Citation for published version (APA):
Kumar, S. (Accepted/In press). Discrimination in credit. In A. Deshpande (Ed.), *Handbook on Economics of Discrimination and Affirmative Action* Springer.

Discrimination in credit

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May 2, 2021

This essay provides a thematic discussion of discrimination in credit. Through a selective review of the literature I illustrate that caste, gender and race are all persistent axes of discrimination in credit, and that discrimination has been shown to exist across diverse contexts. I examine the main conceptual tools used in this literature to shed light on the causal mechanisms that lead to discrimination, and in particular attempt to delineate the role of individuals, institutions and formal regulation. By briefly exploring the links between discrimination in credit and group-based inequality in other arenas of economy and society, I argue why the implications of the former extend far beyond credit alone, and are a powerful force in shaping inequality more generally including across generations.

1 Introduction

In the simplest understanding, discrimination signifies unequal treatment on the basis of group-belonging such as gender, caste or race. This inequality must usually be unjustified for it to qualify as discrimination. In the realm of credit, inequality generally takes two forms: access to credit, and terms including the price of credit. To offset the risk of default, lenders usually require collateral and information on past borrowing, both of which might be obtained through formal structures in the case of a bank, or situated hierarchical relationships in the case of informal lenders. In either context, these requirements result in unequal access or access at unequal terms, reflecting the existing unequal distributions of wealth and past borrowing. Discrimination can strengthen this inequality, again reflecting existing

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patterns of discrimination in other realms of economic and social life. Equally, laws, rules, and institutions can also play a role, either by actively perpetuating discrimination or else indirectly supporting existing discriminatory mechanisms.

Writing as an economist, discrimination is defined in terms of two mechanisms that can operate simultaneously. Taste discrimination (Becker, 1957) reflects animus or prejudice against members of some group, whereas statistical discrimination (Arrow, 1973; Phelps, 1972) is a rational response to limited information in situations where the decision-maker cannot observe a certain relevant attribute, and uses group-belonging as a proxy for this missing information. Intuitively, since lending can involve asymmetric information – for instance about the quality of investment for which a loan is being sought – situations involving lending decisions could a priori involve both taste and statistical discrimination.

However, these definitions focus on the role of individual agents as decision-makers and they demand certain extensions. Borrowers *choose* to seek loans, and might not do so or might apply for smaller amounts if they expect to be turned down by the lender. This implies that any assessment of discrimination needs to take into account borrowers' expectations. If those expectations reflect patterns analogous to existing discrimination – the group more hesitant to seek credit is also the one more likely to be denied credit – then the historical experiences that explain expectations also ought to be accounted for in any analysis of discrimination. This aspect can also apply to to understanding group-wise differences in the sources from which credit is sought, particularly in contexts where informal and formal borrowing exist side by side.

A more nuanced understanding of discrimination additionally involves consideration for contextual factors that can support inequality. Even if discrimination might not be involved, caste, race or gender inequalities can be cemented both over time as intergenerational processes or across arenas where several interlinked processes operate in tandem. Lending is a powerful example that highlights both aspects. Criteria for obtaining a loan such as the ability to provide collateral or show credit history are not only entirely objective but also very relevant – after all, they both exist to counter the risk taken on by the lender. Yet the ability to demonstrate credit history and to offer collateral depends on existing wealth and past access to credit, thereby perpetuating inequality including across generations. Equally, access to credit can influence and be influenced by access to education, capital, and networks, thereby reflecting and strengthening inequalities or discrimination in these arenas as well. In addition, discrimination might be implicitly perpetuated by rules or laws that favour the members of one group over another, even if the decision-maker or institution is not per se guilty of discriminating (Pager and Shepherd, 2008). Algorithms that determine credit scoring and loan decisions are one example, in that they represent part of the rules by which lending decisions take place. As we discuss below, there are substantive concerns about their role in perpetuating inequality and historical discrimination as well as suggestions for how to tackle this.

A closely related concept is that of institutional discrimination. Individual loan officers operate within banks and their actions are shaped by formal rules, regulations, as well as institutional norms, all of which can give rise to discrimination even if individual decision-makers are not guilty of discrimination themselves. Small and Pager (2020, 52) define institutional discrimination as "differential treatment by race that is either perpetrated by organizations or codified into law". Translating this definition into measurable metrics is challenging, not only because it is difficult to find appropriate data but also because there will always be ambiguity in distinguishing between institutional discrimination and the actions of individuals within those institutions. As a result, apart from some stark examples of discrimination codified into law, institutional discrimination has received relatively less attention within economics – the discipline which otherwise has yielded significant empirical insights into taste and statistical discrimination.

Taking these aspects into account, in this essay I have attempted to provide a thematic overview of discrimination in credit. Through a selective review of the literature, I illustrate that caste, gender and race are all persistent axes of discrimination in credit, and that discrimination has been shown to exist across diverse contexts and through different mechanisms. I begin below by reviewing the evidence for discrimination in section 2. Section 3 briefly explores the implications of discrimination in credit, and why even seemingly limited effects so far as access to credit goes can have disproportionate importance so far as its wider effects. Since the aim is to not only recognise the extent and forms of discrimination but to also gain insights into the mechanisms through which it manifests, we return to the question of underlying causal mechanisms in section 4, and conclude in section 5.

2 Evidence

Prejudice or taste discrimination in lending has been documented across different contexts. It can result in lower chances of loan approval, higher costs of credit, or smaller loans.

However, taste discrimination likely coexists alongside statistical discrimination, and a priori neither can be ruled out. The majority of literature focuses on taste discrimination in credit outcomes, and infers this by adjusting for group-wise differences in creditworthiness, credit histories, and other indicators relevant to lending such as the ability to offer collateral. In other words, this approach attempts to adjust for potential sources of statistical discrimination. As we will see, a small subset of the literature focuses directly on statistical discrimination, investigating how beliefs about creditworthiness shape lending decisions and vary across time or circumstances.

Racial discrimination in the USA is one of the best-studied instances, and the USA is one of the few countries which has law that specifically seeks to abolish discrimination in lending – the Equal Credit Opportunity Act of 1974.[1] However a large body of literature continues to document racial discrimination in mortgage and business lending. Ross and Yinger (2002) provide comprehensive evidence on discrimination in mortgage approvals and cost, and Bayer et al. (2018) and Clarke and Rothenberg (2018) similarly find that African American borrowers face higher mortgage costs even after conditioning on relevant variables. In similar vein, Ross et al. (2008) and Hanson et al. (2016) find evidence that African American mortgage applicants face higher rates of non-response and receive less information than their white counterparts. Ross et al.'s (2008) study involved sending Black-White or Hispanic-White pairs of individuals to visit a lender, while Hanson et al. (2016) also send paired requests for information about loans but via email, where client's names are selected to convey race. More generally, Ladd (1998) and Dymski (2006) offer reviews of the literature on racial discrimination in lending in the USA. As we discuss below, discrimination in this context involves more than just lending decisions as it extends to the actions of estate agents, but also and most egregiously, reflects the legacy of 'redlining' where areas overwhelmingly inhabited by non-Whites were designated to carry higher credit risk.

Loans for businesses are a second arena where discrimination can operate, particularly in the case of small businesses where the owner's identity can play a direct role loan approvals. In the USA, Blanchflower et al. (2003) find that black-owned businesses in the USA are twice as likely to be denied credit even after adjusting for creditworthiness. Their findings are based on a combination of qualitative interviews with business owners and econometric

[1] In other contexts discrimination in lending is usually illegal in view of legislation that applies more generally. In India for instance, discrimination on the basis of caste, race, sex and religion is prohibited under Article 15 of the Constitution, related to which are equality before the law (Article 14) and equality of opportunity (Article 16).

analysis of two rounds of surveys with firms that collected detailed information about loan applications, credit histories, and subsequent approvals. Cavalluzzo and Wolken (2005) and Blanchard et al. (2008) find that non-white business owners face higher loan costs. Henderson et al. (2015) find that male as well as White business startup owners have better access to lines of credit even after adjusting for various characteristics including credit scores, and Cavalluzzo et al. (2002) similarly find that female and non-White owners face higher loan denial rates and are less likely to apply for loans than their respective counterparts.[2] Storey (2004) also find evidence of racial discrimination in small business loan approvals in Trinidad and Tobago.

There is likewise evidence of discrimination against women entrepreneurs across a range of contexts. Using census data on micro, small and medium enterprises in India Chaudhuri et al. (2020) find that women-led businesses face lower rates of loan approval from banks, a finding echoed more generally by Muravyev et al. (2009) using data from 34 countries who also find that female entrepreneurs pay higher interest rates. Bellucci et al. (2010) find that women entrepreneurs in Italy face higher collateral requirements and lower credit availability compared to their male counterparts, and explain this difference at least partly in terms of taste discrimination. Bardasi et al. (2011) use data from three regions – Eastern Europe and Central Asia (ECA), Latin America (LA), and Sub-Saharan Africa (SSA) – and find no evidence that women entrepreneurs face discrimination in accessing formal loans, but do find that women in the ECA are less likely to seek formal finance which could be explained by the higher costs for collateral faced by female-owned firms. de Andrés et al. (2020) find that female entrepreneurs in Spain are both less likely to seek credit and also less likely to have loan applications approved. Ongena and Popov (2016) go one step further to link discrimination with gender bias. They elicit gender bias in attitudes via a survey of US-based descendents of citizens from 17 European countries. Analysing firm-level data from these countries, they then show that for countries with high gender bias, female entrepreneurs are less likely to complete loan applications and more likely to seek informal finance even though there is no evidence of actual discrimination in banks' lending decisions. Beck et al. (2017) take a different approach, and examine the effects of borrower-loan officer gender combinations on loan outcomes for a large Albanian lender. Borrowers matched with an officer of the opposite gender pay higher interest rates and are less likely to apply for a

[2] Blanchard et al. (2008) consider white women business owners as a separate category and do not find differences in loan approval rates between them and their male counterparts.

second loan, but they also find that bias against the opposite gender decreases with officers' experience and that competition reduces the scope for biased decision-making.

Exceptions in this literature include Pham and Talavera (2018) who find that female entrepreneurs in Vietnam are more likely to get a formal loan and at lower cost than their male counterparts, and Hansen and Rand (2014) who find that female small-firm entrepreneurs in 16 sub-Saharan countries are less likely to be credit-constrained than their male counterparts with the reverse pattern for medium-sized enterprises. Corsi and De Angelis (2017) likewise find no evidence of discrimination against women in a Ugandan microfinance programme.

There is a large literature from India on caste-based discrimination and inequality in access to credit. This includes small-business owners, farmers and households. Examples of qualitative studies include Prakash (2010) who surveyed 90 SC-owned businesses across 6 states in India and reports the challenges faced in obtaining bank loans to set up a business to set up an enterprise, leading in many cases to borrowing from the informal sector at higher cost, and Jodhka (2010) who documents the difficulties faced by SC entrepreneurs in northwest India in accessing bank credit. Kumar (2013) uses nationally-representative survey data on farmers' access to credit and argues that Scheduled Caste (SC) and Scheduled Tribe (ST) farmers likely face discrimination in bank lending, particularly when they live in areas where higher castes are economically dominant. This conclusion is based on patterns of outstanding bank loans, and therefore potentially conflates any differences in loan-seeking behaviour with loan approvals by lenders. Kumar and Venkatachalam (2019) tackle this problem, by studying loan applications and approvals separately, and find that SCs and STs are less likely to apply for credit and that STs are less likely to have loans approved. They examine sensitivity to potentially unobserved credit histories through a Monte-Carlo simulation approach, and show that ST credit histories would have to be extremely poor to explain the latter finding as statistical discrimination. Kochar (1997) finds that farmers are (formal) credit-constrained using data from Uttar Pradesh by accounting for a hierarchy of loan sources in terms of preference where informal sources are ranked lower than banks. Fisman et al. (2017) analyse data from a large Indian public-sector bank and find that loans officers are more likely to approve, and borrowers are more likely to repay, when both parties belong to the same religion, or within Hindus the same caste-group. They interpret this finding not as discrimination but as preferential treatment based on cultural proximity and better information, and show how this phenomenon might give rise to statistical discrimination against minorities simply because loan officers of those groups are fewer in number.[3]

In contexts where informal sources of credit coexist with formal sources such as banks, studying discrimination can also be linked to the sources from which loans are sought and obtained. For example, Pal (2002) analyses data from three South-Indian villages and finds that higher caste households are more likely to have loans from formal sources. Guérin et al. (2013) combine qualitative fieldwork with quantitative surveys in a study of rural Tamil Nadu households to document how the intersection of gender and caste determines both the sources of credit available to households as well as the terms on which loans are obtained – broadly speaking, to the disadvantage of Dalits (SCs). They examine debt more generally, as a social transaction and not simply loans borrowed, to explain how social hierarchies, class, trust and patronage all combine to shape the nature and sources of debt. In a similar vein, Guérin (2014) argues that microcredit also operates via complex social relationships, and can both strengthen existing hierarchies as well as reduce dependence on unwanted sources of debt. Fafchamps (2000) studies borrowing by manufacturing firms in Kenya and Zimbabwe and finds no evidence of inferior access to bank loans amongst female or black owners, but does find that network effects play a significant role in shaping access to credit from suppliers due to which female and black owners have reduced access to trade credit, potentially also because of discrimination. Pope and Sydnor's (2011) study of peer-to-peer lending via an online platform in the USA shows that discrimination in informal lending can also exist in economies where lending otherwise takes place overwhelming within formal structures. However, while they find that blacks are less likely to receive funding, they also find that these rates are in fact higher than those predicted by default risk – in other words, it possible that taste discrimination in *favour* of blacks coexists with statistical discrimination against them.

2.1 Laws, rules, institutions

The majority of studies referred to above study credit transactions from the perspective of individuals. In most cases, these are the individuals who do or do not apply for credit. Any discrimination thus inferred is implicitly or otherwise attributed to the institutions from which loans were sought, and this could result from institutional practices or the decisions

[3] However, depending on the baseline for defining fair treatment, unequal treatment does still fit the definition of discrimination, even if this is due to preferential treatment in favour of some group rather than unfavourable treatment of another.

of individual bank officers or a combination. A smaller number of studies (e.g. Beck et al., 2017; Fisman et al., 2017) jointly analyse data on the individuals seeking loans and the bank officers who decide on those loans.[4] While institutional norms might influence how the latter make decisions, the fact that these vary according to officers' gender or caste suggests that emerging patterns at least in part reflect the officers' individual preferences. The challenge is to delineate these twin factors of influence. To this end, this section provides a selective discussion to explicitly consider the role of institutions, rules and laws in shaping discrimination, recognising that these can play an important role in shaping the decisions of said individuals.[5]

One approach to distinguish between the extent to which the actions of individuals within institutions reflect their personal preferences or prevailing norms and rules is to examine loan outcomes before and after a change in rules, since individuals' preferences are likely to remain unchanged in the short term. Cozarenco and Szafarz (2018) provide an example of this by studying the effects of a rule change in a French Microfinance Institution (MFI). The rule imposed a ceiling on microcredit loans, and it was brought about by the requirements imposed by co-financing via a bank. This led to the MFI switching from lending biased in favour of females to lending biased against, which the authors argue is most likely because the bank's own lending norms started to be reflected in the MFI's lending practices.

In the absence of a change or natural experiment, patterns of correlation can also provide insight into institutions. Kumar (2013) argues that discriminatory patterns of lending that are unfavourable to lower castes are likely driven by institutional capture of cooperative banks by members of higher castes. This cannot be directly observed in the data, but is supported by the correlation between caste dominance at district level and caste-wise differences in access to loans. This correlation is present for cooperative banks that have decentralised structures, but not for commercial banks that are managed centrally. This interpretation is also supported by Drèze et al.'s (1997) long-term study of Palanpur village in Uttar Pradesh, India, which demonstrates how institutional capture of banks might take place by caste-groups that are locally dominant, besides more generally painting a detailed picture of the lending sources available in the village and how access to credit is shaped by

[4] Fisman et al. (2020) present a somewhat related finding, and show that exposure to religion-based violence makes Hindu bank officers less willing to lend to Muslim borrowers, but again do not relate this to institutional norms and rules or the lack thereof.

[5] While I use the term 'institution' more in a brick-and-mortar sense so as to distinguish between this and rules more generally, it is clear these categories overlap.

politics and hierarchy.

It is also usually difficult to identify the effects of the regulations or laws separately of institutional norms and individuals' behaviour. In India, while the Constitution outlaws discrimination on the basis of caste, religion, race and sex, there is no specific application of this for credit. There are also long-standing regulatory norms set by the central bank viz. Reserve Bank of India that encourage banks to lend to disadvantaged groups, one of which is Scheduled Castes and Scheduled Tribes (e.g. section 16 in Reserve Bank of India, 2020). Priority sector lending is however fungible across categories of disadvantage, and moreover these norms are not binding, nor do they rule out discrimination or inequality in credit access of the sorts we have discussed. In contrast, the USA provides at least one stark historical example of how formal regulation shapes discrimination.[6] Interventions aimed at stabilising and supporting lending for housing and the housing market following the Great Depression directly contributed to discrimination against Blacks. As Small and Pager (2020) explain, purpose-created government agencies worked to make the property appraisal process more systematic. One of these, the Home Owners Loan Corporation, created maps that divided major cities into zones which played a significant role in determining the creditworthiness of a property. Neighbourhood demographics contributed far more to the appraisal than the condition of the property itself (Woods, 2012). Zones ranged from A-D, with 'D' demarcated in red on maps – hence redlining – and socioeconomic status including race was directly used as a metric to demarcate zones. Specifically, the proportion of Blacks in a given neighbourhood was directly and inversely proportional to the zone grade. This resulted in Blacks finding it very difficult to buy a property in a zone with a good grade – existing homeowners would resist this since Black families moving in would reduce that grade, and finding loans for properties located in predominantly black areas was likewise difficult as well. Aaronson et al. (2020) use data from 1940-2010 and show that redline designation causally effected the racial composition and subsequent development of neighborhoods, property values and rents, most likely by reducing access to credit and increasing associated borrowing costs. This led to a cyclical, long-run pattern of reduced investment in erstwhile redlined areas, the effects of which are visible even in 2010 even though redlining had long been abolished, and racial segregation has been declining following the Equal Credit Opportunity Act of 1974 and similar policy actions during 1960-70.

[6] For a comparative overview of affirmative action policies in the USA (race) and India (caste) see Deshpande (2005).

Finally, the algorithms used to create credit scores and to guide loan approval and pricing decisions are a fast-evolving example of the rules that govern lending processes. Unlike laws or institutional rules however, algorithms are far less transparent in terms of how they use data to make decisions, and in the case of machine learning, the types of data on which the algorithms have been trained. Even if an algorithm purposely avoids, say, race as an input, it is difficult to rule out that certain other variables have not been used as a proxy. This problem can be compounded by the more general characteristic of machine-learning algorithms: it is difficult to determine how different variables combine to produce output. Add to this the proprietary nature of algorithms, and it is easy to see that even laws that prohibit the use of group-belonging as a characteristic in making decisions might not be sufficient to curtail discrimination. In common with other applications of prediction through machine learning, there is therefore the risk of direct discrimination against minorities as well as indirect discrimination – where an algorithm relies on group-belonging as a proxy for other relevant but missing indicators thereby giving rise to statistical discrimination. In either case, if the result is that certain groups are less likely to receive loans, this leads to vicious circle wherein data on credit histories for these groups becomes relatively sparse over time, perpetuating the problem of limited information and thereby statistical discrimination.

Cowgill and Tucker (2019) discuss these and related concerns about discrimination and algorithmic fairness, most of which apply to but are not unique to lending.[7] There is also a growing literature on algorithmic fairness specifically in the context of lending. Hurley and Adebayo (2016) and Gillis (2020) discuss the problems of fairness posed by credit-scoring algorithms based on big-data, including the extent to which existing laws do or do not provide suitable protection against these problems, and how better transparency and accuracy can be implemented in aid of fairness and avoiding discrimination. Lee and Floridi (2021) offer a normative assessment of credit-scoring algorithms in terms of different definitions of fairness, focusing on the ethical trade-offs involved in prioritising multiple objectives. Analysing a dataset for startups in the USA, Robb and Robinson (2018) do not find evidence of racial bias in business credit scores, whereas Henderson et al. (2015) find the opposite: Black-owned business startup receive lower than expected credit scores and receive less favourable treatment in accessing credit than do White-owned firms, with similar patterns of inequality

[7]See also Munoz et al. (2016) for a discussion of the main challenges in maintaining objectivity through big-data, including in access to credit where the problem of scarce credit histories can become compounded when big-data are used to guide lending decisions.

against female-owned firms. Fuster et al. (2020) conduct an exercise to compare traditional logit with machine-learning predictions of credit default using data on US mortgages, and find that the latter are better at modelling default risk but do not make progress in addressing missing data problems. This results in more granular predictions of default risk, leading to gains for White and Asian borrowers but losses for Blacks and Hispanics. Bartlett et al. (2019) provide comparative evidence of human versus algorithmic decision-making again by analysing US mortgage data, and conclude that FinTech algorithms also discriminate against minority borrowers but to a far lesser extent than do face-to-face lenders, and that too only in loan pricing, not loan approvals.

3 Implications

The research discussed provides evidence of discriminatory gaps in loan approvals or the cost of credit between men and women, Whites and non-Whites, and Scheduled and higher castes. To appreciate the wider economic and social implications of these gaps, we must also recognise the role of lending in acquiring and growing capital more generally, particularly across generations. Depending on the context, small business entrepreneurship and home ownership are both crucial determinants of wealth accumulation. Discrimination in lending then has significant knock-on implications for inequality and disadvantage beyond loans alone, effects that can be compounded if there is discrimination in allied areas too.

For instance, there are persistent caste and gender-based disparities in small business entrepreneurship encompassing profitability, size, location, and sector (Deshpande and Sharma, 2013, 2016). This, combined with evidence on caste and gender discrimination in access to credit helps build a bigger picture where discrimination and inequality shape access to capital more generally. Indeed, entrepreneurship is often considered an attractive alternative to salaried employment in emerging economies, and particularly so in the context of India. The share of formal sector employment has remained low and members of the lower castes face stubborn barriers in entering these jobs thanks to a combination of cultural capital, discrimination, and network effects. With this view, the economic significance of small business ownership cannot be overstated. Yet, as the studies we have discussed above illustrate, the same disadvantages and discrimination which prevent members of the lower castes from breaking into well-paid formal sector employment are also in operation in the arena of entrepreneurship.[8] Add to this the phenomenon of 'self-censorship' – wherein members of lower castes are less likely to seek bank loans (Kumar and Venkatachalam, 2019), or self-selection towards informal sources of credit depending on gender and caste (Guérin et al., 2013) – and the resulting inequalities are cemented further, potentially across generations.[9]

Similar can be said of mortgage lending in the USA. Home ownership is a crucial determinant of wealth and racial gaps therein (Shapiro, 2006). The lower likelihood of mortgage approval, lower wealth, and hesitancy to apply for a mortgage all combine, with the result that Blacks are less likely to transition to home ownership (Charles and Hurst, 2002). Home buyers and sellers also receive differential treatment from other market players depending on their race. For instance, Ondrich et al. (2003) show that the marketing efforts of estate agents as a function of house price vary by customers' race, as does the portfolio of properties that they show to potential buyers. Set against a backdrop of ingrained spatial segregation by race (Hwang et al., 2014) – supported by erstwhile redlining – these sorts of patterns combined with discrimination in loan approvals contribute to a bigger picture where home ownership is deeply unequal across race, and inequality, discrimination and homophilic preferences can all combine in cyclical ways to perpetuate this inequality. Race also played a role in the effects on the housing market in the wake of the 2008 crisis, with racial patterns of unemployment, mortgage pricing and credit profiles all shaping racial differences in foreclosure rates to the disadvantage of minorities (Reid and Laderman, 2009).

4 Mechanisms and methods

So far as borrowing from formal sources goes, it is clear that discrimination can arise from a combination of the actions of loan officers and the institutional environment in which they operate including norms, rules, algorithms and laws. In reality, even though difficult to estimate empirically, these factors likely operate jointly to shape patterns of access. Given that research in this field aims to measure inequality of access and to pinpoint where discrimination is involved, it is necessary also to explain the *mechanisms* or causal processes through which discrimination operates. In this regard we offer three observations.

[8] See Deshpande (2011) and Mosse (2018) for authoritative overviews on this issue, and on the role of caste in shaping economic development and upward mobility more generally. See also Das (2008) for evidence on the difficulties faced by urban Dalits in entering salaried jobs.

[9] See Iyer et al. (2013) for evidence on caste-based differences in entrepreneurship and that the rate at which these differences are shrinking is very slow.

First, as we have discussed, institutional norms and rules also demand examination alongside analysis of loan approval, size and pricing decisions. Without this dimension, research into discrimination provides loan officer-level averages – implicitly if using borrower-level data; explicitly using borrower-officer paired data – but it is unclear whether such behaviour reflects their preferences solely as individual members of society, or whether institutional factors additionally shape their decision-making. There are relatively few examples of this sort of analysis in the literature, but when possible, they add significantly to our understanding of the mechanisms of discrimination.

Second, the rising use of algorithms in credit decisions makes it easier to study discrimination. Inferring discriminatory decision-making on the part of a human being demands data on actual transactions coupled with a strong set of assumptions regarding the information they have taken into account to make that decision. Specifically, assumptions must be made about the decision-maker's beliefs about creditworthiness, their personal past experience, stereotypes, or knowledge acquired through disparate means, all of which are difficult to observe and measure, but all of which might guide their decisions alongside any prejudice. Algorithms avoid this complexity by making known the universe of input variables. The problem of proprietary access aside, algorithmic decision-making can be studied via real data or simulated synthetic data to understand their decision-making process, as to which objectives or variables play a significant role and whether discrimination results. Compared to human decision-making, in theory at least algorithms are also easier to change, so that the policy implications of researching discrimination in algorithmic decision-making could be more tangible.

Third, inferring discrimination in credit using observational data can draw on insights from research on discrimination in other arenas, and specifically with an eye towards examining beliefs. Data on beliefs are crucial for distinguishing between statistical and taste discrimination, and as outlined above, any analysis of decision-making must also make assumptions about the decision-maker's beliefs regarding creditworthiness. This is difficult to do. While data on *actual* creditworthiness such as credit histories or repayment behaviour are frequently available, these do not equate to data on beliefs, because the latter can be shaped by personal experience and stereotypes and by definition vary across individuals.

The role of information and beliefs has been explicitly examined in other arenas of discrimination. This includes natural experiments such as 'ban the box' legislation (Agan and Starr, 2018; Doleac and Hansen, 2020), laboratory experiments such as Castillo and Petrie

(2010) who find that race-based statistical discrimination disappears with better information, and field experiments such as Bohren et al. (2019) who find that biased beliefs initially lead to gender discrimination which later dissipates with better information. Fewer papers in this area use observational data, but some examples include Laouénan and Rathelot (2020) on Airbnb rentals and Tjaden et al. (2018) who study online carpooling platforms, both focusing minority-ethnic discrimination, and Altonji and Pierret (2001) on how racial discrimination decreases as firms acquire more information about workers' productivity. In forthcoming work Kumar and Venkatachalam (2021) suggest an approach to incorporate beliefs to estimate taste and statistical discrimination using observational data. The approach draws on causal mediation frameworks (see for e.g. Pearl, 2014) that specify the causal effect of treatment both directly as well as indirectly via specific mediators, viz. variables themselves causally effected by the treatment which then also causally effect the outcome. Beliefs are a mediator, since they are effected by group-belonging and in turn shape outcomes. Specifically, in a lending situation we might posit that group-belonging causally effects loan officers' beliefs about creditworthiness and that these beliefs causally affect their decision-making, thereby potentially giving rise to statistical discrimination. In this framework, taste discrimination is the *Natural Direct Effect* of treatment on outcome which operates independent of all mediators (Pearl, 2001) while statistical discrimination is a specific type of indirect effect which operates via beliefs (see Kumar and Venkatachalam, 2021). Implementing these ideas to analyse discrimination in lending would help distinguish more clearly between prejudice and statistical discrimination, thereby helping pinpoint how the provision of better information can reduce statistical discrimination.[10]

5 Conclusion

Discrimination in credit is an involved example of discrimination more generally. The specific characteristics of lending situations can give rise to taste, statistical, and institutional discrimination. Depending on the context, the resulting mechanisms can be placed into three broad categories: the beliefs and prejudice of individual loan officers potentially shaped by the institutional context; differences in the quality and existence of credit histories across

[10]Of course the line distinguishing taste and statistical discrimination might itself not be clear if beliefs about creditworthiness are influenced by prejudice. This is one dimension of the problem of inaccurate statistical discrimination (Bohren et al., 2020). Kumar and Venkatachalam (2021) suggest an approach to model beliefs of varying accuracy as one form of sensitivity analysis to address this problem.

borrowers depending on the group to which they belong; and algorithms that guide decision-making about loans. For informal lenders the list of factors arguably broadens, incorporating social relations, trust, and hierarchy.

These are supply-side factors. To fully appreciate the implications of discrimination we must also recognise patterns of inequality in access to capital – including but not limited to collateral – that mirror group-based disadvantage more broadly, as well as the likely existence of discrimination in other arenas of economy, society and polity that both feed into as well as reflect unequal access to credit. These arenas include education, networks and market transactions. Not least, discrimination or the perceived risk thereof on the supply-side might manifest as the hesitation to seek credit on the demand-side, further perpetuating unequal access to credit.

Finally, it is clear that any appraisal of discrimination in credit covers a wide territory indeed, spanning FinTech algorithms in richer economies to situated hierarchical power relations in rural contexts in emerging ones. Beyond evidencing the diverse causal mechanisms that shape discrimination, this range demonstrates that discrimination operates across societies and markets with starkly different characteristics, degrees of formality and regulation. Markets are not self-correcting so far as weeding out discrimination in lending goes, and for emerging economies in the midst of structural and sectoral transitions, it is difficult to overstate the significance of links between inequality more generally and discrimination in credit.

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