and Ceremony." *American Journal of Sociology* 83:340-363.

Miles, Matthew B., and A. Michael Huberman. 1994. *Qualitative Data Analysis*. Thousand Oaks, CA: Sage.

Miller, Peter and Nikolas Rose. 1990. "Governing Economic Life." *Economy and Society* 19(1):1-31.

Moulton, Lynne. 2007. "Divining Value with Relational Proxies: How Moneylenders Balance Risk and Trust in the Quest for Good Borrowers." *Sociological Forum* 22(3):300–330.

Noble, Safiya Umoja. 2018. *Algorithms of Oppression: How Search Engines Reinforce Racism*. New York: New York University Press.

O'Brien, Rourke L. and Barbara Kiviat. 2018. "Disparate Impact? Race, Sex, and Credit Reports in Hiring." *Socius* 4:1-20.

O'Neil, Cathy. 2016. *Weapons of Math Destruction: How Big Data Increases Inequality and Threatens Democracy*. New York: Random House.

Pager, Devah. 2003. "The Mark of a Criminal Record." *American Journal of Sociology* 108(5): 937-75.

Pasley, Tex, Henry Oostrom-Shah, and Eric Sirota. 2021. "Screened Out: How Tenant Screening Reports Undermine Fair Housing Laws and Deprive Tenants of Equal Access to Housing in Illinois." Shriver Center on Poverty Law.

Power, Michael. 1999. *The Audit Society: Rituals of Verification*. Oxford: Oxford University Press.

Prottas, Jeffrey Manditch. 1979. *People-Processing: The Street-Level Bureaucrat in Public Service Bureaucracies*. Lexington, MA: Lexington Books.

Ratcliffe, Caroline, Signe-Mary McKernan, Brett Theodos, Emma Kalish, John Chalekian, Peifang Guo, and Christopher Trepel. 2014. "Delinquent Debt in America." Urban Institute report.

Reosti, Anna. 2018. "Tenant Screening and Fair Housing in the Information Age." Doctor of Philosophy, University of Washington.

Reosti, Anna. 2020. "'We Go Totally Subjective': Discretion, Discrimination, and Tenant Screening in a Landlord's Market." *Law & Social Inquiry* 45(3):618-657.

Reskin, Barbara F. 2000. "The Proximate Causes of Employment Discrimination." *Contemporary Sociology* 29(2):319-28.

Rich, Motoko. 2001. "SafeRent's Math Speeds Up Tenant Evaluation Process." *Wall Street Journal*, B8 (August 2).

Rona-Tas, Akos. 2020. "Predicting the Future: Art and Algorithms." *Socio-Economic Review* 18(3):893-911.

Rona-Tas, Akos and Alya Guseva. 2014. *Plastic Money: Constructing Markets for Credit Cards in Eight Postcommunist Countries*. Stanford, CA: Stanford University Press

Rosen, Eva. 2014. "Rigging the Rules of the Game: How Landlords Geographically Sort Low-Income Renters." *City & Community* 13(4):310-40.

Rosen, Eva. 2020. *The Voucher Promise: 'Section 8' and the Fate of an American Neighborhood*. Princeton, NJ: Princeton University Press.

Rosen, Eva, Philip Garboden, and Jennifer Cossyleon. 2021. "Racial Discrimination in Housing: How Landlords Use Algorithms and Home Visits to Screen Tenants *American Sociological Review* 86(5):787-822.

Rosenberger, Larry, John Nash, and Ann Graham. 2009. *The Deciding Factor: The Power of Analytics to Make Every Decision a Winner*. San Francisco: Jossey-Bass.

Schauer, Frederick. 2003. *Profiles, Probabilities, and Stereotypes*. Cambridge, MA: Harvard University Press.

Seaver, Nick. 2018. "What Should an Anthropology of Algorithms Do?" *Cultural Anthropology* 33(3):375-385.

Shannon, Sarah K. S., Christopher Uggen, Jason Schnittker, Melissa Thompson, Sara Wakefield, Michael Massoglia. 2017. "The Growth, Scope, and Spatial Distribution of People With Felony Records in the United States, 1948-2010." *Demography*. 254(5):1795-1818.

Simon, Jonathan. 1988. "The Ideological Effects of Actuarial Practices." *Law & Society Review* 22(4):771-800.

Small, Mario Luis. 2009. "'How Many Cases Do I Need?': On Science and the Logic of Case Selection in Field-Based Research." *Ethnography* 10(1):5-38.

So, Wonyoung. 2022. "Which Information Matters? Measuring Landlord Assessment of Tenant Screening Reports." *Housing Policy Debate*.

Straka, John W. 2000. "A Shift in the Mortgage Landscape: The 1990s Move to Automated Credit Evaluations." *Journal of Housing Research* 11(2):207-232.

Stuart, Guy. 2003. *Discriminating Risk: The U.S. Mortgage Lending Industry in the Twentieth Century*. Ithaca, NY: Cornell University Press.

Tavory, Iddo and Stefan Timmermans. 2014. *Abductive Analysis: Theorizing Qualitative Research*. Chicago: University of Chicago Press.

Thacher, David. 2008. "The Rise of Criminal Background Screening in Rental Housing." *Law & Social Inquiry* 33(1):5-30.

Timmermans, Stefan and Steven Epstein. 2010. "A World of Standards but not a Standard World: Toward a Sociology of Standards and Standardization." *Annual Review of Sociology* 36:69-89.

Turco, Catherine. 2012. "Difficult Decoupling: Employee Resistance to the Commercialization of Personal Settings." *American Journal of Sociology* 118(2):380-419.

Underwood, Barbara D. 1979. "Law and the Crystal Ball: Predicting Behavior with Statistical Inference and Individualized Judgment." *Yale Law Journal* 88(7):1408-1448.

Weber, Max. 1978. *Economic and Society,* ed. Guenther Roth and Claus Wittich. Berkeley, CA: University of California Press.

Weick, Karl E. 1976. "Educational Organizations as Loosely Coupled Systems." *Administrative Science Quarterly* 21(1):1-19.

Weiss, Robert S. 1994. "Respondents: Choosing Them and Recruiting Them." *Learning from Strangers: The Art and Method of Qualitative Interview Studies*. New York: The Free Press.

Werth, Robert. 2019. "Risk and Punishment: The Recent History and Uncertain Future of Actuarial, Algorithmic, and 'Evidence-Based' Penal Techniques." *Sociology Compass* 13(2):e12659.

Wheeler, Stanton, ed. 1969. *On Record: Files and Dossiers in American Life*. New York: Russell Sage Foundation.

Zouridis, Stavros, Marlies van Eck, and Mark Bovens. 2020. "Automated Discretion." Pp. 313-329 in *Discretion and the Quest for Controlled Freedom*, edited by T. Evans and P. Hupe. Palgrave Macmillan.

Zuboff, Shoshana. 2019. *The Age of Surveillance Capitalism: The Fight for a Human Future at the New Frontier of Power*. New York: Public Affairs.