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Discrimination in Service

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Report Summary

Litigation concerning firm-against-consumer discrimination has a long history in the U.S. In the past two decades alone, prominent corporations have paid more than half a billion dollars in settlements and fines for consumer discrimination cases — an amount that does not include additional sales losses due to bad publicity, damaging boycotts, or impaired reputation and brand.

Here, Kalinda Ukanwa and Roland Rust seek to (1) uncover the mechanism by which service discrimination can emerge from seemingly rational service policy; (2) investigate how service discrimination interacts with competition and consumer word-of-mouth to affect profits; (3) help firms avoid losing profits due to discrimination.

They develop a theoretical model that illuminates the critical roles that variation in consumer quality (i.e., their profitability to the firm) and measurement error in detecting consumer quality play in the emergence and magnitude of discrimination in service. Empirical evidence in two studies supports their theory that large variation in consumer quality reduces service discrimination while large measurement error increases service discrimination.

Further, agent-based modeling demonstrates that service providers using a "group-blind" service policy that ignores group membership information about consumers have greater total profits over time than those with a "group-aware" service policy that uses group membership information in addition to individual attributes in service decision-making.

Managerial implications
Firms should consider the long-term benefits of switching to a service policy that does not use group membership information. Although discriminatory (i.e., "group aware") practices may seem profitable in the short term, they can damage service demand and profits in the long run. Because of strong word-of-mouth effects, consumers can learn from each other which firms are unlikely to provide favorable service conditions to them, and can switch their preferences to competitive alternatives.

Firms that persist in using group identity information should invest in methods of measurement error reduction such as developing advanced methods of measuring consumer quality or more sophisticated predictive models that improve accuracy in predicting quality based on available measures. These firms could also increase exposure to consumer populations, which could improve information on the mean and variance of group quality.

These findings apply to any service scenario where the service provider can segment consumers into groups based on some observable attribute; and where the service provider uses group membership as well as individual information to make a decision about the provision of service to the consumer.

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Discrimination in Service

In May 2017, the city of Philadelphia filed a lawsuit claiming that Wells Fargo & Company violated the U.S. Fair Housing Act. The lawsuit accused the bank of discriminatory lending practices that resulted in excessive foreclosures of minority-owned properties in the city (Phippen 2017). Philadelphia's lawsuit came on the heels of similar suits by Oakland, Los Angeles, Miami, and Baltimore. Wells Fargo had already made a $175 million settlement with the U.S. Department of Justice in July 2012 for alleged discrimination against minority borrowers from 2004 to 2009 (Broadwater 2012). Given its prior history, how was it possible that Wells Fargo was addressing service discrimination again in 2017?

Neither Wells Fargo nor the financing industry is unique on this issue. Nor does service discrimination concern only ethnicity or gender. Litigation concerning firm-against-consumer discrimination has a long history in the U.S. In the past two decades alone, prominent corporations such as Denny's, Walmart, Macy's, and Ally Financial paid more than half a billion dollars in settlements and fines for consumer discrimination cases based not only on race, ethnicity or gender (Elliott 2003; Gutierrez 2015; Koren 2016), but also on age (Silver-Greenberg 2012), geography (Schroeder 2017), social class (Kugelmass 2016), and occupation (Addady 2016). This amount does not include additional sales losses due to bad publicity, damaging boycotts, or impaired reputation and brand. Societal shifts motivate an increased need for more research on why discrimination in service still happens in the 21st century (Anderson and Ostrom 2015; Bone, Williams, and Christensen 2010; Hill and Stephens 2003). Social fissures created by service discrimination have a direct impact on consumer and societal well-being (Bone, Christensen, and Williams 2014; Crockett, Anderson, Bone, Roy, Wang, and Coble 2011).

Consistent with the sociological literature, we distinguish discrimination from prejudice based on race, gender, sexual orientation, religion, or other consumer attributes. Prejudice, stereotypes, and racism focus on internally-held attitudes, beliefs, and ideologies. In contrast, our research focuses on discrimination as a decision outcome exhibiting unequal treatment of people

based on the category to which they belong. Discriminatory behavior is not necessarily driven by internally-held attitudes such as prejudice or bigotry (Pager and Shepherd 2008; Quillian 2006). Some service providers are undoubtedly prejudiced. However, suppose a firm has no prejudiced nor discriminatory intent, and its employees are not bigots? Under what conditions can service discrimination still emerge? What is the impact on profits over time? Extant literature does not provide a clear consensus on answers, indicating that the mechanisms producing service discrimination and its impact on profitability are still not well understood. Where prior literature primarily focuses on average attributes of consumer groups (e.g., average group wealth or average education) in explaining discrimination, we investigate how the variation of attributes (e.g., the distribution of consumer quality) has a demonstrable effect on the magnitude of service discrimination. Furthermore, to the best of our knowledge, we are the first to investigate how social and competitive dynamics emerging from service discrimination impact long-term profits.

Our research employs a mixed-methods approach. We first present a theoretical model of how variance in consumer quality and magnitude of error in measuring quality impact the magnitude of service discrimination. We validate the mechanism with empirical evidence from human decision makers. We then extend the analytical model with an agent-based model to investigate how competition and word-of-mouth emerging from service discrimination impact profits over time. We find that group-aware service decisions are perhaps profitable in the short-run. However, they can backfire over the long-run due to the effects of word-of-mouth and competition. Large measurement error in detecting consumer quality exacerbates service discrimination, while large variance in customer quality attenuates it.

The implications of this research are three-fold. First, it provides insight into how variance in consumer quality and measurement error can drive the emergence of unintentional discrimination. Second, it demonstrates how service discrimination's interaction with consumer word-of-mouth and competition damages profits. Third, this research suggests remedies that involve reducing error in measuring consumer quality and increasing exposure to members of disadvantaged group populations. We elaborate on these themes in the remainder of the paper as follows: first we

discuss how our research expands extant knowledge on discrimination in service. We then present our theoretical model and propose a definition of discrimination in service. We next present empirical validation of our theory. Then, we present an agent-based model (ABM) to go beyond the limitations of the analytical model: the ABM enables investigation into emergent macro-phenomena from the micro implications of the analytical model and studies. With the ABM, we investigate the long-term impact of service discrimination and its interaction with competition and word-of-mouth. Finally, we conclude with a discussion of the managerial and policy implications of our findings. In the next section, we discuss how this research contributes to the literature.

EXTENDING THE LITERATURE ON SERVICE DISCRIMINATION

Transformative consumer research (Mick 2006; Pettigrew 2001) and transformative service research (Anderson et al. 2010) contain extant literature on service discrimination from the consumer's point of view on topics such as financing options (Bone, Christensen, and Williams 2014), consumer racial profiling (Crockett et al. 2003; Evett et al. 2013; Harris et al. 2005), and consumer discrimination against businesses selling "ethnic" French products in English-language dominated parts of Canada (Ouellet 2007). In contrast, our work models service discrimination from the viewpoint of the firm. There are two primary theoretical camps in which research from the firm's viewpoint lies. The first, the taste for discrimination literature, theorizes that firms may include a disutility for interacting with members of certain groups in their objective function which is not necessarily profit-maximizing (Becker 1957; Schelling 1969). A real-life example is the Colorado bakery which in 2012 refused to provide a wedding cake to a same-sex couple because of its religious-based service policy (Savage 2017). In contrast, our research aligns with the second camp–the statistical discrimination literature (Aigner and Cain 1977; Arrow 1973; Coate and Loury 1993; Phelps 1972). This literature assumes firms are profit-maximizing and do not have a disutility for interacting with certain groups. Instead, the literature models discrimination as a problem of incomplete information where decision-makers use observable

attributes such as group membership to draw inferences about individuals.

Most prior models of service discrimination are static. We model discrimination dynamics, which is relatively sparse in the literature (Fang and Moro 2011). This research gap is critical to fill because of the persistence of service discrimination, despite improving societal policies over time. Notable examples of dynamic discrimination research primarily examine the supply-side impact (labor and employment) of discrimination on the profit function (Antonovics 2006; Bjerk 2008; Blume 2005, 2006; Bohren et al. 2017; Craig and Fryer 2017; Fryer 2007). Our study differs from these studies in the following important ways. We study the implications of service discrimination on demand-side dynamics (customer demand and word-of-mouth). Furthermore, extant literature focuses on average group attributes in the formation of the firm's beliefs about the individual and group. In contrast, we examine how variation of intra-group attributes impacts firm beliefs. Because discrimination is a problem of incomplete information, diagnosing the role that intra-group variation plays in service discrimination is critical to understand. Variation introduces uncertainty which can exacerbate the problem of incomplete information and impact the degree of discrimination. We also differentiate ourselves from prior literature in examining the impact on long-term profits of word-of-mouth that emerges from service discrimination. To the best of our knowledge, ours is the first study to do so. In the next section, we present our theory of how variation in intra-group attributes has both immediate and long-term impact on the emergence of service discrimination.

A MODEL OF SERVICE DISCRIMINATION

Our theoretical model of service discrimination applies to a variety of service contexts that meet two criteria: 1) consumers can be segmented into two or more distinct groups based on an observable attribute; 2) service providers use both group membership and other individual information to screen and determine level of service to the customer. Examples of services that *explicitly* screen potential customers include higher education, financial services, real estate, medical services, and membership-based services (e.g., country clubs). Examples of services

where providers may *implicitly* screen customers include law enforcement, dining, hospitality, and retail. A recent example occurred in April, 2018 at a Philadelphia Starbucks where two African-American real estate brokers were arrested while waiting for a friend to arrive for a meeting. The store manager who called police claimed that the men were trespassing. In a video recording of the incident that went viral, other Starbucks customers can be heard protesting the arrests. White social media commentators wondered aloud why they had not been arrested for doing the exact same thing at Starbucks (waiting for friends before ordering). Subsequently, the incident generated substantial negative publicity, organized protests, a shutdown of the Philadelphia store, and a public apology media tour by the CEO of Starbucks who stated that "practices and training led to the bad outcome" (McLaughlin 2018).

The initial portion of our model is consistent with the statistical discrimination theory of Nobel Prize winner Edmund Phelps (1972). We refer the reader to that paper and Aigner and Cain (1977) for details of their model and derivations. Although our model applies to many service contexts, we ground our exposition in a specific bank lending context to facilitate intuition. We model a loan officer's decision regarding which applicants to give a bank loan. For simplicity, we assume that the bank has one loan officer and that the loan amount and interest rate are predetermined. The loan officer's decision is only whether to offer the loan to the applicant.

We also assume that the loan officer is boundedly rational (March and Simon 1958): the loan officer uses locally available information (i.e., the historical credit scores of applicants at his bank only) and has finite cognitive and computational resources available to him in his decision-making. He updates his beliefs, based on past information, but he is not forward looking nor game-theoretic in his decision-making. He also does not have knowledge of his competitors' information or beliefs. We believe bounded rationality is a reasonable assumption because of what we learned from interviews with loan analysts at financial institutions. Their primary sources of information used in loan decisions include the applicant's credit score, credit history, current income and assets, and a fourth category they called "character factors". Character factors include any qualitative information loan analysts could find about the applicant's general

character. For example, one interviewed loan analyst gave an example of a case where she found evidence of an applicant's history of gambling. Although the applicant had a sufficient credit score, income, and assets, he was not offered a loan. Interviewed loan analysts were consistent in stating that they used their institutional historical data from past applicants and loan recipients to compare current applicants in the decision-making process. They did not use information from competing financial institutions nor looked at future trends of applicant groups in making loan decisions for applicants.

Let us assume that each applicant i is a member of one and only one group $j \in \{Adv, Dis\}$, an advantaged or a disadvantaged group. Advantage (A_j) reflects key resources (e.g., cognitive development, occupation, social position, reputation, wealth, or age) in the social stratification process (DiPrete and Eirich 2006). In our model, advantage is defined at the group level and represents the mean quality of the applicants within the group. However, individual applicant quality can vary within a group. We assume there is inequality in advantage between the groups, where

(1) $$A_{Adv} > A_{Dis} > 0$$

Examples of differences in advantage between groups are upper versus lower social class, men versus women, racial, ethnic, or religious majorities versus minorities, college-educated versus less-educated, etc. For example, let us imagine that the applicants are segmented based on their residential address. The advantaged applicants live in an affluent part of town while the disadvantaged applicants live in a working-class area. We define inequality as $Inequality = A_{Adv} - A_{Dis}$.

The loan officer seeks to maximize profit by selecting applicants with sufficient quality, Q_{ij}, a latent attribute that can be interpreted as the expected profitability to the firm. We assume that Q_{ij} is normally distributed around the group mean, A_j. The loan officer uses available information about the each applicant (credit history, net worth, income, debt, employment history, etc.) to

inform his service decision. This information is summarized in a single numerical score, S_{ij}, which is a noisy measure of Q_{ij}. The relationships between A_j, Q_{ij}, and S_{ij} are as follows:

(2a)
$$Q_{ij} = A_j + \upsilon_{ij}, \quad \upsilon_{ij} \sim \mathcal{N}(0, \sigma^2_{q_j})$$

(2b)
$$S_{ij} \mid Q_{ij} = Q_{ij} + \varepsilon_{ij}, \quad \varepsilon_{ij} \sim \mathcal{N}(0, \sigma^2_{\varepsilon_j}), \text{ where } \upsilon_{ij} \perp\!\!\!\perp \varepsilon_{ij}$$

(2c)
$$S_{ij} \sim \mathcal{N}(A_j, \sigma^2_{q_j} + \sigma^2_{\varepsilon_j})$$

The loan officer wants to predict applicant quality, Q_{ij}, using the applicant's score, S_{ij}. Because S_{ij} has error, the loan officer supplements the score with observable group information A_j to form an expectation of Q_{ij} (e.g., the applicant's zip code). Using Bayes rule and the relationships established in Equation (2), the distribution of the loan officer's beliefs about $Q_{ij} \mid S_{ij}$ is a weighted combination of information about the individual applicant (S_{ij}) and about the group she belongs to (A_j). It can be conceptualized as a linear regression with the following relationships:

(3a)
$$Q_{ij} \mid S_{ij} = \gamma_j S_{ij} + (1 - \gamma_j) A_j + \delta_{ij}$$

(3b)
$$E(Q_{ij} \mid S_{ij}) = \gamma_j S_{ij} + (1 - \gamma_j) A_j$$

(3c)
$$\text{where } \delta_{ij} \sim \mathcal{N}\left(0, \gamma_j \sigma^2_{\varepsilon_j}\right) \text{ and } \gamma_j = \frac{\sigma^2_{q_j}}{\sigma^2_{q_j} + \sigma^2_{\varepsilon_j}}$$

The quantity γ_j is known as the reliability of a measurement in classical score theory (Novick 1965). It indicates how accurately the score measures the targeted latent attribute. The score reliability has the following important properties:

(4)
$$0 < \gamma_j < 1, \quad \frac{\partial \gamma_j}{\partial \sigma^2_{q_j}} = \frac{\sigma^2_{\varepsilon_j}}{(\sigma^2_{q_j} + \sigma^2_{\varepsilon_j})^2} > 0, \text{ and } \frac{\partial \gamma_j}{\partial \sigma^2_{\varepsilon_j}} = \frac{-\sigma^2_{q_j}}{(\sigma^2_{q_j} + \sigma^2_{\varepsilon_j})^2} < 0$$

These properties highlight the impact that variation in quality ($\sigma^2_{q_j}$) and score measurement error ($\sigma^2_{\varepsilon_j}$) have on the loan officer's beliefs about consumer quality. Increasing variation in consumer

quality or decreasing variation in score measurement error increases the score reliability (γ_j). As score reliability increases, the loan officer places increasing weight on the consumer's individual information (S_{ij}) and less on group information (A_j).

The top graph in Figure 1 (Tables and Figures follow the Reference section throughout) visually displays an example of the model using a range of 450 - 650 for S_{ij} (score) on the x-axis and a matching range on the y-axis for expected quality values, conditional on score: $E(Q_{ij} \mid S_{ij})$. The solid and dashed parallel lines are graphs of Equation (3b): the loan officer's expectation of quality of advantaged and disadvantaged applicants respectively. In this example, the two groups have the same score reliability, $\gamma = \gamma_{Adv} = \gamma_{Dis} = .5.$, where $A_{Adv} = 723$, and $A_{Dis} = 640$. A regression line coinciding with the gray line at the $45°$ arc has a slope of $\gamma = 1$. This is where S_{ij} perfectly measures Q_{ij} without error. At this value, the loan officer has no need for group information A_j to form his expectation of customer i's quality. As measurement error is introduced, however, γ_j decreases. As $\gamma_j \to 0$, the regression representing the loan officer's expectation of applicant quality rotates clockwise towards a horizontal line with intercept A_j. At its limit, $\gamma = 0$ and the customer's score S_{ij} no longer has weight. The loan officer has a monolithic belief about group j's members: $E(Q_{ij} \mid S_{ij}) = A_j$.

The model described thus far is consistent with Phelps (1972). However, the Phelps model does not address service discrimination's impact on firm profits. Because Phelps' model is static, it also offers no insights on the impact of dynamics. We expand the model by exploring these two areas. The loan officer's expected profit from a single loan is

$$(5) \qquad\qquad E(\pi_{ij} \mid S_{ij}) = E(Q_{ij} \mid S_{ij}) - Q^{min}$$

Q^{min}, assumed to be exogenous, is the quality of the marginal customer where loan profit is 0. The bank is only willing to serve customers whose quality exceeds Q^{min}. If the loan officer uses group information as well as the customer's score to form expectations about each applicant, then the loan officer uses a service policy where he offers a loan to applicants whose score, S_{ij}, meets

or exceeds a minimum score criterion for their group. We subsequently refer to this service policy as the *Group-Aware* policy. We refer to the alternative policy of not using group information as the *Group-Blind* policy where all applicants face a single score criterion, regardless of group membership.

We derive the Group-Aware minimum score criterion for each group, S_j^{min}, by setting Equation (3b) equal to Q^{min} and rearranging terms.

$$
(6) \qquad S_j^{min} = Q^{min} + (Q^{min} - A_j) \left(\frac{1 - \gamma_j}{\gamma_j} \right)
$$

In the top graph of Figure 1, the Group-Aware minimum score criteria of the example model are located at the vertical dotted lines labeled "Advantaged Min. Score (S_{Adv}^{min})" and "Disadvantaged Min. Score (S_{Dis}^{min})". Note that these vertical lines intersect with a horizontal dashed line labeled "Profit Threshold (Q^{min})" at the top right corner of the graph. Each intersection point is precisely where the expected quality of a member of the given group, conditional on score, is equal to the Q^{min} that represents the marginally profitable customer.

In contrast, the Group-Blind loan officer aggregates all applicant information in terms of advantage level and variation in quality to form his expectations of quality and a single minimum score criterion, S_{all}^{min} (not shown on the graph). Because the errors associated with Q_{ij} and $S_{ij} \mid Q_{ij}$ are independent of each other (see Equation (2b)), aggregation of the two groups has no impact on σ_ε^2. However, aggregation does impact the variation in customer quality and overall advantage level. Let p_{Adv} ($p_{Dis} = 1 - p_{Adv}$) represent the proportion of all applicants that are members of the advantaged (disadvantaged) group. Using the equations for blended means and pooled variance, the advantage, variance in quality, score reliability , and minimum score criterion of

applicants under the Group-Blind policy is as follows:

(7a)
$$A_{all} = p_{Adv}A_{Adv} + (1 - p_{Adv})A_{Dis}$$

(7b)
$$\sigma^2_{q_{all}} = \sigma^2_q + p_{Adv}(1 - p_{Adv})(A_{Adv} - A_{Dis})^2 > \sigma^2_q$$

(7c)
$$\gamma_{all} = \frac{\sigma^2_{q_{all}}}{\sigma^2_{q_{all}} + \sigma^2_\varepsilon} > \gamma$$

(7d)
$$S^{min}_{all} = Q^{min} + \left(Q^{min} - A_{all}\right)\left(\frac{1 - \gamma_{all}}{\gamma_{all}}\right)$$

Let $f_j(S)$ and $F_j(S)$ represent the probability density function and cumulative distribution function of group j scores. The loan officer's expected profit (Π) under the Group-Aware and Group-Blind policies are respectively:

(8a)
$$E(\Pi \mid S^{min}_{j \in Adv,Dis}) = \sum_{j \in Adv,Dis} \int_{S^{min}_j}^{\infty} \frac{p_j\, E(Q_{ij} \mid S_{ij}) f_j(S) dS}{2 - F_{Adv}(S^{min}_{Adv}) - F_{Dis}(S^{min}_{Dis})}$$

(8b)
$$E(\Pi \mid S^{min}_{all}) = \sum_{j \in Adv,Dis} \int_{S^{min}_{all}}^{\infty} \frac{p_j\, E(Q_i \mid S_i) f_j(S) dS}{2 - F_{Adv}(S^{min}_{all}) - F_{Dis}(S^{min}_{all})}$$

Under conditions of incomplete information about true consumer quality, thus far the loan officer has taken a profit-maximizing, non-prejudiced approach to forming a service policy. So where is the discrimination in service? We formalize our definition of service discrimination (D_i) as follows:

Definition 1 *Discrimination in service occurs when the service provider differentially treats two equally qualified consumers (i.e., consumers with the same quality and score) just because they are members of different groups. It is equivalently defined as the service provider's change in treatment of consumers i if consumer i changes group membership, conditional on maintaining*

the same quality and score. Discrimination (D_i) is defined as

$$D_i = E(Q_{i,Adv} \mid S_i^*, Q_i^*) - E(Q_{i,Dis} \mid S_i^*, Q_i^*)$$

(9)
$$= (\gamma_{Adv} - \gamma_{Dis})Q_i^* + [(1 - \gamma_{Adv})A_{Adv} - (1 - \gamma_{Dis})A_{Dis}]$$

$$\text{where } S_i^* = S_{i,Adv} = S_{i,Dis} \text{ and } Q_i^* = Q_{i,Adv} = Q_{i,Dis}$$

The top graph in Figure 1 shows by example the magnitude of discrimination for consumers with

a score $S_i^* = 550$. From Equation (9), we can see that if $\gamma_{Adv} \neq \gamma_{Dis}$, there are consumers with

quality level $Q_i^* = Q_{D0} = \frac{(1-\gamma_{Dis})A_{Dis}-(1-\gamma_{Adv})A_{Adv}}{(\gamma_{Adv}-\gamma_{Dis})}$ who experience no service discrimination.

However, other consumers with quality levels higher or lower than Q_{D0} experience discrimination

at magnitudes that increase in absolute value the further quality is from Q_{D0}. However, if

$\gamma = \gamma_{Adv} = \gamma_{Dis}$, then the magnitude of discrimination is constant across all consumers.

Discrimination in Equation (9) then simplifies to $D_i = (1 - \gamma)(A_{Adv} - A_{Dis})$.

We derive three key insights from this static model, which we formalize in the following

propositions (see Appendix A for proofs).

Proposition 1 *A profit-maximizing service provider using a Group-Aware policy will set service*

criteria where $S_{Dis} > S_{Adv}$ if $\gamma_{Dis} = \gamma_{Adv}$) or if $Q^{min} \in [A_{Dis}, A_{Adv}]$. If these conditions are not met,

the service provider will still set $S_{Dis} > S_{Adv}$ for all $\gamma_{Dis} \in (0,1)$ if the following conditions with a

threshold $\gamma^* = \frac{\gamma_{Dis}(Q^{min} - A_{Adv})}{Q^{min} - [\gamma_{Dis}A_{Adv} + (1 - \gamma_{Dis})A_{Div}]}$ are true:

1. $Q^{min} \in (0, A_{Dis})$ and $\gamma_{Adv} \in (0, \gamma^*)$

2. $Q^{min} \in (A_{Adv}, \infty)$ and $\gamma_{Adv} \in (\gamma^*, 1)$

Under these conditions, disadvantaged customers must meet a higher service policy criterion

than advantaged customers to receive the same level of service.

Taking the derivative of D_i in Equation (9) with respect to σ_ε^2, σ_q^2, and γ yields:

Proposition 2 *Assume each group $j \in \{Adv, Dis\}$ has equal σ_ε^2, σ_q^2, and γ. Discrimination (D_i)*

varies in σ_ε^2, σ_q^2, and γ as follows:

1. D_i increases in σ_{ε}^2, the magnitude of error in measuring true customer quality.

2. D_i decreases in σ_q^2, the variation of customer quality within each group.

3. D_i decreases in γ, the reliability of individual information (score) about each customer.

The intuition behind this proposition is that the greater the inequality between two groups, the greater the difference will be in the loan officer's assessment of two equally qualified customers from each group. However, the greater the reliability of individual customer information is in assessing quality, the less the loan officer will rely on group information to form his expectation. Reliability of individual information improves when there is more information about members within a group (i.e, more intra-group variation in customer quality) and when there is decreased error in measuring the quality of individuals. Increased reliance on the customer's score/decreased reliance on group information leads to decreased discrimination.

Under these conditions, we find that it can be profitable to discriminate. The average per period (short-term) profits are greater from a Group-Aware service policy than from a Group-Blind one:

Proposition 3 *Let there be two consumer groups represented by $j \in \{Adv, Dis\}$ where one group has greater advantage than the other ($A_{Adv} > A_{Dis}$). Also, assume that the service provider aggregates all customer information to set a single, group-blind minimum score criterion policy S_{all}^{min}. Furthermore, assume that aggregation has no impact on on variation in measurement error, σ_{ε}^2. Then $E(\Pi \mid S_j^{min}) \geq E(\Pi \mid S_{all}^{min})$. In other words, the service provider's expected average per period profits from a Group-Aware service policy is greater than one using a Group-Blind service policy.*

The discrimination model described thus far is static, similar to most prior literature. However, consumer attributes can change over time. In the U.S., for example, a woman's median hourly earnings was 64% of a man's in 1980. As of 2015, it was 83%. This pattern is consistent for many disadvantaged groups in the US (Brown and Patten 2017). For this reason, it is

important to understand how dynamics in advantage inequality can affect the dynamics of service discrimination. Next, we consider a time dimension in our model, which is a departure from standard statistical discrimination models such as Phelps (1972) and Aigner and Cain (1977).

To explore dynamics, we expand the time frame to two periods and add the subscript t to the model (i.e., we now have A_{jt}, Q_{ijt}, S_{ijt}, $\sigma^2_{q_{jt}}$, $\sigma^2_{\varepsilon_{jt}}$, γ_{jt}, S^{min}_{jt}, and D_{it}). Let us assume that each group has a new set of applicants at $t = 2$ with an advantage level that may differ from the advantage level of applicants from $t = 1$. Let $p_{j1} + p_{j2} = 1$, where p_{j1} is the proportion of all group j applicants across time periods that applied at $t = 1$ and has advantage level A_{j1}. The proportion that applied at $t = 2$ is $p_{j2} = 1 - p_{j1}$ with advantage level $A_{j2} = g_j A_{j1}$. The value $g_j \in [0, \infty)$ is the magnitude of change in group j advantage from $t = 1$ to $t = 2$. A $g_j = 1$ implies no growth in group j's advantage between periods 1 and 2, $g_j < 1$ implies a decline, and $g_j > 1$ suggests growth. In the example about women's pay relative to men's over the last three decades, $g_{women} > 1$. For simplicity's sake, also assume that each group's new set of applicants has the same magnitude of intra-group variation in quality and variation in measurement error as their predecessors at $t = 1$ (i.e., $\sigma^2_{q_{j1}} = \sigma^2_{q_{j2}}$ and $\sigma^2_{\varepsilon_{j1}} = \sigma^2_{\varepsilon_{j2}}$).

If the loan officer uses information from just the new set of applicants in $t = 2$ to form expectations of quality, the only change in his belief relative to $t = 1$ is driven by g_j, the change in group advantage. There is no comparative change in variation in quality and measurement error between $t = 1$ and $t = 2$, therefore $\gamma_{j1} = \gamma_{j2}$. On the other hand, if the loan officer uses the entire history of information about applicants from both periods to form expectations, then the cumulative impact (represented by subscript c) as of $t = 2$ is as follows:

Lemma 1 *Assume there are time periods $t \in \{1, 2\}$. If a service provider pools all available group j information across time periods to form his expectations of consumers from group j, then the following is true about his beliefs of j's advantage level, variation in quality, score reliability,*

and the minimum score criterion (where subscript c represent beliefs cumulative as of t = 2):

(10a)
$$A_{jc}(g_j) = p_{j1}A_{j1} + p_{j2}A_{j2}$$

$$= A_{j1}\left[p_{j1} + g_j(1 - p_{j1})\right]$$

(10b)
$$\sigma^2_{q_{jc}}(g_j) = p_{j1}\sigma^2_{q_{j1}} + p_{j2}\sigma^2_{q_{j2}} + p_{j1}p_{j2}\left[A_{j1} - A_{j2}\right]^2$$

$$= \sigma^2_{q_{j1}} + p_{j1}(1 - p_{j1})\left[A_{j1}(1 - g_j)\right]^2 \geq \sigma^2_{q_{j1}}$$

(10c)
$$\gamma_{jc}(g_j) = \frac{\sigma^2_{q_{jc}}(g_j)}{\sigma^2_{q_{jc}}(g_j) + \sigma^2_{\varepsilon}} \geq \gamma_{j1}$$

(10d)
$$S^{min}_{jc} = Q^{min} + \left(Q^{min} - A_{jc}(g_j)\right)\left(\frac{1 - \gamma_{jc}(g_j)}{\gamma_{jc}(g_j)}\right)$$

From Equations (10b) and (10c), we see that as long as there is a change in a group's advantage from $t = 1$ to 2 (i.e., $g_j \neq 1$), then j's intra-group variance in quality and j's score reliability increases. These increases can either decrease or increase the group's minimum score criterion. If a group's advantage increases, it is intuitive that its minimum score criterion would decrease. After all, increasing group advantage implies that more members are qualified (profitable) to the service provider for services. It also intuitively follows that decreasing group advantage should lead to an increasing minimum score criterion. However, we also find conditions where a group's minimum score criterion can increase (decrease) despite its increasing (decreasing) group advantage. This is formalized in the next proposition:

Proposition 4 *The effect of growth or decline (g_j) of a group's advantage over time on the group's most recent minimum score criterion, S^{min}_{jc} depends on the group advantage levels relative to Q^{min}. When a group's advantage changes over time (i.e., $g_j \neq 1$), its minimum score criterion*

changes in the following ways:

$$(11) \quad S_{jc}^{min} \begin{cases} > S_{j1}^{min} \text{ when } \sigma_{q_{jc}}^2(g_j) < (\sigma_{q_{jc}}^2)^* \text{ and } \begin{cases} g_j & > 1 \text{ and } Q^{min} < A_{jc}(g_j) \\ \\ g_j & < 1 \text{ and } Q^{min} > A_{jc}(g_j) \end{cases} \\ \\ = S_{j1}^{min} \text{ when } g_j = 1 \text{ or } Q^{min} = A_{jc}(g_j) \\ \\ < S_{j1}^{min} \text{ otherwise} \end{cases}$$

$$\text{where } (\sigma_{q_{jc}}^2)^* = 2p_{j1}(1-p_{j1})A_{j1}(1-g_j)(Q^{min} - A_{jc}(g_j))$$

This means that when intra-group variation is not too high, a group can face unchanging or even rising minimum score criteria for service despite the group's improving advantage. The intuition behind proposition 4 is that as score reliability improves, there is less uncertainty regarding the score's measurement of true quality. Since scores are more reliable, consequently the service provider choses a minimum score criterion that draws closer to Q^{min}. At its limit where $\gamma_j = 1$ which implies perfect score reliability, $S_j^{min} = Q^{min}$. If $A_{jc} > Q^{min}$, any improvement in score reliability reduces the amount of adjustment needed, which thereby increases the minimum score criterion towards Q^{min}. On the other hand, if $A_{jc} < Q^{min}$, any improvement in score reliability decreases the adjustment needed and thereby reduces the minimum score criterion.

If the two groups differ in their rates of growth in advantage, then there are additional implications on discrimination. As is the case of men and women's growth in pay rates over the past three decades, let us assume that $g_{Adv} < g_{Dis}$: the disadvantaged group has a faster advantage growth rate than the advantaged group. We established from Equation (9) that if a group grows in advantage, the variance of quality of its members increases. Increased variance in the disadvantaged group implies that $\gamma_{Dis,2} > \gamma_{Adv,2}$ (recall that the groups had equal score reliability at $t = 1$). This has the effect that the loan officer places greater weight on individual information for the disadvantaged group than he does for the advantaged. The regression for the disadvantaged rotates closer towards the 45° line where S_{ij} perfectly measures Q_{ij}.

The bottom graph in Figure 1 displays an example of the effect of advantage growth for the

disadvantaged group. The bottom graph represents the service provider's expectations at $t = 2$. The advantaged group has remained unchanged relative to $t = 1$ (the top graph). However, the disadvantaged group has grown in advantage, resulting in a change in score reliability from a $\gamma_{Dis,1} = .5$ in $t = 1$ to a $\gamma_{Dis,c} = .8$ in $t = 2$. The minimum score criterion for the disadvantaged group has subsequently increased by 15 units to 615 in $t = 2$.

This change in the score reliabilities of each group due to changes in variation has a demonstrable effect on the magnitude of discrimination against the disadvantaged group. Although the disadvantaged group has grown in advantage, the inequality gap shrinks for only some of its members. Where $Q_{\Delta D=0}$ is the quality level where the magnitude of $D_{i1} = D_{i2}$, disadvantaged applicants with quality $Q_{i,Dis}$ on one side of $Q_{\Delta D=0}$ actually experience greater magnitudes of discrimination than they did in the prior period. Disadvantaged members on the other side of $Q_{\Delta D=0}$ benefit from their group's growing advantage–discrimination is less than its magnitude at $t = 1$. This insight brings us to our final proposition.

Proposition 5 *Let $\Delta \gamma_j = \gamma_{j2} - \gamma_{j1}$ and $\Delta A_j(1 - \gamma_j) = A_{j2}(1 - \gamma_{j2}) - A_{j1}(1 - \gamma_{j1})$. A change in the advantage of a group can change the degree of discrimination that members of the disadvantaged group experience over time. The quality level for which the magnitude of discrimination is the same in both time periods, $Q_{\Delta D=0} = \frac{\Delta A_{Dis}(1-\gamma_{Dis}) - \Delta A_{Adv}(1-\gamma_{Adv})}{\Delta \gamma_{Adv} - \Delta \gamma_{Dis}}$, the magnitude of discrimination that customer i experiences at $t = 2$ can be less or greater than at $t = 1$. The conditions where the magnitude of discrimination changes over time t has the following relationship:*

1. *$D_{i2} > D_{i1}$ if*

    (a) *$\Delta \gamma_{Adv} > \Delta \gamma_{Dis}$ and $Q_{ij} > Q_{\Delta D=0}$*

    (b) *$\Delta \gamma_{Adv} < \Delta \gamma_{Dis}$ and $Q_{ij} < Q_{\Delta D=0}$*

2. *$D_{i2} < D_{i1}$ if*

    (a) *$\Delta \gamma_{Adv} > \Delta \gamma_{Dis}$ and $Q_{ij} < Q_{\Delta D=0}$*

    (b) *$\Delta \gamma_{Adv} < \Delta \gamma_{Dis}$ and $Q_{ij} > Q_{\Delta D=0}$*

Proposition 5 demonstrates that reducing the inequality gap does not reduce discrimination for everyone. When a disadvantaged group grows in advantage faster than the advantaged group, its members with sufficiently high quality level can experience reduced discrimination over time. However, disadvantaged customers of sufficiently low quality can actually experience greater discrimination over time, even though the inequality gap is shrinking. Proposition 5 also asserts the reverse. Paradoxically, a growing inequality gap can reduce the magnitude of experienced discrimination for some disadvantaged members. When the inequality gap grows (the growth for the advantaged exceeds the disadvantaged), disadvantaged customers of sufficiently low quality can experience reduced discrimination. The bottom graph in Figure 1 displays an example of the effect of Proposition 5. Note that the magnitude of discrimination for consumers with a score $S_i^* = 550$ is demonstrably greater than it is for them in $t = 1$ (top graph).

This completes our analytical model of service discrimination, which provides insight on how variation in customer quality and measurement error and have direct impact on the magnitude of discrimination in service. It also highlights how changes in group advantage over time can change not only the variation in the quality of the group, but also the magnitude of discrimination. However, we now need to understand whether our analytical model is empirically realistic and valid. In the next section, we test our propositions with a set of empirical studies to understand if real behavior is consistent with our theory.

EMPIRICAL VALIDATION

To test the empirical validity of our theory of service discrimination, we designed two studies to test propositions presented in the prior section. For our first study, we recruited 400 participants (56.4% male, 5.5% between 25-34 years old, all U.S. residents) on Amazon mTurk. Study 1 tests the first three propositions under conditions where the advantaged and disadvantaged groups are constant in advantage over time. For our second study, we recruited 409 participants on Amazon mTurk (54.0% male, 45.7% between 25-34 years old, all U.S. residents). In Study 2, advantage is held constant for the advantaged group while we allow the disadvantaged

to grow monotonically in advantage (approximately 1.36% after each round) during the study. By the last round, both groups are equal in advantage. This condition enables us to test the last two propositions regarding dynamic inequality. This specification implies that $\gamma_{Dis} > \gamma_{Adv}$ over time, which meets the conditions of Proposition 5.1 (b) and Proposition 5.2 (b).

Each study had a 2 (group information: present vs. absent) X 2 (true quality variation: low vs. high) X 2 (credit score error variation: low vs. high) between-subjects design. Participants were randomly assigned to one of the eight conditions. We conducted the studies using Qualtrics survey software customized with JavaScript programming to dynamically update stimuli based on participants' prior decisions. Each participant played the role of a bank loan officer in 10 rounds of a lending game, which took on average 40 - 60 minutes to complete. The participant reviewed 10 loan applicant profiles for each of 10 rounds. Each profile revealed the applicant's identification number, address, and credit score. All applicants are members of one of two groups: either a square group or triangle group. We used these abstract symbols to represent groups in order to remove potential for any prior bias. Unknown to participants, one applicant group was the advantaged group whose average quality and credit scores were higher than the other group. We counterbalanced between subjects the designation of whether the squares or triangles were the advantaged group. In the Group-Aware (Group-Blind) condition, the study participant saw (never saw) of which group the applicant was a member.

The game asked the participant three questions about each applicant profile: 1) whether or not to offer the applicant a loan; 2) how confident the participant is in her decision; and 3) how confident the participant is that the loan will be repaid by the applicant. At the end of each game round, the game presented the participant a table displaying outcomes of the participant's loan decisions. The participant earned 30 Credit Units ($.075) on any repaid loans and lost 30 on loan defaults. After conclusion of the 10-round game, the participant answered survey questions about demographics and risk-aversion. The participants also earned a flat $3 fee for completion of the game. In total, we spent almost $10,000 on the two studies (including compensation to participants, pretests, software development, and Amazon fee). We gave relatively large mTurk

compensation to ensure that participants took the task seriously and to test true decision-making behavior with financial consequences. Furthermore, we wanted to ensure participants were properly motivated and compensated to complete this lengthy study.

Randomly generated credit scores and loan repayment outcomes in the study were based on 2006 and 2010 Equifax data on mortgage applicants (Bhutta and Canner 2013). The credit scores have a range of 300 - 850 in possible values, consistent with retail credit markets. We set $Q^{min} = 620$ (unobserved by participants), which is the value employed in the Equifax Risk report. Note that Q^{min} is below the advantage levels of both groups in the studies ($A_{Adv} = 723$ and $A_{Dis} = 640$). Between study conditions, we manipulated the variance in applicant quality (σ^2_{qt}) and measurement score error ($\sigma^2_{\varepsilon t}$) to be high or low values[1]. Participants did not see these values, but they directly influenced the credit scores on each applicant profile. Within each study condition, squares and triangles had the same intra-group variance in quality and measurement error. All participants in a study condition saw the same sequence of profile information. Our goal was to ascertain the impact of these conditions on our three dependent variables: probability of offering a loan to an applicant, confidence that the applicant will repay the loan (measured on a 0 - 100 point scale with 100 implying complete confidence), and profit made by the participants on loans offered. Next, we discuss how we test and measure the data collected to determine empirical validity of our theory.

Tests and Measures

Because the empirical study has repeated measures of participant response, we analyzed the data using hierarchical models to address likely intra-participant correlation of responses. Level 1 unit variables were study conditions and attributes of applicant profiles while participant dummies were at level 2. We used an OLS regression to test Proposition 3 because the dependent variable was simply total profits earned by each study participant. Dependent variables were a dummy indicator for whether the participant offered a loan to an applicant (*Loan*) and his confidence that

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[1] standard deviation=45.5 (Low) vs. 80.2 (High), based on the Equifax data

the applicant would repay a loan (*Repay*, based on a 100-point scale). Study condition variables were dummy indicators for the Group-Aware condition (*Group*), low variation in applicant quality condition (*QualityLowVar*), low measurement error condition (*ScoreLowVar*), and Study 2: Dynamic Inequality (*Dynamic*). We also included continuous variables for study round (*Round* and *Round^2*). Applicant profile variables were applicant quality, score, and group membership (*Quality Score*, *Disadvantaged* dummy).

To test Propositions 1 and 4, we modeled participant p's decision to offer a loan to applicant i from group j with a hierarchical logit.

$$Logit[Loan]_{pij} = X_{pij}\beta_{10} + \beta_{0p} + \varepsilon_{pij}$$
(12)
$$\beta_{0p} = \upsilon_{00} + \xi_{0p}$$

Although we did not observe each participant's implicitly determined minimum score criterion for applicants, we reason that if there is a higher score criterion in operation for disadvantaged applicants, we should observe a lower likelihood of loans offered to disadvantaged applicants than to equally qualified advantaged applicants.

To test Propositions 2 and 5, we estimated the following hierarchical linear model. The dependent variable is *Repay*, which is participant p's response to the question "How confident are you that this applicant will repay the loan?".

$$Repay_{pij} = X_{pij}\beta_{10} + \beta_{0p} + \varepsilon_{pij}$$
(13)
$$\beta_{0p} = \upsilon_{00} + \xi_{0p}$$

Because we did not observe each participant's implicitly determined expectation of the applicant i's quality, conditional on score, we used this measure as a proxy. Our reasoning is that if there is discrimination against disadvantaged applicants, we should observe lower average *Repay* values for disadvantaged applicants than for equally qualified advantaged applicants.

Tests of Propositions 1 and 2 use the same design matrix, X_{pij} which contains dummy

variables for *Disadvantaged*, study conditions (*Group*, *QualityLowVar*, *ScoreLowVar*), and their interactions. The design matrix also contains continuous-measure variables that control for applicant quality (*Quality*), score (*Score*), and their interaction. The final two variables included in the design matrix control for time and learning effects (*Round*, $Round^2$). For Propositions 4 and 5, we compared Study 1 (static inequality) and Study 2 (dynamic inequality) responses of participants from the study condition where group information is available. We modified the design matrix used for Propositions 1 and 2 in the following way: we dropped the *Group* dummy, added a dummy for *Dynamic* (indicating Study 2), and interacted *Quality* with *Dynamic*, *Disadvantaged*, *Round*, and $Round^2$ for Proposition 2. All continuous variables were first standardized before estimation; therefore, effects associated with these variables should be interpreted in terms of the impact of one standard deviation away from the mean. We used an OLS model to test Proposition 3. We regressed participant *p*'s total game earnings on $Group_p$. We included *ScoreLowVar*, *QualityLowVar*, and their interaction to control for study conditions. A positive coefficient on *Group* would indicate that utilizing group information in addition to individual information is more profitable than just individual information in making service decisions. All models were estimated with standard maximum likelihood methods using the panel data set of participant responses from the two studies. We now turn to discussing results in the next section.

Empirical Results

Figure 2 (see after Reference) visually summarizes some of the main results from both studies. The graphs display quality levels of applicants (x-axis) vs. loan offer rates (y-axis). Loan offer rates are the mean percentage of applicants, conditional on quality, that were offered loans by participants across all study conditions. The left column of graphs displays Study 1 results and the right column displays Study 2 results. The top row of graphs results are under the study condition where group membership information is present (Group-Aware) condition. The bottom row results represent the group information is absent (Group-Blind) condition. In both graphs,

there is a black vertical line labeled Q^{min} which, unknown to participants, is the minimum applicant quality level needed in order for the participant to earn profit on a loan. All applicant quality values to the right of Q_{min} in the graph are profitable, and those to the left are unprofitable. The curves in each graph with square markers represent loan offer rates for advantaged applicants while those with triangle markers represents disadvantaged applicants. Because the raw data are visually noisy, we smooth the data with Gaussian LOESS curves (Cleveland and Devlin 1988; Rust and Bornman 1982). We use quadratic polynomials with smoothing parameters automatically selected to minimize a bias-corrected AIC (Hurvich, Simonoff, and Tsai 1998). These parameters range from 0.941 to 0.946 and are robust to different degrees of polynomial and to an alternative method of optimized parameter selection (generalized cross-validation). Note from the graphs that in general, loan offer rates for advantaged applicants dominate those for disadvantaged. Although our definition of discrimination is conditional on quality *and* credit score, the gaps between the advantaged and disadvantaged curves give an indication of the magnitude of discrimination between equally qualified advantaged and disadvantaged applicants. One can see that the gaps are greater in the Group-Aware graphs than in the Group-Blind graphs.

Table 1 (see after Reference) summarizes the key results of the two studies.

Study 1 and Study 2 results indicate that participants in the Group-Aware condition under both static and dynamic inequality scenarios exact a higher minimum score criterion for disadvantaged than equally qualified advantaged applicants. Participants in the Group-Aware condition were less likely to offer a loan to a disadvantaged candidate than to an equally qualified advantaged applicant (Study 1: -1.013, $p < .001$; Study 2: -1.837, $p < .001$). This finding is consistent with Proposition 1. Studies 1 and 2 are also consistent with Proposition 2. When group information is absent, we found no statistical difference in the repayment expectations of equally qualified advantaged and disadvantaged candidates. However, when group information was present and measurement error was low, we find that participants had an increased *Repay* evaluation of disadvantaged applicants; this implies a smaller difference in evaluation between equally qualified disadvantaged and advantaged applicants (Study 1: 2.982, $p < .001$; Study 2:

3.358, $p < .001$).

On the other hand, when variance in applicant quality was low, participants had a decreased *Repay* evaluation of disadvantaged applicants in Study 1 (-6.383, $p < .001$). In Study 2, the effect of lower variance in applicant quality is not significant when considering all rounds of the study (.565, p *is n.s.*). However, when considering only the second half of the study, the effect approaches significance and has the expected sign (-1.499, $H_a < 0$ $p = .051$). One possible explanation for this result could be that growth in the disadvantage group's level of advantage effectively increases the variation in quality for both low and high variance conditions of the study. Perhaps participants perceived both conditions as high variance. The results suggest that under conditions where growing advantage (and thus expanding variation in quality) is present, participants needed more time to learn the distinctions between the groups. Furthermore, given that Study 2 has a change in inequality between the applicant groups in each round, it is effectively a 2X2X2X10 study. Statistical power in this study may be an additional factor. This opens up more questions about the long-run effects of time on the perception of variance and its impact on discrimination outcomes. This offers an avenue of interesting future research.

Overall, we do not find statistically significant support for Proposition 3 in either study. Although the coefficient on the *Group* dummy has the expected sign, it is not statistically significant (Study 1: .152; Study 2: .092). We could not say with confidence that, on average, using group information is more profitable than ignoring group information. In fact, we found only one set of conditions where using group information does have a statistically significant profit impact. In Study 1 (where inequality is static), when both variance of quality and variance of measurement error are low, using group information actually *hurts* total participant profits ($-.344$, $p < .05$). This could be because the credit scores are already very diagnostic in this condition since there is low variation in quality and measurement error. Perhaps group information under these conditions can mislead the participant, especially when its implications are in conflict with those of the credit score.

Study 2 also demonstrates that dynamics in advantage levels can change minimum score

criteria and change the magnitude of discrimination exhibited. Recall that in Study 2, $Q^{min} = 620 < A_{Dis,1} = 640 < A_{Adv,1} = 723$. Given that throughout the study, advantage levels of both groups exceed Q^{min} and that the disadvantaged are growing in advantage, we would expect, based on Proposition 4, that the minimum score criterion for disadvantaged applicants should rise likelihood of loan offers should fall over time when group information is available. We find that the coefficient on the interaction of *Dynamic*, *Disadvantaged*, and *Round* is consistent with this prediction ($-.729$, $p < .05$). Despite the fact that the disadvantaged grow in advantage with each successive round in the game, Study 2 participants were indeed less likely than Study 1 participants to offer loans to equally qualified disadvantaged candidates over time.

The bottom two graphs in Figure 2 give a visual example of how dynamics in group advantage can impact the direction of loan decisions in the Group-Aware condition. The graphs display the mean loan offer rates to applicants whose latent quality and credit scores are within the 650 - 700 range. We selected this quality and score range because it contains the largest group of comparably qualified applicants in the study. The left graph shows Study 1 loan offer rates, and the right graph shows the same information from Study 2. Advantaged applicants are represented by the curve marked with squares; disadvantaged are marked with triangles. Because their latent quality values exceed $Q^{min} = 620$, all applicants in this group should ideally receive loans. Using the loan offer rates to advantaged applicants as a point of comparison, one can see that in the static condition, the rate of loan offers to disadvantaged applicants gradually decreases during the progress of the study. In contrast, in the dynamic condition the gap between the advantaged and disadvantaged candidates is greater.

Furthermore, we find that increases in discrimination over time are not uniformly experienced across members of the disadvantaged group. Recall that our study conditions match the conditions of Proposition 5 sections 1b and 2b. Under these conditions, we predict that disadvantaged members with lower (higher) quality scores would face increasing (decreasing) discrimination in subsequent rounds. We find that the coefficient on the interaction of *Dynamic*, *Disadvantaged*, *Round*, and *Quality* is not significant when considering all rounds of the study

$(-.288)$. However, when examining the second half of the study (Rounds 6 - 10), the results are significant and support Proposition 5 $(27.210, H_a > 0 \; p = .042)$. As the disadvantaged group improved in advantage over time in the study, higher quality disadvantaged applicants experienced less discrimination while lower quality applicants experienced more over time. The implications are that although decreasing inequality between groups can lead to reduced discrimination against some disadvantaged, it can also lead to increasing degrees of discrimination against other disadvantaged.

To summarize, the findings from the analytical model, validated by empirical evidence, suggest that when a service provider has access to observable group membership information, the service provider will be less discriminatory against disadvantaged consumers from a group with high variance in quality than they will against a disadvantaged group with low variance in quality. The service provider will also be less discriminatory when the error in measuring consumer quality is low. The findings demonstrate that variability in group members as well as measurement error in detecting quality are each a driving mechanism of discrimination. The findings also show that the service provider will exact a higher minimum score criterion to provide service for disadvantaged consumers than for equally qualified advantaged consumers. Furthermore, the results show that dynamics in advantage can play a critical role in service discrimination outcomes. If a disadvantaged group improves its advantage over time (which reflects the reality of many U.S. disadvantaged groups, such as women and minorities), there are certain conditions where the minimum service score criterion can increase despite the group's advantage improvement. Moreover, although the disadvantaged group as a whole may be improving in advantage, our results show that not everyone will benefit. While some members will experience decreasing discrimination as a result of the improved advantage, others will experience increasing discrimination as a result.

However, the analytical model and empirical studies do not fully address the system complexity over time of discrimination in service and its impact on demand and profits. We next examine the impact of competition, word-of-mouth (WOM), and social factors that can influence

variation in customer quality (assimilation, population mix) on the dynamics of service discrimination and on demand and profits. To investigate these, we turn to agent-based modeling. Agent-based modeling (ABM) is a research tool that enables the researcher to simulate the behavior and interactions of autonomous individual agents (people, organizations, etc.) in order to analyze emergent macro phenomena. It is often used to understand the dynamics of collective patterns in a complex system (Delre, Broekhuizen, and Bijmolt 2016a; Goldenberg, Libai, and Muller 2001b, 2010; Rand and Rust 2011). By using both ABM and analytical modeling, we leverage the strengths of each (full parameter space exploration for analytical modeling, modeling of complex interactions for ABM) to answer our research questions more fully than by using one or the other alone (Peres and Van den Bulte 2014). Using ABM in conjunction with studies can produce new insights through the revelation of macro-level, long-run implications of micro-level observations derived from the studies (Smith and Rand 2017). ABMs can be used for two different purposes. One purpose is to use an ABM as an extension of an econometric model. In such applications, careful validation of all the input parameters is essential (e.g., see Libai, Muller, and Peres 2013). An alternative use, however, is to use an ABM as an extension of an analytical model in order to show directional results of how variables affect outcomes (Delre, Panico, and Wierenga 2016b). This reflects our purpose. However, we still strive to use realistic, data-justified values where possible. In that spirit, in the next section we discuss our use of ABM to investigate the long-run implications from our study findings.

AN AGENT-BASED MODEL OF SERVICE DISCRIMINATION

To analyze the dynamics of discrimination in service, we employ a 2^8 full factorial design (256 separate simulations) in the agent-based model (ABM). The ABM models supply and demand for loans in a simulated city. The city contains four competing banks and a population of 200 consumers comprised of people from an advantaged or disadvantaged group. Banks and consumers are randomly distributed throughout the geographic area. Based on the distributional assumptions used in the studies, the ABM randomly assigns quality and credit score attributes to

consumers. Each bank has one loan officer. Two randomly determined banks have a Group-Aware service policy (a minimum score criterion for each population group) while the others have a Group-Blind service policy (a single minimum score criterion). This allows us to examine competition and its impact on consumer demand and firm profits over time in the ecosystem. Becker (1957) theorized that market forces can ultimately drive out firm discriminatory behavior if non-discriminatory competitors exist. We test the spirit of this theory by including firms in the ABM ecosystem that employ a group-blind minimum score criterion. In each time period in the ABM, a random selection of consumers applies for a loans. These applicants select one and only one bank in any given period based on their utility for the bank (to be elaborated on shortly). Subsequently, each bank loan officer offers loans to applicants with scores exceeding the minimum score criterion determined by bank service policy. Loan officers use historical data of past applicants to update their beliefs about group advantage levels and to set new minimum score criteria in each period. Each applicant retains a history of loan applications and rejection/acceptance outcomes. Banks cannot observe each applicant's history, but consumers can observe the application history of other consumers in their network.

The ABM uses combinations of high and low values for each of the eight factors. Three of the eight factors come directly from the analytical model and studies: intra-group quality variance, measurement error variance, and degree of inequality (σ_{qt}^2, $\sigma_{\varepsilon t}^2$, and $Inequality_t = A_{Adv,t} - A_{Dis,t}$). We use the same values and decision rules employed in our empirical studies. By doing so, we directly link the empirical study results with the ABM, thereby enabling us to gain insight on the long-run, macro implications of micro-level study observations. Consistent with the empirical studies, we test both static and dynamic inequality conditions over time. In simulations with dynamic inequality, we allow A_{Dis} to grow at a rate of .16% per period[2] while holding A_{Adv} fixed.

The remaining five factors are assimilation, population mix, number of applicants, and two dimensions of word-of-mouth (WOM). Assimilation can be thought of as adopting observable characteristics or cultural practices associated with the advantaged group. We expect that greater

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[2]Based on the annual growth rate of average Black wealth relative to Whites from 1967 to 2010 in the U.S. Source–Pew Research Center

degrees of assimilation reduce discrimination. Assimilation reduces the chance that a disadvantaged member is identifiable as disadvantaged because the person possesses attributes of both the advantaged and disadvantaged group. For example, a religious minority who attends a bank loan interview dressed in a business suit (characteristic of the advantaged majority) may experience less discrimination than if he attends in traditional religious garb. We operationalize assimilation in the ABM model by varying the proportion of characteristics (advantage) that the disadvantaged group shares with the advantaged group (0% vs. 50%).

Varying the population mix of the applicant pool allows us to test whether the frequency of exposure to applicants impacts discrimination in service. An increased balance in population mix – a 50/50 split in two populations represents perfect balance – increases the loan officer's exposure to members of both groups. More exposure provides the loan officer with more information. We operationalize population mix in the ABM by varying the percentage of population that is advantaged (9% vs. 63%)[3]. The lower percentage of 9% represents a less balanced population. We predict that the magnitude of discrimination will be lower when the advantaged population represents 63% of the population mix. This is because a 63/37 population mix is much closer to a balanced population than a 9/91 split. Discrimination decreases because the loan officer has more information from both groups about consumer quality.

Varying the intensity of demand allows us to test how demand for service impacts service discrimination. We operationalize this by varying the percentage of the city population that applies for a loan in each ABM time period (20% vs. 80%). We posit that a greater frequency of applications would lead to less service discrimination. A greater frequency of applications provides banks with more information. More information should improve variation in quality over time and thus decrease discrimination. This scenario reflects potential differences between highly trafficked banks (e.g. city banks) versus less trafficked banks (e.g. rural banks), even after controlling for other factors like population mix.

We investigate how the final factor, customer word-of-mouth (WOM), affects demand for

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[3]Based on the percentage of the population that is White in South Africa and U.S respectively. Source: South African National Census of 2011 and 2011 Pew Research Center Report

services over time. Prior literature has established that WOM can have strong influence on consumer choice (Goldenberg, Libai, and Muller 2001a; Libai, Muller, and Peres 2013; Trusov, Bucklin, and Pauwels 2009). Our model assumes loan applicants are utility-maximizing. Utility for bank b has an inverse relationship with distance ($Dist_{ib}$) between applicant i and bank b. It increases with i's assessment of her probability of receiving a loan from the bank. The inclusion of distance as a factor in the utility function is consistent with models in the consumer store choice literature (e.g., Huff 1964; Rust and Donthu 1995). We account for additional unobservable factors that influence an applicant's utility with an extreme-valued distributed error term, ε_{ibt}.

WOM about banks is an important factor in each consumer's bank selection. Each consumer in the ABM "talks" to other consumers in her network to find out who has received loans and from which banks. We operationalize WOM through each consumer's ability to access the application history of other consumers in their network. WOM utility that applicant i has for applying to bank b is driven by applicant i's assessed probability that she will be offered a loan from bank b at time t ($P_{ibt}^{WOM} = Pr(Loan_{ibt} \mid \alpha, \mathbf{w_i})$). The probability is equal to the proportion of the applicant's social ties that has received loan offers from bank b weighted by the strength of the social connection between i and each social tie k. Consistent with prior research, strong ties have a greater probability of affecting an individual's choice than weak ties (Brown and Reingen 1987). The strength of the social connection is measured as the inverse of the distance (Soc_{ik}) between i and k in the simulated city. WOM is also weighted by whether the source of WOM is an in-group vs. out-group member. For example, if i is a member of the squares group in the ABM, then i considers other squares as in-group sources of WOM and triangles as out-group sources. Extant literature has shown that consumers give consideration to in-group versus out-group sources of WOM (Podoshen 2006; Lam et al. 2009; Uslu et al. 2013).

We vary $\alpha \geq 1$, the weight that consumers place on WOM received from in-group relative to out-group sources, with input values of 1 vs 3 (based on Brown and Reingen (1987); Podoshen (2006); Zhao and Xie (2011) findings). When $\alpha = 1$, applicant i equally weights in-group and out-sources of WOM. An $\alpha > 1$ implies that i places greater weight on WOM from other in-group

the population that is advantaged (moving from an imbalanced to a balanced, integrated society) decreases discrimination (Static Advantage: -1.982, $p < .001$; Dynamic Advantage: -9.214, $p < .001$). Recall that discrimination is measured as a difference in expected quality, conditional on two consumers from two groups having the same quality and score. A greater percentage of the population applying for loans increases discrimination (Static Advantage: 19.433, $p < .001$; Dynamic Advantage: 13.377, $p < .001$). Decreased assimilation also has the significant effect of increasing discrimination (Static Advantage: 46.990, $p < .001$; Dynamic Advantage: 33.980, $p < .001$). Recall that the degree of assimilation relates to the proportion of characteristics, and thus advantage level, that the disadvantaged group shares with the advantaged. The ABM results support the expectation that the more assimilated the disadvantaged group is, the less the group is discriminated against in receiving service.

We find that WOM and competition can drive loss of applicant market share and long-term profits. On average, Group-Blind banks have a significantly greater share of all applicants in the market (Static Advantage: 52.4% vs. 47.6%, $p < .001$; Dynamic Advantage: 52.8% vs. 47.2%, $p < .001$). WOM also can have a large impact on long-term profits. We regressed cumulative profits on *Group*, α (weight placed on in-group sources of WOM), β (weight placed on WOM in general in the applicant's utility function), and their interactions. We also included controls for other ABM simulation factors (*ScoreLowVar*, *QualityLowVar*, assimilation, population mix, number of applicants). Consistent with findings from prior WOM literature (Trusov et al. 2009; Libai et al. 2013), we find that WOM in general (β) has a positive impact on long-term profits (Static Advantage: \$2,333.27, $p < .001$; Dynamic Advantage: \$3,537.74, $p < .001$). However, the interaction of WOM parameters with the *Group* dummy reveals that the greater the weight consumers place on WOM in general, the more negative its impact on the long-term profits of Group-Aware banks relative to Group-Blind banks (Static Advantage: \$-4,487.35, $p < .001$; Static Advantage: \$-6,431.03, $p < .001$). Regarding the weight placed on in-group sources of WOM (α), we find mixed statistical support of its impact on profits. Overall, the weight on in-group sourced WOM has a directionally positive but not

statistically significant impact on long-term profits (Static Advantage: $1,460.26, $p = .170$; Dynamic Advantage: $2,241.08, $p < .091$). However, its effect on Group-Aware banks' long-term profits is negative and statistically significant (Static Advantage: $-2,597.01, $p = .085$; Dynamic Advantage: $-4,176.76, $p = .026$)

Comparing average Group-Aware and Group-Blind banks' short-term profits across all ABM conditions, we find that the Group-Aware banks have, on average, higher profits per loan under static advantage conditions (Static Advantage: $72.83 Group-Aware vs. $69.05 Group-Blind, $p < .001$). This is consistent with our hypothesis in Proposition 3 which suggests that discrimination is profitable in the short-run. However, under dynamic advantage conditions, we find directional but not statistically significant support (Dynamic Advantage: $100.54 Group-Aware vs. $100.20 Group-Blind, $p = .83$). This is likely because the disadvantaged group grows in advantage throughout the simulation to eventually equal the advantaged population by the end of the simulation. Note that under both static and dynamic disadvantage conditions, the difference between the Group-Aware and Group-Blind policies in average profit per period is small. This may provide some indication as to why we were unable to find any statistical difference between participant earnings in the Group-Aware vs. Group-Blind conditions in the empirical studies. The studies have far less statistical power than the ABM.

However, when we compare average Group-Aware and Group-Blind banks' long-term profits across all ABM conditions, we find a reversal. Figure 3 (see after Reference) shows average cumulative profits of each type of bank across ABM conditions. On average, Group-Blind banks have sizably greater cumulative profits than Group-Aware banks (Static Advantage: $255,437.73 Group-Blind vs. $240,966.49 Group-Aware, $p < .001$; Dynamic Advantage: $339,956.23 Group-Blind vs. $313,239.71 Group-Aware, $p < .001$). By regressing cumulative profits on *Group*, *time*, *time*^{2}, and their interactions, we find that while the main effect on *Group* (representing Group-Aware banks) is negative but not significant, its interaction with *time* indicates that Group-Aware bank profits substantially erode over time (Static Advantage: $-134.73, $p < .05$; Dynamic Advantage: $-196.93, $p < .01$). In the long-run, myopically

profitable, rationally-based discrimination does not pay.

DISCUSSION

Summary

Our study shows how discrimination in service can emerge from seemingly-rational, non-prejudiced decision-making. We define discrimination in service as different service treatment of equally qualified consumers who differ only in group membership. We distinguish discrimination from prejudice in that prejudice, stereotypes, and racism focus on internally-held attitudes, beliefs, and ideologies. In contrast, discrimination, consistent with sociological literature, is independent of internally-held attitudes. Discrimination concerns decision outcomes that exhibit unequal treatment of people based on the category to which they belong; discrimination is not necessarily driven by internally-held attitudes such as prejudice or bigotry (Pager and Shepherd 2008; Quillian 2006).

Although many associate discrimination with race, ethnicity, and gender, our theory and findings should equally apply to many more contexts beyond these categories. They apply to any service scenario where the service provider 1) can segment consumers into groups based on some observable attribute; and 2) the service provider uses group membership as well as individual information about the consumer to make a decision about the provision of service to the consumer. For example, consider how our theory applies to the scenario of the auto salesman who must decide whether to spend his next hour showing Mercedes-Benz E-Class Cabriolets to an 18-year old man versus a 65-year old man waiting in the dealership lobby. Or perhaps the salesman's decision is about a 65-year old in a garbage man's uniform versus a 65-year old man in a business suit. Service decisions such as these, in isolation, may seem to have little impact on firm profits. But the macro social patterns that can emerge from service decisions that rely on group information can produce discriminatory outcomes with negative long-term profit implications.

We illustrate our theory with an example context of bank lending to applicants from either an affluent (advantaged) or working-class (disadvantaged) part of town. Our study demonstrates that discrimination in service can be profitable in the short-run, yet unprofitable in the long-run in competitive markets. This is especially true if consumer word-of-mouth is extensive, as is increasingly the case with modern social media. In our agent-based model, we find that service providers using a Group-Blind service policy that ignores group membership information about consumers have greater total profits over time than those with a Group-Aware service policy that uses group membership information in addition to individual attributes in service decision-making.

Theoretical Contribution

Our research provides three theoretical contributions to the literature. First, we examine the critical role that variance plays in the emergence and persistence of service discrimination. Our research shows that service discrimination can arise from low intra-group variation in consumer quality and high measurement error of customer quality. Second, our findings demonstrate that temporal changes in group advantage level can potentially improve or exacerbate service discrimination. We found conditions where a disadvantaged group can experience increasing discrimination despite its improving advantage levels over time. This is of concern because historically disadvantaged groups have been improving in advantage over time in the U.S. Third, we show conditions where a Group-Aware service policy using a minimum score criterion can be more profitable in the short-run, but less profitable in the long run compared to a Group-blind service policy. This matters because a myopic firm can be led down a damaging path by short-term profitability when using group information in its service decisions.

Managerial, Consumer, and Public Policy Implications

These findings have important managerial implications. First, we recommend that firms who use a Group-Aware policy in decision-making switch to a Group-Blind policy. The firm should

consider the long-term benefits of switching to a Group-Blind service policy that does not use group membership information. We have shown that employing a Group-Blind service policy can provide a strong competitive advantage. It initially seems that a Group-Aware service policy should be more profitable because such a policy provides the service provider an effective device to screen out of risky customers and screen in profitable ones. However, we have shown that such a policy can produce discrimination that erodes profits and market share over time. Because of strong word-of-mouth effects, consumers can learn from each other which firms are unlikely to provide favorable service conditions to them. If services with Group-Blind policies are available as competitive alternatives, disadvantaged consumers will switch their preferences for these services over time, and sufficient numbers of advantaged consumers will patronize Group-Blind services as well. Although discriminatory practices may seem profitable in the short term, they can damage service demand and profits in the long-run.

However, if the firm must persist in using a Group-Aware policy, then we recommend that the firm measure and continually monitor the degree to which there is service discrimination, as well as its impact on profits. Furthermore, we recommend that Group-Aware firms invest in methods of measurement error reduction such as developing advanced methods of measuring consumer quality or more sophisticated predictive models that improve accuracy in predicting quality based on available measures. The Group-Aware firm could also increase its exposure to consumer populations, which could improve information on the mean and variance of group quality. For example, decision-makers could purchase outside data about target markets to supplement its internal data. This could be a way to reduce service discrimination by increasing the decision-maker's exposure to a potentially wider range of consumer quality. This investment should be done at sufficiently frequent intervals with richer predictive models to capture trends in group advantage levels over time. Another potential solution which may be particularly useful to service providers who implicitly screen customers (e.g. Starbucks, Macy's, Denny's, etc.) is to incorporate in its employee training programs methods and materials that deliberately increase perceived variability of members of different consumer groups. For example, Brauer and Er-rafiy

(2011) show that exposing study participants to posters, pictures, articles, and video that highlight the heterogeneity of members of Middle-Eastern and Chinese groups consistently reduced participant discrimination against the each of the groups. By doing so, a firm can put itself on the path to reducing discrimination in service and increasing its profits over time.

These findings also have consumer implications. Our findings imply that consumers seeking less discriminatory experiences in service would do well to seek out services that are, by nature, Group-Blind. For example, many e-commerce sites are more akin to Group-Blind service providers since they have either no access or far less access to group membership information than their bricks-and-mortar counterparts (e.g., think of buying shoes on DSW.com versus walking into a DSW store). Another consumer implication directly results from the knowledge that Group-Aware services are likely to have different minimum service criteria for groups that differ in advantage. With this knowledge, if a consumer must seek service from a Group-Aware service provider, he or she would do best by masking or omitting information on group membership. Alternatively, the consumer could seek the provider that has the most favorable minimum service criterion for his or her group. The consumer could also improve her outcome by acquiring attributes of the advantaged group (assimilation) when seeking service. For example, the man seeking to buy a Mercedes-Benz at an auto dealership may have a better service experience by wearing a business suit, regardless of his age or occupation.

Our research has public policy implications as well. Currently in the U.S., there are laws, such as the Civil Rights Act of 1964, the Equal Credit Opportunity Act, and the Fair Housing Act, that strive to protect consumers from discrimination in service. However, the task of identifying and proving existence of discrimination in support of enforcing these laws has been a difficult and controversial one. For example, the U.S. Senate recently voted to strike down a rule designed to curb racial discrimination in auto financing. Striking down the rule would provide auto lenders the right to use different score cutoffs for different groups (Merle 2018). This is a public policy debate which our research addresses precisely. One of the reasons given for repealing the rule is the controversy surrounding how the Consumer Financial Protection Bureau determines whether

discrimination exists in the first place (Hayashi 2018). Our research theory, definition of discrimination, and our findings can provide a framework for developing analytical tools to detect and measure discrimination. Furthermore, the same framework could be the basis of measurement in litigation cases of consumer discrimination.

Limitations and Opportunities for Future Research

There are limitations to this research which suggest many ways that researchers can broaden our knowledge on this topic. For example, our theory assumes customers are members of only one population group. In reality, a consumer can be a member of multiple groups, some of which may be advantaged while others may not (e.g., a wealthy entrepreneur who has no high-school or college degree). It would be interesting to explore the boundaries of our theory under conditions where consumers may have two or more group memberships with varying levels of advantage. A second limitation is that we assume in our theory that firms continuously update beliefs using all historical information available about customers who have sought their service. Although we have found qualitative support in our interviews that this can happen in loan services, this may not be true in all service contexts. A promising avenue for future research is investigating how varying the frequency of updates and varying the historical window of data about consumers can affect service provider beliefs. A third limitation of our research is that we assume that the distribution of consumer quality is normally distributed. Although this is a generally reasonable approximation, it would be interesting to explore the effects of other distributional assumptions on service discrimination and on profits. A great deal of work is still needed to fully understand the nature and boundaries of service discrimination, but we believe that the theoretical framework created here serves as a launching point to exploring these and many more questions about the effects of discrimination in service.

Conclusions

We had three goals at the outset of the research discussed in this paper: 1) to uncover the mechanism by which service discrimination can emerge from seemingly rational service policy; 2) to investigate how service discrimination interacts with competition and consumer word-of-mouth to affect profits; 3) to help firms avoid losing profits due to discrimination. We did so by developing a theoretical model that illuminates the critical roles that variation in consumer quality and measurement error in detecting quality play in the emergence and magnitude of discrimination in service. Our theoretical model also demonstrated that changes in group advantage over time can erode or improve the magnitude of discrimination over time, even if the inequality gap is decreasing. We validated our theoretical model with empirical evidence in two studies. The evidence supported our theory that large variation in consumer quality reduces service discrimination while large measurement error increases service discrimination. Furthermore, the empirical evidence demonstrates that under certain conditions, decreasing inequality between groups can actually *increase* service discrimination. With our agent-based model, we showed the long-term macro effects on profits when firm competition and consumer word-of-mouth embedded in a complex system are taken into consideration. We found that although Group-Blind service providers, who do not use consumer group membership information in its service decisions, are less profitable than their Group-Aware competitors in the short-run, Group-Blind service providers are more profitable in the long-run. This is because consumer word-of-mouth drives consumers to select the most service-friendly alternatives among competitive options.

We provide managerial recommendations on reducing service discrimination's profit-damaging effects. This research emphasizes the long-term benefits of switching to a service policy that does not use group identity information. However, for firms that must persist in using group identity information, this research has additional recommendations which include increasing investment in methods of measurement error reduction and increasing exposure to consumers of different populations. By doing so, a firm could reduce service discrimination while

improving its long-term profits and societal well-being.

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Table 1: Summary of Empirical Results

|	Proposition	Dependent Variable	Coefficient of Interest	Study 1 Effects: Static Inequality	Study 2 Effects: Dynamic Inequality	Supported?
1	The service provider's minimum score criterion will be higher for the disadvantaged than advantaged group. This means that the disadvantaged consumer will need to exceed a higher criterion than an equally qualified advantaged consumer to receive same level of service.	Pr(Loan)	Disadvantaged*Group	-1.013 $p < .001$	-1.837 $p < .001$	Yes
2.1	Discrimination decreases when the error in measuring consumer quality decreases.	Repay	Disadvantaged*Group *ScoreLowVar	2.982 $p < .001$	3.358 $p < .001$	Yes
2.2	Discrimination increases when variance in consumer quality decreases.	Repay	Disadvantaged*Group *QualityLowVar	-6.383 $p < .001$	-1.499 $p = .051$	Yes
3	The service provider's average profit per period (short-term profit) is greater when he discriminates than when he does not (uses a Group-Aware policy rather than a Group-Blind policy).	Profit	Group	.152 p is n.s.	.092 p is n.s.	No
4	If the disadvantaged group improves in advantage over time, there are conditions where the group's minimum service criterion rises over time because of the group's improving advantage.	Pr(Loan)	Disadvantaged *Dynamic*Round	N/A	-.729 $p < .05$	Yes
5	Although a disadvantaged group improves in advantage over time, only some members will benefit by experiencing decreasing discrimination. Other members will see increasing discrimination due to the group's improving advantage.	Repay	Disadvantaged*Dynamic *Round*Quality	N/A	27.210 $p < .05$	Yes

Figure 1: Two-Period Model of Service Discrimination
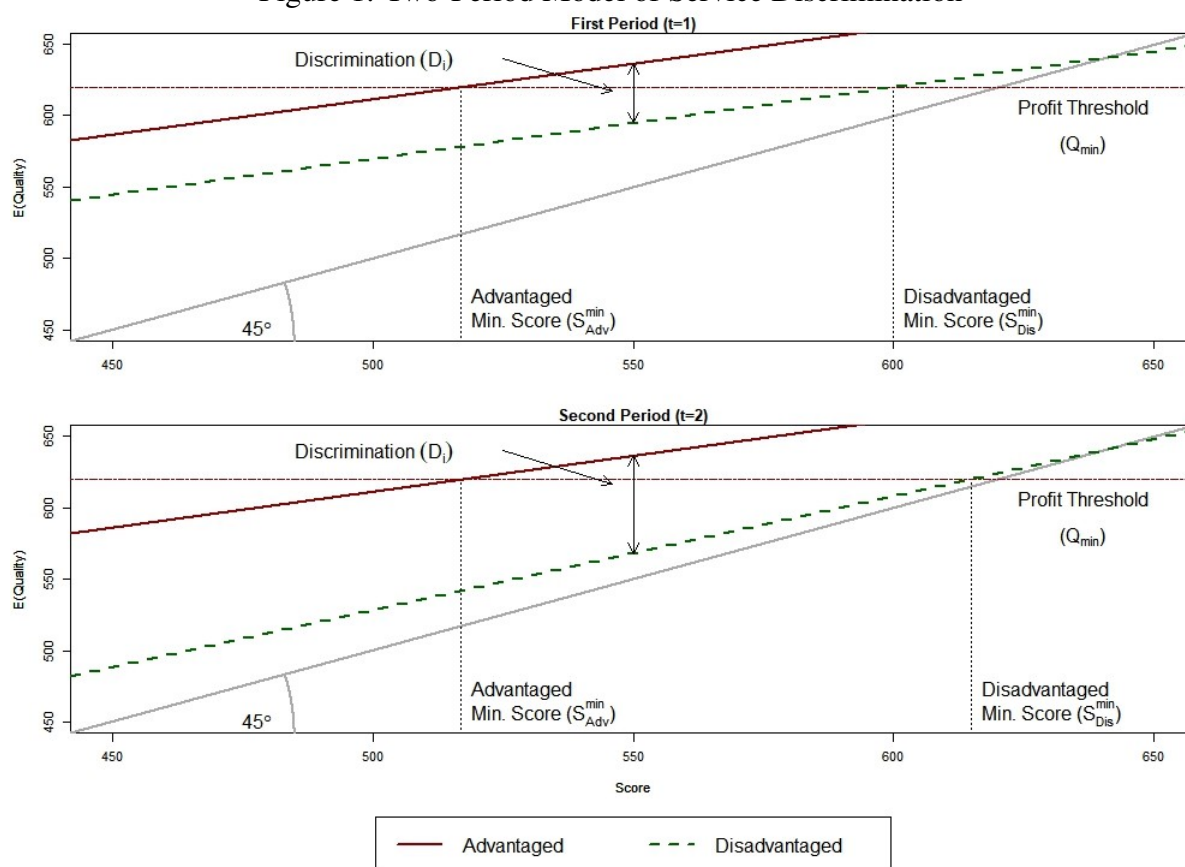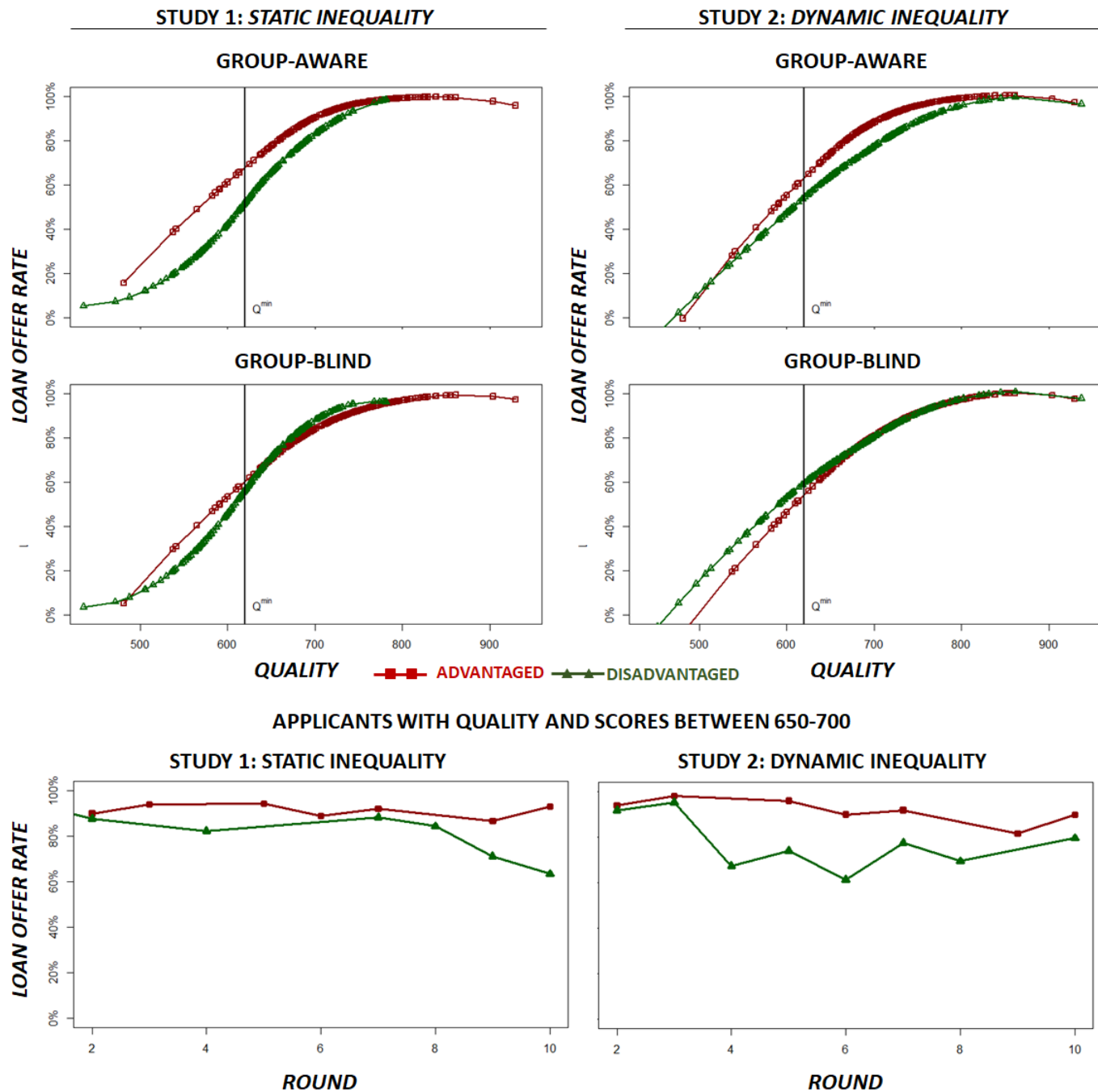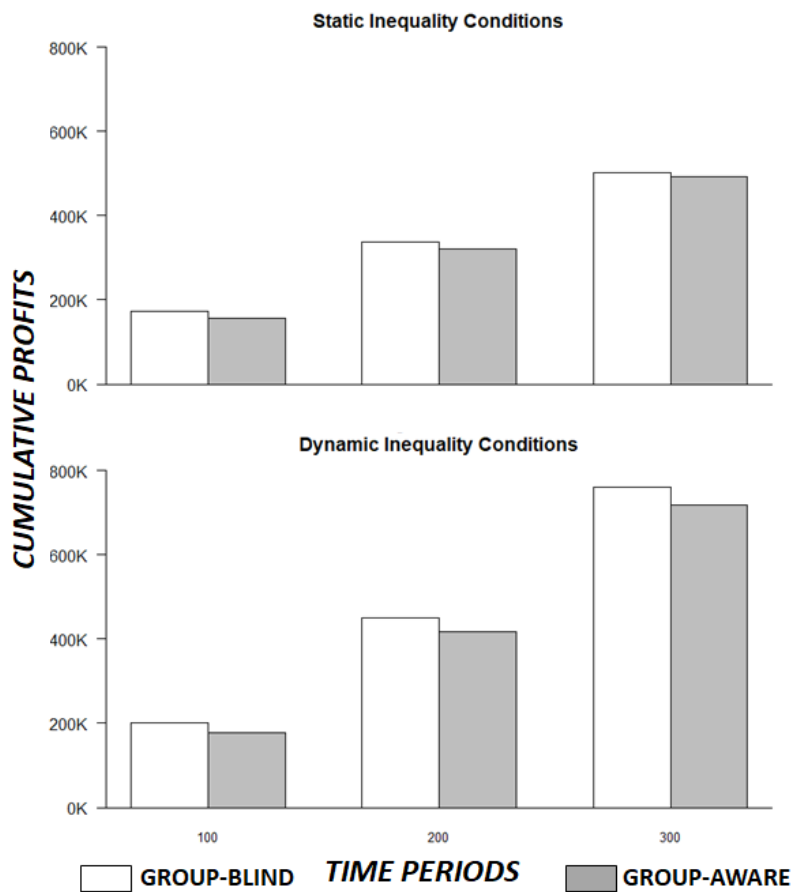
Figure 2: Mean Loan Offer Rates

Figure 3: Long-Term Profits: Group-Blind vs. Group-Aware Banks

APPENDIX A: PROOFS

For all proofs, we assume the following: Each loan applicant i is a member of one of two population groups $j \in \{Adv, Dis\}$. Initially, the advantaged group has an advantage level that is greater than the disadvantaged group ($A_{Adv} > A_{Dis}$). The groups are initially equal in intra-group variation in quality ($\sigma_q^2 = \sigma_{q_{Adv}}^2 = \sigma_{q_{Dis}}^2$). We also assume that the bank's ability to measure quality is unaffected by changes in composition of the groups (thus σ_ε^2 is constant across groups and across time).

In order to compare Group-Aware and Group-Blind policies in terms of average per period profits, we first must determine the ordinal relationship of $S_{all}^{min}, S_{Dis}^{min}$, and S_{Adv}^{min}. Proposition 1 establishes that the minimum score criteria derived from a Group-Aware policy have the ordinal relationship $S_{Dis}^{min} > S_{Adv}^{min}$ under most conditions. We their ordinal relationship with respect to S_{all}^{min} this in the following Lemma.

Lemma 2 *The Group-Aware policy minimum score criterion for the disadvantaged is always greater than the minimum score criterion of a Group-Aware policy (i.e., $S_{all}^{min} < S_{Dis}^{min}$).*

Proof by contradiction: Let us suppose the contrary, that $S_{all}^{min} > S_{Dis}^{min}$. Drawing from Equations (6) and (7), that implies:

$$S_{all}^{min} > S_{Dis}^{min}$$

$$Q^{min} + \left(Q^{min} - A_{all} \right) \left(\frac{\sigma_\varepsilon^2}{\sigma_{q_{all}}^2} \right) > Q^{min} + \left(Q^{min} - A_{Dis} \right) \left(\frac{\sigma_\varepsilon^2}{\sigma_q^2} \right)$$

(15)
$$\frac{Q^{min} - A_{all}}{Q^{min} - A_{Dis}} > \frac{\sigma_{q_{all}}^2}{\sigma_q^2}$$

$$\text{Since } (Q^{min} - A_{all}) < (Q^{min} - A_{Dis}) \text{ and } \sigma_{q_{all}}^2 > \sigma_q^2, \text{ then}$$

$$\frac{Q^{min} - A_{all}}{Q^{min} - A_{Dis}} < 1 < \frac{\sigma_{q_{all}}^2}{\sigma_q^2}, \text{ which is a contradiction.}$$

$$\therefore S_{all}^{min} < S_{Dis}^{min} \; \forall \; \sigma_q^2, \sigma_\varepsilon^2, Q^{min}, A_j$$

Proof of Proposition 3

We wish establish the conditions where $E(\Pi \mid S_j^{min}) \geq E(\Pi \mid S_{all}^{min})$: the average per period profit resulting from a Group-Aware service policy is greater than that of a Group-blind service policy. Based on the equations in (8), we can expand this inequality and rearrange terms as follows:

$$E(\Pi \mid S_{j\in Adv,Dis}^{min}) > E(\Pi \mid S_{all}^{min})$$

$$\sum_{j\in Adv,Dis} \int_{S_j^{min}}^{\infty} \frac{p_j\, E(Q_{ij} \mid S_{ij})f_j(S)dS}{2 - F_{Adv}(S_{Adv}^{min}) - F_{Dis}(S_{Dis}^{min})} > \sum_{j\in Adv,Dis} \int_{S_{all}^{min}}^{\infty} \frac{p_j\, E(Q_i \mid S_i)f_j(S)dS}{2 - F_{Adv}(S_{all}^{min}) - F_{Dis}(S_{all}^{min})}$$

$$\int_{S_{Adv}^{min}}^{S_{all}^{min}} \frac{E(Q_{i,Adv} \mid S_{i,Adv})f_{Adv}(S)dS}{F_{Adv}(S_{all}^{min}) - F_{Adv}(S_{Adv}^{min})} + \int_{S_{all}^{min}}^{\infty} \frac{p_{Adv}\left[E(Q_{i,Adv} \mid S_{i,Adv}) - E(Q_i \mid S_i)\right]f_{Adv}(S)dS}{2 - F_{Adv}(S_{Adv}^{min}) - F_{Dis}(S_{Dis}^{min})}$$

$$> \int_{S_{Dis}^{min}}^{\infty} \frac{p_{Dis}\left[E(Q_i \mid S_i) - E(Q_{i,Dis} \mid S_{i,Dis})\right]f_{Dis}(S)dS}{2 - F_{Adv}(S_{all}^{min}) - F_{Dis}(S_{all}^{min})} + \int_{S_{all}^{min}}^{S_{Dis}^{min}} \frac{E(Q_i \mid S_i)f_{Dis}(S)dS}{F_{Dis}(S_{Dis}^{min}) - F_{Dis}(S_{all}^{min})}$$

$$\therefore E(\Pi \mid S_{j\in Adv,Dis}^{min}) > E(\Pi \mid S_{all}^{min})$$

The following proofs involve dynamics. We first present the following additional assumptions: There are two time periods $t \in \{1,2\}$, two population groups of consumers $j \in \{Adv, Dis\}$, and each loan applicant i is a member of one group and applies in one time period only. At time $t = 1$, the advantaged group has an advantage level that is greater than the disadvantaged group ($A_{Adv,1} > A_{Dis,1}$), the groups are equal in intra-group variation in quality ($\sigma_{q_1}^2 = \sigma_{q_{Adv,1}}^2 = \sigma_{q_{Dis,1}}^2$). We also assume that the bank's ability to measure quality is unaffected by changes in composition of the groups (thus σ_{ε}^2 is constant across groups and across time).

Let us assume that there are two cohorts of applicants where cohort 1 applies for a loan at time $t = 1$ and cohort 2 applies at $t = 2$. Applicants from both cohorts are members of group j. Let p_{jt} represent the proportion of all applicants from group j that are comprised of cohort 1 applicants. This means that the proportion of all j applicants that are in the first cohort is $p_{j1} \in (0,1)$ and cohort 2 is $(1 - p_{j2})$. Also assume that the two cohorts are equal in intra-cohort variation in quality ($\sigma_{q_{j1}}^2 = \sigma_{q_{j2}}^2$). However, the advantage level of cohort 2 is g_j times the level of cohort 1 advantage ($A_{j2} = g_j A_{j1}$, where $g_j \in [0,\infty)$).

Proof of Proposition 4

If the loan officer uses all available information about group j as of time $t = 2$, then based on Lemma 1 and Equation (6), the loan officer's minimum score criterion for group j is

$$S_{jc}^{min} = Q^{min} + \left(Q^{min} - A_{jc}(g_j)\right) \left(\frac{\sigma_{\varepsilon}^2}{\sigma_{q_{jc}}^2(g_j)}\right)$$

To understand the impact of growth of group j's advantage on the minimum score criterion, we take the derivative of S_{jc}^{min} with respect to g_j.

(16)
$$\frac{\partial S_{jc}^{min}}{\partial g_j} = \frac{A_{j1}(1 - p_{j1})\sigma_{\varepsilon}^2}{\sigma_{q_{jc}}^2(g_j)} \left[\frac{2A_{j1}p_{j1}(1 - p_{j1})(1 - g_j)(Q^{min} - A_{jc}(g_j))}{\sigma_{q_{jc}}^2(g_j)} - 1\right]$$

Trivially, $S_{jc}^{min} = S_{j1}^{min}$ when $g_j = 1$. Otherwise, when $g_j \neq 1$, $\dfrac{\partial S_{jc}^{min}}{\partial g_j}$ has the following behavior, which depends on the relationship of Q^{min} with respect to a threshold value A^*:

(17)
$$\frac{\partial S_{jc}^{min}}{\partial g_j} \begin{cases} > 0 & \begin{cases} \text{when } g_j > 1 \text{ and } Q^{min} < A^* \\[2mm] \text{when } g_j < 1 \text{ and } Q^{min} > A^* \end{cases} \\[6mm] = 0 & \text{when } g_j \neq 1 \text{ and } Q^{min} = A^* \\[4mm] < 0 & \text{otherwise} \end{cases}$$

where

$$A^* = A_{jc}(g_j) + \frac{\sigma_{q_{jc}}^2(g_j)}{2A_{j1}p_{j1}(1 - p_{j1})(1 - g_j)}$$

$$= A_{j1}\left[p_{j1}(1 - g_j) + \frac{1}{2}(1 + g_j)\right] + \frac{\sigma_{q_{j1}}^2}{2A_{j1}p_{j1}(1 - p_{j1})(1 - g_j)}$$

Proof of Proposition 5

We wish to show that a consumer can experience an increasing degree of discrimination over time even if her group's advantage is improving. We establish this with the following proof. Let

consumers i and $-i$ from groups j and $-j$ have constant quality level Q^*. Recall from Definition 1 that discrimination is defined as:

$$(18) \qquad D_{it} = (\gamma_{Adv,t} - \gamma_{Dis,t})Q^* + \left[(1 - \gamma_{Adv,t})A_{Adv,t} - (1 - \gamma_{Dis,t})A_{Dis,t}\right]$$

We define the change in discrimination i experiences over time as

$$(19) \qquad \Delta D_i = D_{i2} - D_{i1} = (\Delta\gamma_{Adv} - \Delta\gamma_{Dis})Q^* + \left[\Delta(1 - \gamma_{Adv})A_{Adv} - \Delta(1 - \gamma_{Dis})A_{Dis}\right]$$
$$\text{where} \quad \Delta\gamma_j = \gamma_{j2} - \gamma_{j1} \text{ and } \Delta(1 - \gamma_j)A_j = \left[(1 - \gamma_{j2})A_{j2} - (1 - \gamma_{j1})A_{j1}\right]$$

If $\gamma_{j2} = \gamma_{j1}$, then all consumers i experience no change in discrimination over time. However, if $\gamma_{j2} \neq \gamma_{j1}$, then the consumer i that experiences no change in discrimination ($\Delta D_i = 0$) has quality

$$(20) \qquad Q^* = Q^*_{\Delta D0} = \frac{\Delta(1 - \gamma_{Dis})A_{Dis} - \Delta(1 - \gamma_{Adv})A_{Adv}}{\Delta\gamma_{Adv} - \Delta\gamma_{Dis}}$$

Consumers with $Q^* \neq Q^*_{\Delta D0}$ experience changing discrimination under the following conditions:

$$(21) \qquad
\begin{aligned}
\Delta D_i > 0 &\begin{cases} \Delta\gamma_{Dis} > \Delta\gamma_{Adv} & \text{when } Q^* < Q^*_{\Delta D0} \\[1mm] \Delta\gamma_{Dis} < \Delta\gamma_{Adv} & \text{when } Q^* > Q^*_{\Delta D0} \end{cases} \\[4mm]
\Delta D_i < 0 &\begin{cases} \Delta\gamma_{Dis} > \Delta\gamma_{Adv} & \text{when } Q^* > Q^*_{\Delta D0} \\[1mm] \Delta\gamma_{Dis} < \Delta\gamma_{Adv} & \text{when } Q^* < Q^*_{\Delta D0} \end{cases}
\end{aligned}$$

Hence, different members of the same group j can experience different degrees of discrimination over time as a result of their group's change in advantage.