The role of reputation systems in digital discrimination

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Abstract

Reputation systems are often proposed as the most promising solution to (ethnic) discrimination in online markets. This claim is based on earlier studies showing that the ethnic gap is smaller for users with reviews than for users without reviews. Using simulations, we show that this conclusion may be premature, as reviews can only be written after completed interactions. Hence, initial differences between users in the probability to be selected as transaction partner may accumulate over time, thereby diminishing the potential of reputation systems to decrease discrimination. We use a unique dataset that contains information on all interactions that ever took place on a peer-to-peer motorcycle rental platform to test this hypothesis. We find that per filed request, ethnic minority renters receive fewer reviews than ethnic majority renters with otherwise similar characteristics. Moreover, with time the reputation system does not reduce the initial inequalities between otherwise comparable renters of different ethnicity.

Keywords: Discrimination, Economic Sociology, Inequality, Reputation, Uncertainty

JEL classification: Household Production and Intrahousehold Allocation (D13)

Asymmetric and Private Information; Mechanisms Design (D82)

1. Introduction

Across a wide range of markets, individuals have been found to avoid transacting with minorities. Such discrimination is a widespread phenomenon in labor markets (Rich, 2014; Zschirnt & Ruedin, 2016) as well as in online marketplaces for goods and services (Edelman & Luca, 2014; Nunley, Owens, & Howard, 2011). Many of such marketplaces are supported by Internet platforms that enable direct communication between peers. The use of extensive personal profiles that include names and photos of users has been found to lead to discrimination (Cui, Li, & Zhang, 2016; Edelman & Luca, 2014; Edelman, Luca, & Svirsky, 2017; Ert, Fleischer, & Magen, 2016; Ge, Knittel, MacKenzie, & Zoepf, 2016; Jaeger, Sleegers, Evans, Stel, & Beest, 2018; Laouénan et al., 2017; Mohammed, 2017; Pope & Sydnor, 2011; Tjaden, Schwemmer, & Khadjavi, 2018; Wu & Jin, 2018; Wu, Ma, & Xie, 2017). Discrimination in the platform economy results in fewer opportunities for users with certain demographic characteristics to buy, rent, sell and borrow goods and services. This outcome is disadvantageous both for the people who are discriminated against and for the platforms, as it leads to suboptimal market outcomes where otherwise fruitful interactions are not realized.

It has been argued that reputation systems solve this problem of digital discrimination (Abrahao, Parigi, Gupta, & Cook, 2017; Cui et al., 2016; Ert et al., 2016; Mohammed, 2017; Tjaden et al., 2018).[1] The argument goes that discrimination on platforms mostly originates from a lack of information about other users. This information is especially important for interactions in the (peer-to-peer) platform economy, as these platforms are characterized by lower levels of institutionalization and higher levels of interpersonal trust (Katz, 2015; ter Huurne, Ronteltap, Corten, & Buskens, 2017). By providing user-specific information on performance and trustworthiness through reviews from past transactions, reputation systems would supersede group stereotypes as a basis of partner choice and reduce or even eliminate unfounded inequalities. Whereas the use of photos and names always entails the risk of discrimination based on demographic characteristics, reviews are often considered a better and fairer way of reducing information asymmetry between users and providers.

Several studies have provided empirical support for the claim that reputation systems help overcome discrimination by showing that a difference between (ethnic) groups in the acceptance chances of a transaction request disappears once users have received at least one positive review. For example, while guests on Airbnb with African American-sounding names are 19.2 percentage points less likely to be accepted than those with whitesounding names, this difference disappears when both guests have a review (Cui et al., 2016). Likewise, in an online experiment with Airbnb users, reputation partly offsets the tendency of people to trust others who are similar to them more (Abrahao et al., 2017).

However, here we argue that earlier research may have overstated the extent to which reputation systems mitigate discrimination, as it is critical to consider that not all users are equally likely to achieve that initial reputation necessary for acquiring trust on the platform. Most platforms only allow users to write a review about each other after a transaction via the platform. As previous research shows, the probability that a first request from a user without any reviews is accepted, and thus the probability of receiving a first review, strongly depends on a trustee's (ethnic) background (Abrahao et al., 2017; Cui et al., 2016). While a reputation system may decrease the importance of information retrieved from names and pictures once users have acquired reviews, it may altogether fail to reduce inequality in transaction volume as it gives majority members the ability to more quickly build a good reputation.

In the current research, we first demonstrate these inequality-sustaining effects of reputation systems with a simple model. To study the empirical relation between reputation systems and discrimination, we then analyze a unique dataset containing the complete historical records of user activity on a Dutch peer-to-peer motorcycle renting platform. This platform is similar in function and design to many other platforms, such as hospitality platform Airbnb and various carsharing platforms. However, whereas previous studies have analyzed platforms statically, e.g. comparing differences in the number of clicks an offer received (Tjaden et al., 2018) or prices Airbnb hosts could charge (Edelman et al., 2017), the full historic record of all interactions on the motorcycle renting platform allows us to investigate inequality dynamics. In order to test whether reputation systems with time eliminate or increase discrimination in a real online platform, information about interactions at the platform at different timepoints is necessary, as it takes time for users to accumulate reviews. We can thus evaluate whether on the platform at hand the reputation system indeed manages to overcome digital discrimination.

2. Theory

Modern day exchange is increasingly mediated by online platforms. 'Platform economy' is an umbrella term encompassing several activities, such as selling, exchanging, borrowing and renting of goods and services. Leong and Belzer (2017) identify two distinctive features of platforms. First, platform economy businesses make money not by providing goods or services per se, but rather by connecting people who need particular goods or services with people who want to provide them. Second, to facilitate this connection efficiently, platform economy businesses rely on online platforms.

Trust and reputation formation are crucial on sharing platforms, as interactions pose a high risk for the owners of the goods. Owners may thus be strongly inclined to derive trustworthiness of others from past experiences of other owners as well as borrower demographics. When an owner decides to rent out their goods to another user, who is generally a stranger, he or she runs the risk of not getting back the good in a good state. Although most sharing platforms usually offer some support in solving problems between users, the legal structures owners can rely on are usually limited (ter Huurne et al., 2017). Owners will therefore be motivated to carefully consider which renters can and which cannot be trusted before deciding to accept or reject a rental request. Our theoretical focus is the decision of the owner to accept or reject a request of a potential renter.

2.1 Discrimination in the platform economy

Unlike traditional exchange, in online markets people often exchange goods and services with perfect strangers from all around the world (Frenken & Schor, 2017). There is limited opportunity to get to know a person before a transaction or to acquire information about the other person's unobserved qualities. The online nature of the platform economy implies several information asymmetries (ter Huurne, Ronteltap, Guo, Corten, & Buskens, 2018). First, consumers and providers are unsure about each other's intentions, leading to perceived personal safety risks, especially when the two actors meet offline after the online interaction. Second, consumers cannot check upfront whether the quality of the good or service they are buying, renting or borrowing is good. Following Akerlof's (1970) classical lemons problem, the risk of buying a low-quality good will result in market failure.

To mitigate this risk, platforms allow their users to create extensive user profiles, including names and profile pictures. Compared to traditional e-commerce companies, anonymity is lower in these platforms (Abrahao et al., 2017). Names, photos and descriptions are used as a means of identity verification and are intended to foster an increased sense of personal contact (Dubois, Willinger, & Blayac, 2012; Guttentag, 2015). They also convey information about someone's ethnicity, gender and age and may thereby lead to two types of discrimination on the basis of these demographic characteristics.

Statistical discrimination (Arrow, 1973) refers to discrimination on the basis of the perceived association between a person's demographic characeristics (such as ethnicity) and other characteristics that cannot be directly observed that impact the value or merit of that person (Becker, 1957). Applied to trust problems in the platform economy, statistical discrimination is the tendency to derive expectations about the trustworthiness of exchange partners from demographics on their personal profiles. When owners assume that renters with a specific ethnicity are less trustworthy (e.g. because of stereotypes), they may place less trust in these individuals. Taste-based discrimination (Becker, 1957) on the other hand refers to a preference for certain characteristics over other characteristics, without an underlying expectation of qualities related to these characteristics. According to social identity theory, people classify themselves and others in social categories (Abrams & Hogg, 1990). Individuals identify with and treat ingroup members more favorably than out-group members, making trust biased towards similar individuals. Indeed, people are found to have a general preference for others who are similar to them (McPherson, Smith-Lovin, & Cook, 2001).

In the current study we test if owners place more trust in renters with certain demographic characteristics, and if this difference results from a tendency to place more trust in renters who are more similar to them than in renters who differ. We focus on ethnicity as socio-demographic dimension of discrimination, because we know from the labor market literature and earlier studies on the platform economy that this is a widely spread and persistent form of discrimination (Rich, 2014; Zschirnt & Ruedin, 2016). A preference for in-group members would result in more trust placed in ethnic majority renters than in ethnic minority renters. Therefore we formulate the following hypothesis:

Hypothesis 1: Rental requests from ethnic majority renters are more often accepted than rental requests from ethnic minority renters.

2.2 Reputation systems as a solution to discrimination

Reputation systems are proposed as the most promising solution to statistical discrimination, as they are believed to provide more specific and therefore more accurate information about a renter's behavior in a transaction through the platform than more diffuse sociodemographic information (Resnick, Kuwabara, Zeckhauser, & Friedman, 2000; Robbins, 2017). After an interaction, users are asked to leave a rating and a review about their interaction partner. These ratings and reviews are displayed on their profile page for potential future interaction partners. Reputation systems allow users to assess the expected quality of an interaction with a potential partner ('learning' according to Buskens & Raub, 2002). Users with better reviews are more likely to have prosocial interests and are therefore more likely to live up the expectations and agreements, while users with negative reviews likely care less about the interest of their partner, and are therefore more likely to abuse trust again in the future. In this way, ratings and reviews serve as a costly signal of trustworthiness and other unobservable characteristics of individuals, while they at the same time provide an incentive for prosocial behavior (Bolton, Katok, & Ockenfels, 2004; Fehrler & Przepiorka, 2013; Resnick & Zeckhauser, 2002; Tadelis, 2016). For these reasons, requests from renters with a better reputation (i.e. more positive ratings) should be more likely to be accepted by the owners, and requests from renters with more negative reviews less likely.

Ratings on online platforms are typically highly left-skewed, with many very high ratings and only few ratings lower than 4.5 out of 5 stars (Teubner & Glaser, 2018; Teubner, Hawlitschek, & Dann, 2017; Zervas, Proserpio, & Byers, 2015). This may be due to underreporting of negative experiences (Fradkin, Grewal, & Holtz, 2017), or may be a direct effect of the reputation system. As users' present behavior on the platform may affect their possibilities for future behavior, they may be motivated to behave well to build and maintain their reputation (Buskens & Raub, 2002). The lack of variation in average rating reduces the informativeness of the average rating of a user, but may increase the importance of the number of ratings a user has on the accept rate. We formulate the following hypothesis:

Hypothesis 2: a) The more positive reviews a renter has, the larger the probability that his/her rental request is accepted, b) The more negative reviews a renter has, the smaller the probability that his/her rental request is accepted.

Indeed, previous research found that trustees with a better reputation are trusted more often (Boero, Bravo, Castellani, & Squazzoni, 2009; Charness, Du, & Yang, 2011; Duffy, Xie, & Lee, 2013; Fehrler & Przepiorka, 2016; Gong & Yang, 2010). Previous research shows that especially the first review matters a lot (Duffy et al., 2013; Frey & Van De Rijt, 2016): compared to users without any reviews, users with one positive review received between 8.4% and 29.5% more trust (Cui et al., 2016).

When a renter has no reviews, the owner relies on the limited information that is available, such as names and photos. Yet demographic information is only a proxy of trustworthiness, so when reviews are available, which contain a higher quality of information about a renter's trustworthiness, this should trump demographic characteristics in trust assessment. This supremacy of reviews over demographic information is confirmed in empirical studies: The difference between individuals of different ethnicity in the probability to participate on platforms is much smaller or completely disappears when more relevant information about the quality of a user is available (Abrahao et al., 2017; Cui et al., 2016; Ert et al., 2016; Mohammed, 2017; Tjaden et al., 2018). Reputation systems are thus suggested to constitute a solution to digital discrimination by researchers (Abrahao et al., 2017; Cui et al., 2016; Ert et al., 2016; Mohammed, 2017; Tjaden et al., 2018) and practitioners (Murphy, 2016) alike. We therefore hypothesize that minority renters with more positive reviews are discriminated less.

Hypothesis 3: The difference in the probability that a request is accepted between ethnic majority renters and ethnic minority renters is smaller for renters with more positive reviews.

2.3 Reputation systems as an amplifier of discrimination

However, while reputation systems may indeed decrease discrimination for those users who have positive reviews, the expectation that reputation systems decrease overall discrimination on the platform is based on the implicit assumption that all users are equaly likely to obtain a good reputation. Yet, as reviews can generally only be written after an interaction on the platform, not all users are equally likely to obtain reviews. The results from previous research suggest that users who already have a good reputation are more often selected for new interactions, which in turn improves their reputation and thus the probability that their next request will be accepted. In a laboratory experiment (Frey & Van De Rijt, 2016) show that these 'reputation cascades' lead to arbitrary inequality between equally trustworthy individuals. The chance to build a reputation is thus dependent on the probability that an initial request is accepted. If this probability differs between people with different ethnicity, members of some ethnic groups may have fewer opportunities for reputation building than others. We hypothesize that minorities' requests for a transaction are less likely accepted, so that per filed request (either accepted, declined, or not responded), ethnic minority renters receive fewer reviews than ethnic majority renters.

Hypothesis 4: Per request filed, ethnic minority renters receive fewer reviews than ethnic majority renters.

We use simulations to isolate and better understand the interplay between reputation and discrimination and to predict how overall inequality between renters may differ between platforms with and without a reputation system.

In the simulations, both minority and majority group renters propose transactions. These proposals are accepted and rejected based on a combination of minority group status and the number of positive reviews received. When a request is accepted, a renter receives a positive review. We vary the extent to which there is initial trust in members of the majority group (12-88%) and minorities (2-73%), the extent to which reputation has a positive effect on the acceptance probability, and the extent to which ethnic minority renters may compensate their initial disadvantage with reputation. We evaluate how these parameters affect the difference in intergroup inequality between the situation with and without a reputation system.

Although the chances on a good outcome will eventually converge for ethnic majority and ethnic minority renters because acceptance probabilities eventually approach 1 as good reputations are established, we show that under specific conditions there may be more inequality between renters of different ethnicities on a platform with a reputation system than on a platform without a reputation system. We simulate a sequence of ten periods in each of which every renter submits a rental request. After ten periods we evaluate to what extent the success rate of majority and minority renters differs between the situation with a reputation system and the situation without a reputation system.[2] A detailed description of the model and the analyses can be found in Appendix A.

It turns out that the initial level of trust in ethnic minorities is the most important predictor of the difference in inequality between the platforms with and without a reputation system (see Appendix). Figure 1 shows the average rate with which requests from ethnic majority and ethnic minority renters are accepted over the rounds in the simulations for three different levels of initial trust. The converging lines in panel C of Figure 1 show that when the initial level of trust in ethnic minority renters is high, their initial disadvantage can be compensated through reputation. In that case there may be less inequality on the platform with a reputation system than in the platform without a reputation system. Panel B and C show that when requests from ethnic minority renters are only rarely accepted, these renters do not get the opportunity to build a reputation and can therefore not benefit from the reputation system and the acceptance rates of the different renters diverge. Hence intial differences between renters in the probability to be accepted for an interaction may accumulate over time, thereby diminishing the potential of reputation systems to decrease discrimination. Only when trust is less of an issue to begin with, the reputation system may reduce inequality. The other parameters only have a small influence on the difference in inequality.

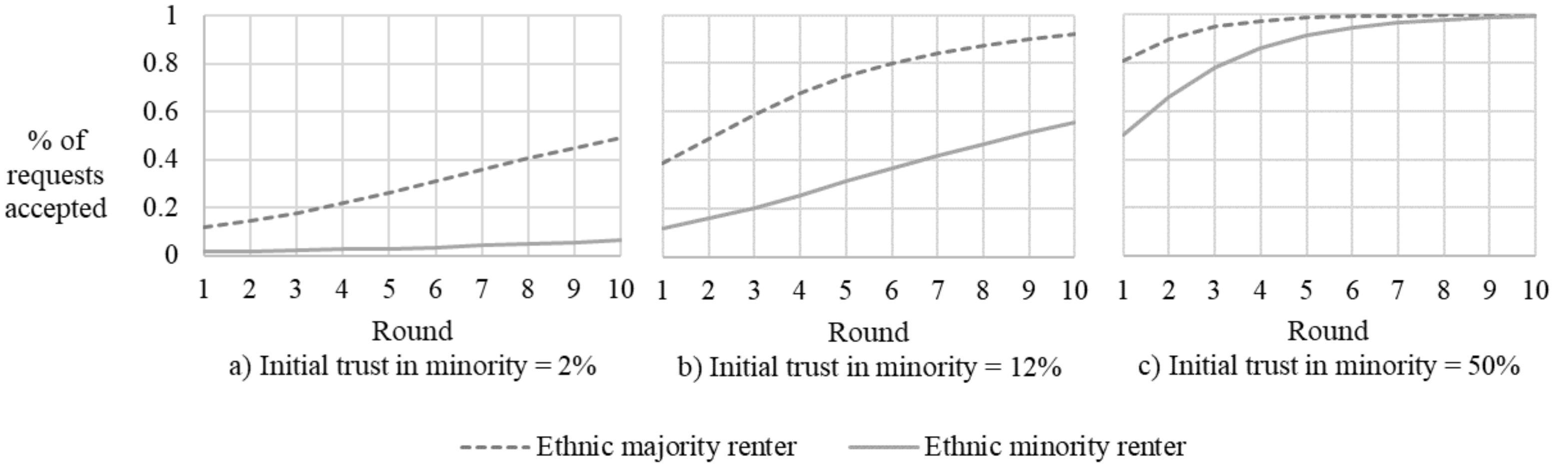

Figure 1: Simulation results: average acceptance rate of native and non-native Dutch renters over the rounds.

Following the simulation results, we predict that under specific conditions there may be more inequality on a platform with a reputation system than on a platform without a reputation system. Since the platform we study has always had a reputation system and we thus cannot compare a platform with a reputation system with a platform without a reputation system, we need to test the effect of the system in a different way. We make use of the fact that it takes time for a user to build a reputation. By tracking how the extent to which renters of minority groups are discriminated changes with the number of requests made by that renter, we can evaluate how the reputation system increases or decreases discrimination. We formulate two constrasting hypotheses about changes in the ethnic gap, which we define as the difference in the probability that a request is accepted between renters with different ethnicity but who have filed an equal number of requests.

If having a positive reputation benefits ethnic minority members more than ethnic majority members, and if the possibility to receive an initial review is not too low for ethnic minority renters, we expect that the ethnic gap gets smaller the more requests a renter has filed. In other words, there is expected to be a larger difference in the probability that their request is accepted between an ethnic majority renter and an ethnic minority renter when they both file their first request compared to when they file their fifth request. We formulate two contrasting hypotheses.

Hypothesis 5: The ethnic gap decreases with the number of requests the renters have filed.

If however intial differences between renters of different ethnicity are magnified to such an extent that the decreasing importance of demographic information for renters with reviews cannot compensate for it, the ethnic gap is expected to increase with every request made.

H*ypothesis 6: The ethnic gap increases with the number of requests the renters have filed.*

3. Data and methods

We study a Dutch peer-to-peer motorcycle sharing platform that was founded in 2016. The platform operates within the so-called sharing economy and has a similar design and functionality as peer-to-peer carsharing platforms and hospitality platforms such as Airbnb. The platform allows motorcycle owners to advertise their motorcycle on the platform. Renters can browse through the listed motorcycles and the personal profiles of the owners and send rental requests for specific time slots and for a predefined price. Before accepting or declining the request, the owner can view the personal profile of the renter, including first name, photo, personal description and reviews. When the request is accepted, the renter pays the rental price to the platform and the owner and renter meet offline to hand over the motorcycle. After the rental period the platform transfers the money paid by the renter to the owner. Both renter and owner are asked to write a review that is publicly displayed in their user profile. The platform automatically arranges a full insurance for the motorcycles during the rental period and checks the drivers licence and fraud history of all users.

The peer-to-peer motorcycle renting platform facilitates the sharing of a fragile good of high value, motorcycles, with strangers. Risk is thus particularly high. Moreover, motorcycle owners attach certain non-material values to their motorcycles that cannot be reimbursed by insurances, as illustrated by the following quotes: "How do you let some random person ride your motorcycle? I would never do that! It's quite hard to watch your baby go the first time. No mater how attached you are to your motorcycle, it's difficult watching someone else ride it off. Even when you sell it!" (Hooshmand, 2018). "The first mental hurdle to get over is the fact that you'd be "cheating" on your bike if you decide to ride someone else's" (Klinger, 2018). In addition to the material and emotional risk of entrusting a stranger with a motorcycle, the transaction requires that the parties meet offline before and afterwards which may pose personal safety concerns, especially in case of conflict.

We analyze the complete historical records of user activity on the platform. The dataset provided to us by the platform contains information on all (11,418) interactions that took place since the start of the platform, May 2016, to July 2017. We excluded unfinished requests that were not filed, requests that were cancelled by the platform[3], and requests from renters who had rented from the same owner in the past (as we are interested in trust between strangers). The remaining dataset contains 7,181 requests for 973 motorcycles sent by 2,896 renters to 851 owners. All user and motorcycle variables are fixed across the dataset.

3.1 Dependent variable

Our dependent variable is the decision of the owner. They can either actively accept (2,626 requests, 36.6%) or decline (2,443 requests, 34.0%) a request, or not send a response at all, after which the request expires (2,112 requests, 29.4%).

3.2 Independent variables

To operationalize the reputation of the renter, we created two continuous variables, indicating the number of postive ratings and the number of negative ratings. Since 92.1% of all reviews are a 5-star rating, we define a positive rating as having five stars and a negative rating as having fewer than five stars. Renters without any reviews serve as the reference category.

We make use of data from the the Dutch civil registration (DCR) to operationalize the users' ethnicity (Edelman et al., 2017; Hofstra & de Schipper, 2018; Laouénan et al., 2017). All names are verified by the insurance company with which the platform collaborates, so the names visible to the owners are the renters' real names. The DCR data are register data of those who have Dutch nationality and were alive and living in the Netherlands. We have aggregated DCR data that comprises 3,800 unique first names (85.0% of the unique names in the platform dataset, covering 93.0% of the users of the platform). Per name we know the frequencies of combinations of the parents' birth countries. Based on the definition of Statistics Netherlands, country-combinations are classified into one of two ethnic origin groups: Native Dutch or non-native Dutch (Statistics Netherlands, n.d.). When both parents are born in the Netherlands, the combination is assigned to the native Dutch group. When one or both parents are not born in the Netherlands, the combination is classified as non-native Dutch. Per name we then calculate the probability that a user with that name is native Dutch. We include this continuous variable in the analyses. For some of the tables and figures we have used dichotomous ethnicity variables rather than a continuous one, in that case we have assigned a user to the ethnicity (s)he most likely belongs to.

The last independent variable is the cumulative request count of the renter, which is the total number of requests made by the renter at the time of the request, including the current request.

3.3 Control variables

We included all other information visible to motorcycle owners: the price and duration of the rental, the number of years a renter has been a member on the platform and the age and gender of the renter[4], whether the renter has a profile picture and a linked Facebook account. We include the same information about owners and the following control variables related to the motorcycles: weight, cc, hp, age of the motorcycle, and the number of positive and negative ratings of the motorcycle.

The last control variable is time. Since the requests are not evenly distributed over time, with large peaks in the summer months and virtually no interactions in winter, we operationalize time by the total number of completed requests at the platform at the time of the new request.

3.4 Analytical strategy

The data have a cross-classified structure: requests are nested within renters and owners, but renters and owners are not nested within each other: the same renter interacts with multiple owners and vice versa. To test the hypotheses, we ran a cross-classified multilevel logistic regression with as dependent variable a dummy variable indicating whether the request was accepted or not. We used a Bayesian estimator with two MCMC chains and noninformative priors in Mplus (Muthén & Muthén, 2017). We used the default convergence criterion of Mplus (Proportional Scale Reduction factor lower than 1.1). We used 50,000 iterations for the analyses without control variables and 100,000 iterations for the regressions with control variables, of which the first half is considered as a burn-in phase.

We included random intercepts for renters and owners in all analyses. In the second and third model we added random slopes for reputation. We used full information maximum likelihood (FIML) to deal with missing values.

This method includes partial information in observations with missing values, which allowed us to use all available information.

In the first model we included the renter's ethnicity and reputation to test hypotheses 1 and 2. To the second model we added the interation between the renter's ethnicity and reputation to test hypothesis 3. The third model included the renter's reputation and ethnicity, which is interacted with the cumulative request count of the renter, interacted with the renter's ethnicity to test hypotheses 5 and 6.

We ran the same models with and without control variables. We ran the models in several steps. First we only included variables at the level of the transaction (level 1). We then removed insignificant variables before adding renter- and owner-level variables (level 2 and 3). We also removed insignificant variables before adding cross-level interactions, except when we were testing cross-level interactions between insignificant variables.

To test hypothesis 4 we ran a linear regression with the number of reviews about the renter per completed request as the dependent variable and the renter's ethnicity as independent variable. We included random intercepts for renters and owners.

4. Results

4.1 Descriptive statistics

Table 1 contains the descriptive statistics on all variables.

Table 1: Descriptive statistics

Variable	**Level**	**N_{miss}**	Mean	SD	Min	Max
Dependent variables						
Accepted	I	0	0.37	0.48	0	1
Declined	I	0	0.34	0.47	0	1
No response	I	0	0.29	0.46	0	1
Independent variables						
Renter Dutch ethnicity	R	223	0.79	0.30	0	1
Renter # of positive reviews	I	0	0.24	0.70	0	12
Renter # of negative reviews	I	0	0.03	0.19	0	2
Renter request #	I	0	2.84	2.75	0	27
Control variables						
# of rental days	I	0	1.81	1.49	1	33
Day price	I	2	66.06	25.53	20.90	184.59
Motorcycle # of reviews: positive	I	0	3.60	6.60	0	53
Motorcycle # of reviews: negative	I	0	0.78	1.54	0	9
Motorcycle age	I	4	12.83	7.47	0	61
Motorcycle weight	I	189	217.97	40.53	93	585
Motorcycle CC	I	12	865.24	269.13	113	2,294
Motorcycle HP	I	0	87.74	29.99	10	173
Renter age	I	2	35.56	10.81	20	80
Renter member #years	I	0	0.20	0.36	0	2.12
Owner # of reviews: positive	I	0	2.31	3.67	0	33
Owner # of reviews: negative	I	0	0.16	0.50	0	6
Owner age	I	2	35.74	10.21	18	73
Owner member #years	I	0	0.64	0.53	0	2.29
Renter female	R	191	0.12	0.31	0	1
Renter has profile picture (%)	R	0	0.61	0.49	0	1
Renter has Facebook verification	R	0	0.26	0.44	0	1
Owner Dutch ethnicity	O	142	0.85	0.22	0	1
Owner female	O	117	0.08	0.25	0	1
Owner has profile picture (%)	O	0	0.81	0.39	0	1
Owner has Facebook verification	O	0	0.37	0.48	0	1
Cumulative total # of requests (/1000)	I	0	3.591	2.073	0.001	7.181

Variables are measured at the level of the interaction/request (I), renter (R) or owner (O).
$R_{equests}$ = 7,181
$N_{renters}$ = 2,896
N_{owners} = 851

Figure 2 shows the relationship between the accept rate and the renter's ethnicity. Requests from renters with more Dutch-sounding names seem to be accepted more often. Native Dutch requesters are about twice as likely to receive a positive response as non-native Dutch requesters.

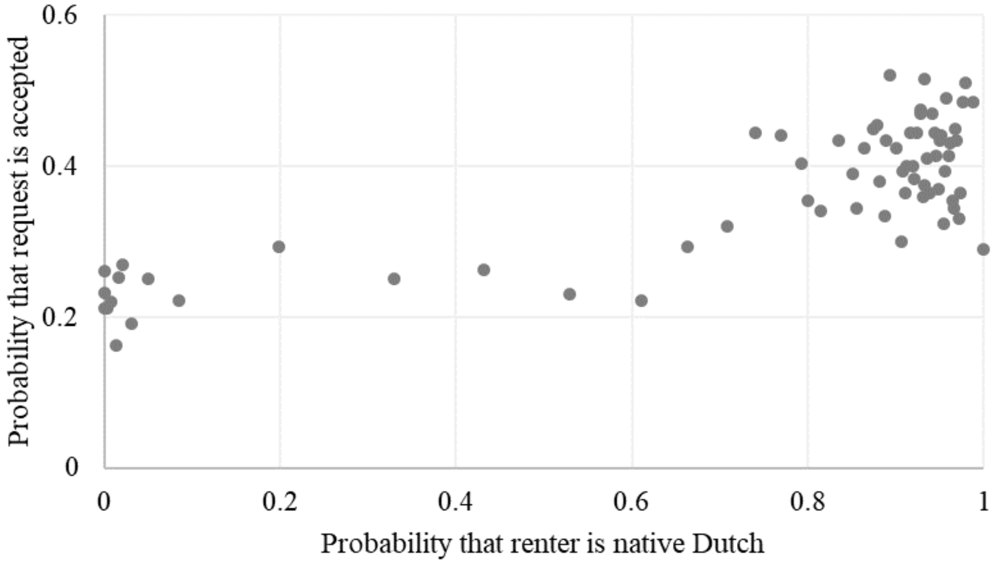

Figure 2: Average fraction of requests accepted, by renter's ethnicity. Each point represents 100 requests.

Figure 3 shows the relationship between a renter's reputation and the probability that a request is accepted. Having more positive reviews seems to have a positive effect on the accept rate, both for native Dutch and non-native Dutch renters (left panel). Having negative reviews seems to be detrimental for the probability to receive trust, especially for non-native Dutch renters (right panel). A note here is that there are no non-native Dutch renters with more than five positive reviews, suggesting that indeed they have a harder time establishing a reputation.

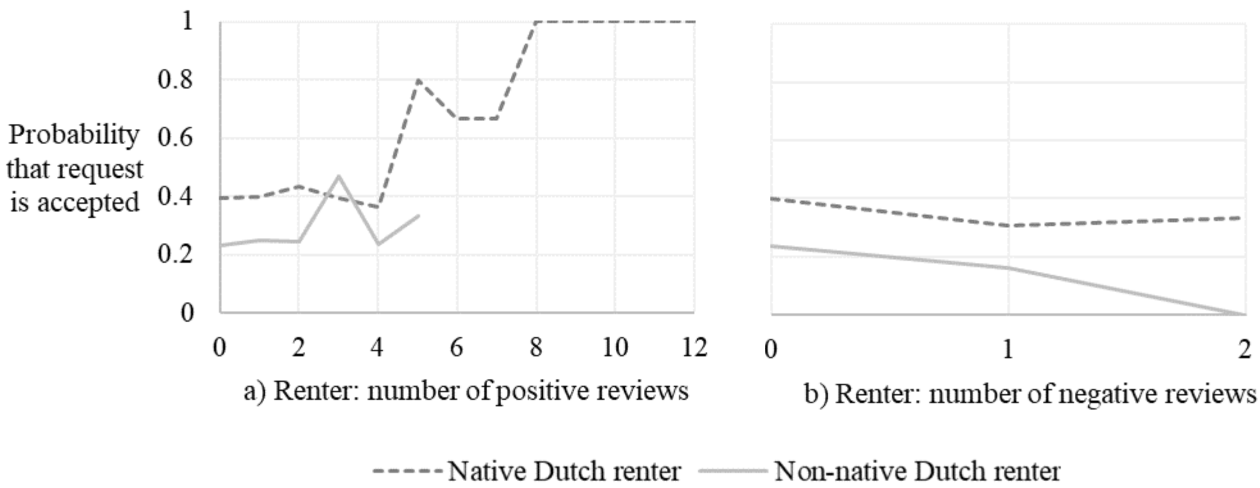

Figure 3: Average fraction of requests accepted, by renter's ethnicity and number of reviews

Figure 4 shows how the accept rate changes with every request filed for native Dutch and non-native Dutch renters. Per renter we have randomly drawn one request to account for individual differences. The figure is based on the average acceptance rate for 500 draws. Overall, the accept rate seems to decrease with every request. Note that this trend may be due to differences in the sample between the first and later requests, for example because renters who were previously unsuccessful are more likely to submit another request. The ethnic gap is again visible: native Dutch renters seem to have a higher probability to get a positive response than non-native Dutch renters. The ethnic gap seems to decrease with the cumulative number of requests made by a renter, although the points on the right side of the graph are based on very few observations, especially for the non-native Dutch renters.

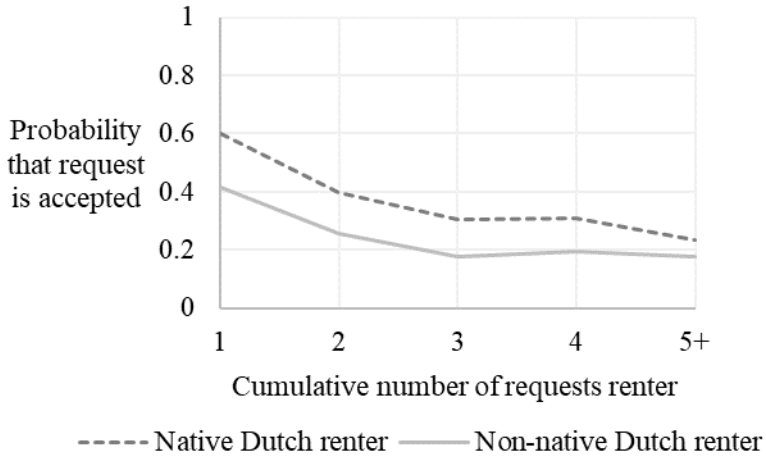

Figure 4: Average fraction of requests accepted, by the cumulative number of requests made by the renter and the renter's ethnicity. Average accept rate is based on 500 random draws of one request per renter. Datapoints representing the five or more requests are collapsed into one category.

4.2 Regression results

Table 2 contains the results from the regressions without control variables and Table 3 the results with control variables.

Table 2: Results of the multilevel cross-classified logistic regression of outcome of the request: accepted (0/1) without control variables.

Independent variables	**Model 1**	**Model 2**	**Model 3**
Threshold	1.086*** (0.967, 1.203)	1.072*** (0.940, 1.210)	1.077*** (0.888, 1.253)
Main effects			
Renter Dutch ethnicity	0.708*** (0.583, 0.825)	0.694*** (0.556, 0.837)	0.715*** (0.514, 0.907)
Renter # positive ratings (ref. cat. = no reviews)	0.058* (0.005, 0.111)	0.004 (-0.181, 0.178)	-
Renter # negative ratings	-0.199* (-0.399, 0.001)	-0.730** (-1.383, -0.121)	-
Renter request #	-	-	-0.024 (-0.087, 0.035)
Interactions			
Renter Dutch * Renter # postive ratings	-	0.079 (-0.130, 0.329)	-
Renter Dutch * Renter # negative ratings	-	0.464 (-0.243, 1.101)	-
Renter Dutch * Renter request #	-	-	0.030 (-0.041, 0.099)
Variance intercept renter-level	0.054*** (0.016, 0.108)	0.088*** (0.054, 0.139)	0.131*** (0.065, 0.251)
Variance intercept owner-level	0.552*** (0.449, 0.674)	0.577*** (0.470, 0.708)	0.534*** (0.419, 0.675)
PPP	0.499	-	-
N	7181	7181	7181

* indicates significance at p = .05 (two-tailed tests)
** indicates significance at p = .01(two-tailed tests)
*** indicates significance at p = .001(two-tailed tests)
95% Confidence interval in parentheses.

Table 3: Results of the multilevel cross-classified logistic regression of outcome of the request: accepted (0/1) with control variables

Independent variables	**Model 4**	**Model 5**	**Model 6**
Threshold	2.045*** (1.670, 2.441)	2.184*** (1.804, 2.577)	2,226*** (1,835, 2,631)
Main effects			
Renter Dutch ethnicity	0.620*** (0.510, 0.731)	0.634*** (0.499, 0.769)	0.644*** (0.426, 0.869)
Renter # positive ratings (ref. cat. = no reviews)	0,117*** (0.056, 0.177)	0.044 (-0.167, 0.263)	0.049 (-0.027, 0.128)
Renter # negative ratings	-	-0.763* (-1.908, -0.045)	-0.201 (-0.461, 0.054)
Renter request #	-0.027** (-0.043, -0.009)	-0.008 (-0.028, 0.014)	-0.015 (-0.078, 0.046)
Interactions			
Renter Dutch * Renter #reviews: positive	-	0.083 (-0.183, 0.334)	-
Renter Dutch * Renter #reviews: negative	-	0.534 (-0.310, 1.738)	-
Renter Dutch * Renter request #	-	-	0.033 (-0.041, 0.110)
Control variables			
# Rental days	0.025* (0.002, 0.048)	0.025* (0.000, 0.049)	0.023* (-0.002, 0.048)
Cumulative total # of interactions (/1000)	-0.021* (-0.046, 0.004)	-0.021 (-0.048, 0.005)	-0.022 (-0.050, 0.006)
Motorcycle age	-0.015** (-0.023, -0.007)	-0.015*** (-0.024, -0.007)	-0.015*** (-0.024, -0.006)
Motorcycle # negative ratings	0.043* (0.003, 0.082)	0.045* (0.003, 0.085)	0.040* (-0.003, 0.083)
Renter age	0.006*** (0.003, 0.010)	0.006*** (0.003, 0.010)	0.006** (0.002, 0.010)
Renter female	-0.075 (-0.188, 0.035)	-	-
Renter has profile pic	0.122** (0.051, 0.202)	0.131** (0.045, 0.218)	0.134** (0.041, 0.225)
Renter has Facebook verification	-0.113** (-0.202, -0.026)	-0.133** (-0.227, -0.039)	-0.145** (-0.245, -0.044)
Owner Dutch ethnicity	-0.086 (-0.372, 0.202)	-	-
Owner age	0.022*** (0.015, 0.028)	0.022*** (0.016, 0.029)	0.022*** (0.016, 0.029)
Owner member # years	-0.282*** (-0.397, -0.167)	-0.305*** (-0.426, -0.186)	-0.307*** (-0.431, -0.185)
Owner female	0.114 (-0.125, 0.354)	-	-
Owner has profile pic	0.578*** (0.370, 0.790)	0.554*** (0.347, 0.766)	0.563*** (0.348, 0.782)
Owner has Facebook verification	-0.095 (-0.237, 0.047)	-	-
Variance intercept renter-level	0.009*** (0.000, 0.042)	0.072*** (0.043, 0.121)	0,138*** (0.071, 0.278)
Variance intercept owner-level	0.493*** (0.396, 0.611)	0.528*** (0.424, 0.655)	0,511*** (0.391, 0.653)
PPP	0.000	-	-
N	7181	7181	7181

* indicates significance at p = .05. ** indicates significance at p = .01. *** indicates significance at p = .001 (two-tailed tests)
95% Confidence Interval in parentheses.

Supporting hypothesis 1, we find that requests from renters with more Dutch-sounding names have a higher probability of being accepted by the owners (Table 2, Model 1). This gap is persistent even when control variables are added (Table 3, Model 4).

We also find support for hypothesis 2: having more positive reviews increases the probability of getting a positive response, while having more negative reviews results in having a lower acceptance probability (Table 2, Model 1). When control variables are added, the effect of positive reviews is persistent in the model without interactions (Table 3, Model 4), but turns insignificant once interactions are added (Table 3, Model 5 and 6). The negative effect of negative reviews disappears when control variables are added (Table 3, Model 4).

We hypothesized that the ethnic gap would be smaller for renters with more and positive reviews (H3), but we do not find evidence for this in both the regressions with and without controls (Table 2 and 3, Model 2 and 5). The finding suggests that having more positive reviews is equally beneficial for native Dutch and non-native Dutch renters and that negative reviews harm renters with different ethnic backgrounds to an equal extent. This implies that the ethnic gap does not become smaller once renters have reviews.

We hypothesized that renters without Dutch sounding names would get fewer reviews (H4). The linear regression of the number of reviews per filed request on the renter's ethnicity shows that this is indeed the case. Per request, renters with completely Dutch-sounding names receive 0.18 reviews more than renters with names that do not sound Dutch at all (b=0.181, z = 7.34, p < .001). This difference is entirely caused by the difference in acceptance rate between renters with the Dutch ethnicity and renters with other ethnicity, as renters with less Dutch-sounding names receive slightly more reviews per accepted request (b = -0.055, z = -2.05, p = .041). There is a significant difference in the rating owners give to renters of different ethnicity: compared to names that are completely native Dutch, renters with non-native Dutch names on average get 0.13 points lower ratings (b = 0.134, *95% CI* = (0.058, 0.207), p <.001*)*.

To test hypotheses 5 and 6, we examine changes in the ethnic gap with every request filed by a renter. The results of this analysis are shown in Table 2, Model 3 (without controls) and Table 3, Model 6 (with controls). We do not find that the probability that a request is accepted changes with the number of requests a renter has already filed. Neither do we find that there is a difference between renters with Dutch-sounding names and non-Dutch sounding names in extent to which the probability that a request is accepted changes with the number of requests done by that renter. This means that the disadvantage non-native Dutch renters have vis-a-vis native Dutch renters does not decrease as they file more requests.

4.3 Robustness checks

In the main analyses we operationalized reputation as the number of positive and negative reviews. When adding the quadratic effect of the number of reviews or when taking the natural logatithm of the number of reviews the results do not change, nor when reputation is operationalized as having no positive reviews versus one or more reviews.

4.4 Control variables

Table 3 includes the coefficients of the control variables that were included in the main analyses. We find that requests from older renters and from renters with a profile picture have a higher probability of being accepted. Older owners and owners with a profile picture accept more requests. Requests for longer rental periods and for motorcycles with a higher number of negative reviews are accepted more often.

Requests for older motorcycles have a lower probability of being accepted, as well as requests by renters who have linked their Facebook account to the platform account. The longer an owner has been a member of the platform, the lower the probability that a request is accepted. The probability that a request is accepted seems to decrease over time (Table 3, Model 1), but this effect is not significant in the models with the interaction variables (Table 3, Model 5 and 6). The probability that a request is accepted does not vary with the owner's ethnicity, nor with the gender of the owner and the renter. Whether the owner has linked his or her profile to Facebook also does not affect the accept rate.

Table 3 does not include the coefficients for insigificant control variables at the request level, which were removed before adding higher level control variables. Appendix B shows the model with all request-level control variables. We found that the day price, weight, cc and hp of the motorcycle, duration of the membership of the renter, reputation of the owner and the number of positive reviews of the motorcycles do not affect the probability that a request is accepted.

4.5 Exploratory analysis

To better understand the findings, we explored a number of potential explanations. First, we explored whether the discrimination on the platform is indeed driven by homophily. In another set of cross-classified logistic regression models regressing the acceptance of requests as dependent variable, we included the difference between the renter's ethnicity and the owner's ethnicity (i.e. the difference in the extent to which their names sound native Dutch) as the independent variable. We also included the renter's ethnicity to see whether the distance between the ethnicity of the renter and the owner explains all of the discrimination. The results of these regressions are given in Table 4, model 7. When the renter and owner are of the same ethnicity, the probability that the request is accepted is higher. However, even when controlled for the difference between the owner's and renter's ethncitiy, requests from renters with non-Dutch sounding names are accepted less often. This means that homophily is not the only explanation for the ethnic gap. Table 5 shows the acceptance rates of different combinations of renters and owners. It seems that the homophily effect is mostly present for native Dutch owners and owners of Turkish ethnicity.

Table 4. Results of the exploratory analyses.

Independent variables	**Model 7: DV = Accepted**	**Model 8: DV = Submit another request**	**Model 9: DV = Accepted**
Intercept / threshold	0.939*** (0.763, 1.119)	-0.748*** (-0.838, -0.649)	1.038*** (0.883, 1.189)
Distance ethnicity	0,196* (-0.375, -0.013)	-	-
Renter Dutch	0.580*** (0.411, 0.756)	-0.131* (-0.246, -0.015)	0.737*** (0.572, 0.898)
Success rate	-	-1.682*** (-1.887, -1.508)	-
Experience owner	-	-	-0.092*** (-0.139, -0.050)
Renter Dutch * success rate	-	-0.043* (-0.091, -0.003)	-
Renter Dutch * experience owner	-	-	0.029 (-0.010, 0.071)
Variance intercept renter-level	0.058*** (0.021, 0.112)	0.016*** (0.002, 0.046)	0.115*** (0.066, 0.191)
Variance intercept owner-level	0.554*** (0.452, 0.681)	0.028*** (0.007, 0.056)	0.015*** (0.012, 0.020)
PPP	0.499	-	-
N	7181	7181	7181

* indicates significance at $p = .05$ (two-tailed tests)
** indicates significance at $p = .01$(two-tailed tests)
*** indicates significance at $p = .001$ (two-tailed tests)
95% CI in parentheses.

Table 5. Number of accepted requests and acceptance rate (in parentheses) per renter-owner ethnicity combination.

		Owner				
		Dutch	Moroccan	Turkish	Other	Total
Renter	Dutch	2123 (39.9%)	61 (33.7%)	50 (32.7%)	134 (46.2%)	2296 (39.7%)
	Moroccan	174 (24.5%)	16 (21.1%)	16 (30.8)	13 (26.5%)	203 (24.3%)
	Turkish	114 (28.6%)	11 (33.3%)	7 (36.84%)	9 (33.3%)	137 (29.3%)
	Other	107 (24.1%)	5 (16.7%)	1 (7.1%)	16 (38.1%)	134 (24.7%)
	Total	2395 (36.8%)	88 (29.2%)	73 (30.5%)	176 (41.8)	2626 (36.6%)

Second, we explored why the ethnic gap does not change with the cumulative number of requests filed by a renter. By definition, renters can only accumulate reviews by submitting more requests, since reviews can only be written after succesful requests. We would therefore expect that the probability that a request is accepted increases with the number of requests submitted, but we do not find evidence for this. A potential explanation for this is that renters who have experienced many rejections try to compensate this negative outcome by sending more requests to increase the probability that at least one of them is accepted. We tested whether this is a plausible explanation for our findings using a cross-classified multilevel logistic regression with the dependent variable indicating whether a renter submitted at least one more request after the current one. The renter's ethnicity, the fraction of previous succesful requests, and the interaction between the two are included as independent variables. The results are in Table 4, model 8. We find that renters who have experienced more rejections are indeed more likely to file a new request. Moreover, we find that the interaction between the historical success rate and the renter's ethnicity is significant and negative. That means that even though renters who submit another request tend to have a lower success rate than renters who do not file another request, this is less so for non-native Dutch renters than for native Dutch renters. Among the renters who submit another request, the fraction of successful non-native Dutch renters increases relative to the fraction of unsuccesful native Dutch renters. This may explain why we did not find an increasing ethnic gap, while non-native Dutch renters received fewer reviews per filed requests and while they did not benefit more from reputation.

To control for the different tendencies to submit new requests, we constructed Figure 5, which is similar to Figure 4, except that we only included renters who submitted five or more requests. The figure shows show the acceptance chances for every request filed for native Dutch (N = 255) and non-native Dutch renters (N = 87). Whereas Figure 4 showed a decrease in the probability that a request was accepted with every additional request filed, the trend is reversed when only including renters who submitted five or more requests[5]. Thus, when controlling for the changing composition of the sample, the results are in line with the theory. Crucially, the acceptance rates of native and non-native Dutch renters do not converge. Apparently, the reputation system is not able to overcome to persistently lower acceptance rates of minority requesters.

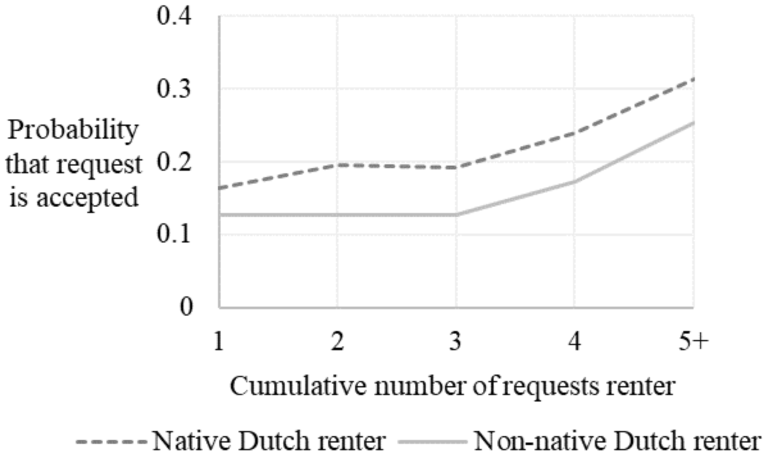

Figure 5: Fraction of requests accepted, by the cumulative number of requests made by the renter and the renter's ethnicity (with 95% Confidence Interval). Only renters who submitted five or more requests are included. Datapoints representing the five or more requests are collapsed into one category.

Lastly, we explored whether more experienced owners behave differently than less experienced owners. Since there are very few cases in which the renter turns out to be untrustworthy (as reflected in the extremely high reputation scores and the low frequency of claims made to the insurance company), we would expect that more experienced owners are better able to select the relevant information for assessing the trustworthiness of the renter. Hence, we expect that more experienced owners trust more and discriminate less. To test this hypothesis we ran a multilevel logistic regression with the outcome of the request (accepted or not) as the dependent variable. We included the renter's ethnicity and the number of completed transactions of the owner, as well as the interaction between the two. The results of this regression are in Table 4, Model 9. We find that more experienced owners are less likely to accept a request, and that they are not less likely to discriminate.

5. Discussion

Reputation systems are often proposed as the most promising solution to (ethnic) discrimination in online markets (Abrahao et al., 2017; Cui et al., 2016; Ert et al., 2016; Mohammed, 2017; Tjaden et al., 2018). In the current paper we argue that reputation systems fail to solve discrimination except in cases where minorities have little problem finding a transaction partner to begin with. Using simulations, we develop a new theory about the interplay between discrimination and reputation systems. We hypothesize that reputation systems may sustain inequality between renters with different ethnic backgrounds, even when discriminated renters can compensate their initial disadvantage with reputation. We tested this hypothesis using data from a Dutch motorcycle sharing platform. Consistent with our predictions, we find that the reputation system fails to reduce the ethnic gap. The difference between majority and minority members in the likelihood of having a request granted persists even for renters with positive ratings. Regardless of the reputation of the renter, requests from renters with an ethnic minority background are less likely to be accepted. This decreases their probability of getting a (positive) review, which in turn further decreases their chances to participate in future interactions.

A limitation of our test of the theory is that there are only very few ethnic minority renters with many positive reviews on the platform we studied. This limits the possibility to test to what extent reputation may compensate for the initial disadvantage of these renters. At the same time, this limitation in itself serves as a proof of our theory: we predicted that ethnic minority renters are less likely to obtain reviews, which is reflected in the low number of ethnic minority renters with many positive reviews.

Our contibution to the literature on discrimination and reputation is twofold. First, we reevaluated the claim that if objective information derived from third parties (positive ratings) is available, in-group preferences no longer matter for acceptance rates or are at least significantly reduced (Abrahao et al., 2017; Cui et al., 2016; Ert et al., 2016; Laouénan et al., 2017; Tjaden et al., 2018). Although reputation is beneficial both for native ethnic majority and ethnic minority renters, we do not find evidence for this “compensation hypothesis”. Motorcycle owners may generally attach more non-material value to their motorcycles than users of other platforms to their shared possessions, as the quotes in the introduction suggest. This may make strengthen the preference for renters with specific characteristics, as owners may simply prefer not to have certain renter with certain characteristics ride their bike (their ‘baby’), regardless of how trustworthy that renter has proven to be. Another explanation for why we do not find this ‘compensation effect’ may be that reputaiton information is not the type of information that owners are looking for. While reputation information did not decrease the ethnic gap, other types of information may succeed in doing so.

We argue that our research setting allows for a particularly clean test of the hypothesis that reputation systems may increase discrimination, given that it involves a clear trust problem. Moreover, rather than investigating the effect of ethnicity and reputation on the number of clicks an offer receives or on a proxy of the number of bookings, we had access to a complete dataset of all interactions that ever occurred on the platform. Moreover, our dataset contains data on real and complete user profiles, which allowed us to study a more natural setting than in labexperiments where user profiles are constructed by the researchers.

Second, and more importantly, we argued that rating systems may fail to overcome inequalities caused by discriminatory tendencies, even in the presence of a compensation effect. While past field experiments convincingly show that ethnic background is less of a determinant of success on online platforms among users with profiles that contain (artificially created) positive ratings than among profiles lacking such ratings, we emphasize that groups that are discriminated against are less likely to obtain positive ratings in the first place, precisely because they are less likely to be accepted. Our simulation model shows that, as a result, the ethnic gap in acceptance chances may actually grow rather than recede within empirically reasonable time spans. Our dataset provides a unique opportunity to assess the dynamic process in which initial inequalities may be reproduced, because we observe complete trajectories of acceptance rates of individual users, across all their interactions on the platform. While we find that reputation benefits renters of all ethnicities, we show that with time the reputation system maintains the disadvantage of ethnic minority renters.

Endnotes

[1] Reputation systems collect, aggregate and distribute feedback about trustees’ past decisions to trustors (Resnick et al., 2000).
[2] On many platforms, like eBay, AirBNB and Couchsurfing, most users but especially consumers (i.e. buyers, renters), transact only a handful of times (Lauterbach, Truong, Shah, & Adamic, 2009; Resnick & Zeckhauser, 2002; Teubner, 2017). Renters on the motorcycle sharing platform that we study in the next sections on average submitted 2.5 requests since the start of the platform, so with ten periods in our simulation model we study a time frame that includes the vast majority of user histories on our platform and most other platforms. Most renters will never submit ten requests, and if the reputation system fails to reduce the inter-ethnic inequality in acceptance chances in a few rounds, most minorities will never experience equal chances.

[3] The platform automatically cancels requests for two reasons: 1) the renter does not have the required driver's license; 2) renters can send multiple (similar) requests at the same time. When one of the requests is confirmed, the other requests are automatically cancelled.

[4] We apply the same methodology to estimate the gender of the users as for estimating their ethnicity.

[5] The figure looks similar when including only renters who submitted at least three or seven requests.

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Appendix A – Simulation

Model

The goal of the simulation is to illustrate under what conditions inequality between renters with different ethnicity is higher in a situation with a reputation system than when there is no reputation system. We simulated a sequence of rounds in each of which two renters ($i = 2$) who have a different ethnicity ($E = 0$ for renter with majority ethnicity, ($E = 1$ for renter with minority ethnicity), submit a rental request. We simulate how the outcome of that request depends on the renter's ethnicity and reputation. When every extra review increases the chances that a request is accepted, the acceptance probabilities of the two renters will eventually always converge because the maximum probability is 1 by definition. However, we argue that when the number of requests a single renter makes is limited, inequality between two renters may be higher in the case with a reputation. We therefore evaluate inequality between the two renters after ten rounds ($T = 10$), which is low enough to observe the increase in inequality, while it is also high enough to be realistic.

The outcome of a request in a given round, A_{it}, equals 1 if the request is accepted and 0 otherwise. We assume that a renter receives a positive review after every accepted request, the number of reviews a renter has thus solely depends on the sum of previously accepted requests. The probability that the request is accepted in a given period is $0 \leq P_{it} \leq 1$. We use a logistic regression function to simulate the probability: $P_{it} = \frac{\exp(L_{it})}{1+\exp(L_{it})}$, where L depends on the ethnicity and reputation of the renter. We vary the initial level of trust in the market, the importance of ethnicity and the importance of reputation for both renters: $L_t = G - E * D * (1 + R * \sum_1^{t-1} A_{2t})^{-C} + R * \sum_1^{t-1} A_{2t}$.

G is the baseline level of trust in the market. We assume that there is discrimination for actors without reputation: requests from renter 1 are accepted more often than requests from renter 2: $D > 0$. The more reviews a renter has, the higher the probability that the request is accepted: $R > 0$. Following the argument that discrimination in the platform economy is mostly statistical discrimination, owners may pay less attention to ethnicity when the renters have more reviews. This 'compensation effect' is denoted as $C \geq 0$. The larger C and the more reviews renter 2 has, the smaller the influence of discrimination. C is operationalized as a power term to avoid that minority renters will eventually have a higher acceptance probability than majority renters.

We operationalize inequality between the renters as the average difference in the acceptance rate between two highly trustworthy renters of different ethnicity. We do so by calculating the successrate S_1 of each renter which is the fraction of accepted requests after ten requests: $S_i = \sum_1^T A_{it}/T$. We then use this number to calculate two-person version of the Gini-coefficient: $Gini = (S_1 - S_2)/(S_1 + S_2)$. A larger Gini-coefficient indicates that there is more inequality between renter 1 and 2. We compare the Gini-coefficient between systems with a reputation system ($R > 0$) and without reputation system $R = 0$ but that are otherwise similar. Our final outcome variable is the difference between the Gini-coefficient with a reputation system and the Gini-coefficient for the case without reputation: $Gini_{R>0} - Gini_{R=0}$. If this number is positive, there is more inequality between minority and majority members in the case with reputation system than in the case without reputation system. When $Gini_{R>0} - Gini_{R=0} > 0$, the opposite holds: there is less inequality in the case with a reputation system.

Table A1 shows the parameter settings used in the simulations. The intial level of trust in renter 1 is between 12% and 88% the intial level of trust in renter 2 is between 5% and 73%. In total we have $5 * 3 * 11 * 2 = 330$ conditions. We ran 10,000 iterations per condition, resulting in 3,3 million datapoints.

Table A1: Parameter settings used in the simulation

Parameter	Values tested
Number of renters	$E \in \{1, 2\}$
Number of rounds	$T = 10$
Number of renters	$i = 2$
Initial level of trust in the market	$G \in \{-2, -1, 0, 1, 2\}$
Discrimination	$D \in \{1, 2\}$
Importance reputation	$R \in \{0, 0.5, 1, 1.5, 2\}$
Compensation effect	$C \in \{0, 0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, .8, 0.9, 1\}$

Simulation results

On average over all parameters and iterations, inequality is 0.11 points lower in the case with a reputation system than the case without a reputation system, and ranges between -2 and 2. In 26.9% of the iterations inequality is higher in the case with a the reputation system than without a reputation system. In 14.7% of the cases inequality was equal in the simulation with and without the reputation system. In the remaining cases (58.4%) discrimination was lower in the case with a the reputation system.

Figure A1 shows the relation between the parameters and the difference in inequality between the simulations with and without reputation system. The positive area reflects more inequality in the simulations with a reputation system. The line indicates the mean difference in inequality between the system with and without reputation system. The shaded area indicates the standard deviation. The line of the initial level of trust in the ethnic minority decreases until -1 and then slowly increases. More strikingly, a higher level of initial trust in this group greatly reduces the variance in the difference in inequality between the simulations with and without reputation system. The lines of the discrimination and reputation are more or less horizontal and the standard deviation in the inequality difference does not differ along different levels of these parameters. The line of the compensation effect fluctuates between 0 (no difference between the two systems) and 0.25 (more inequality in the simulations without a reputation system).

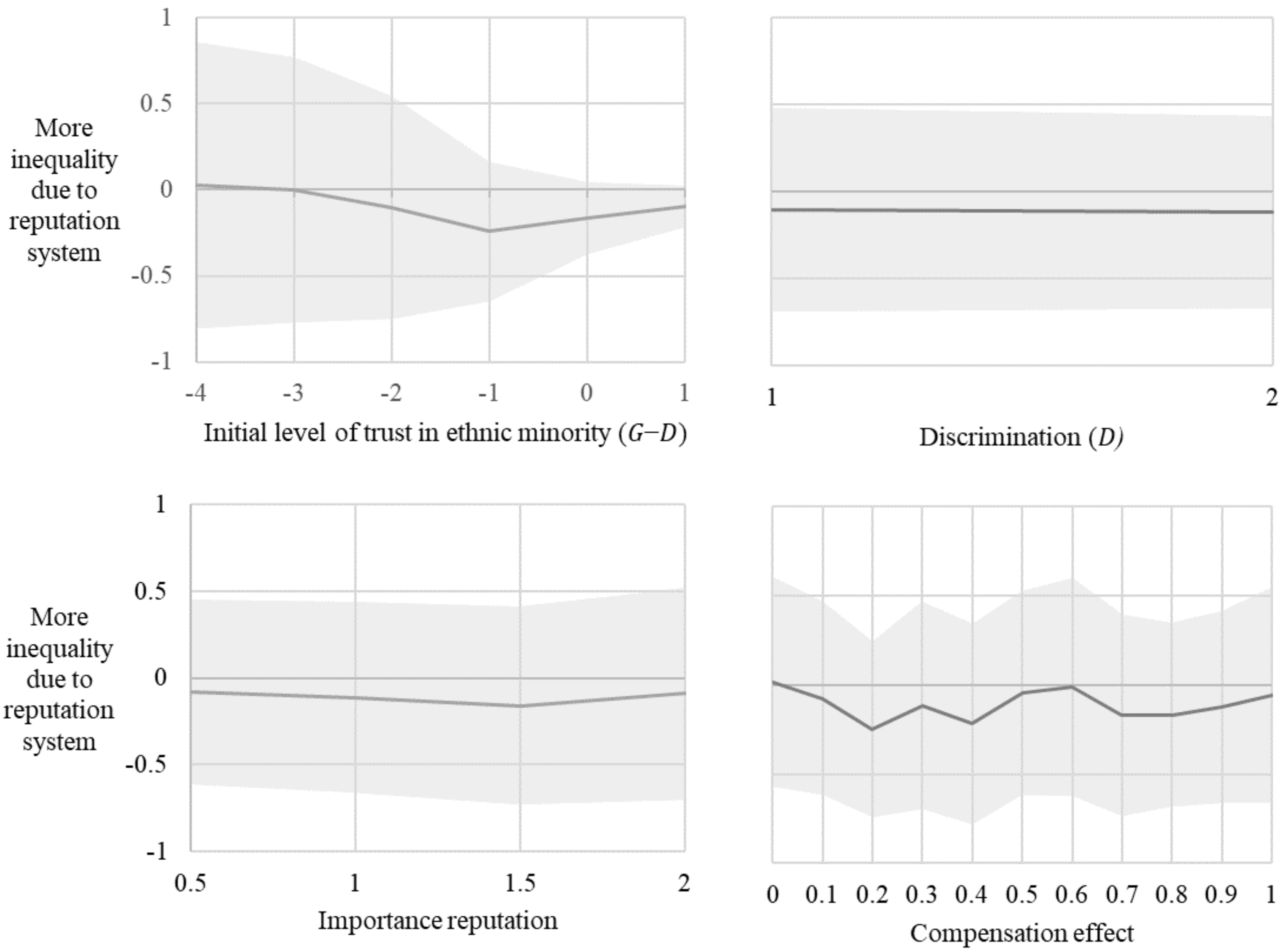

Figure A1: Difference in inequality between renters of different ethnicity between simulations with and without a reputation system. The positive (upper) area reflects more inequality in the simulations with a reputation system than in the system without a reputation system.

We ran a linear regression with the difference in inequality between simulations with and without reputation system as the dependent variable and all the parameters as the independent variables. We standardized all variables. We included the initial level of trust in the ethnic minority renter, calculated as $G - D$. To capture the nonlinear relation between the initial level of trust in the ethnic minority and the difference in inequality between the simulations with and without reputation system, we include the quadratic term of the initial level of trust in the ethnic minority: $(G - D)^2$. Table A2 shows the results of the regressions.

Table A2: Linear regression of the simulation results of the difference in inequality between simulations with and without reputation systems (two-person Gini-coefficient). A positive number indicates that there is more inequality in the simulations with a reputation system.

Independent variables	**DV = Inequality higher in simulation with rep. sys.**
Constant	-0.090*** (0.001)
Main effects	
Initial level of trust in the market (G)	-
Discrimination (D)	-0.051*** (0.000)
Importance reputation (R)	-0.013*** (0.000)
Compensation effect (C)	-0.011*** (0.000)
Initial level of trust in minority ($G-D$)	-0.128*** (0.000)
$(G-D)$^2	0.090*** (0.000)
N	4,400,000
R^2	0.015

All variables are standardized. * indicates significance at p = .05 (two-tailed tests)
** indicates significance at p = .01(two-tailed tests)
*** indicates significance at p = .001(two-tailed tests)
Standard error in parentheses.

We find that the initial level of trust in ethnic minority renters is the most important predictor of the difference in inequality between the simulations with and without a reputation system and that the relation is nonlinear. For low levels of trust, an increase in the level of trust leads to a decrease in the difference in inequality in the case with a reputation system relative to the case without reputation system. For higher initial trust levels this effect is reversed. This can be explained by a combination of factors. When intial trust increases, it becomes easier for ethnic minority renters to acquire reviews and to profit from their reputation. However, an higher initial trust rate also implies that there is less room inequality reduction as the maximum probability that a request accepted is fixed.

When the initial gap between the two renters is larger, inquality is relatively lower in the case with a reputation system. This may seem counterintuitive, but that may be explained by a ceiling effect. When the initial difference between the renters is small, there is more room for improvement through the reputation system. Only when the initial level of trust in ethnic minority renters is low, the system may fail to do so. The regression results also suggest that the more important the effect of reputation and the stronger the compensation effect, the lower the inequality in the simulations with the reputation system than in the simulation without a reputation system.

Appendix B: Additional regression results

Table B: Results of the multilevel cross-classified logistic regression of outcome of the request: accepted (0/1) with request level control variables

Independent variables	**Model 1**
Threshold	1.085***
	(0.726, 1.516)
Main effects	
Renter # positive ratings (ref. cat. = no reviews)	0.137***
	(0.074, 0.201)
Renter # negative ratings	-0.090
	(-0.289, 0.101)
Renter request #	-0.036***
	(-0.053, -0.018)
Control variables	
# Rental days	0.026*
	(0.003, 0.049)
Cumulative total # of interactions (/1000)	-0.026*
	(-0.053, 0.000)
Day price	-0.001
	(-0.005, 0.002)
Motorcycle # of positive reviews	0.006
	(-0.004, 0.016)
Motorcycle # of negative reviews	0.045*
	(-0.003, 0.094)
Motorcycle age	-0.011*
	(-0.021, -0.001)
Motorcycle weight	-0.001
	(-0.003, 0.001)
Motorcycle CC	0.000
	(0.000, 0.001)
Motorcycle HP	0.000
	(-0.003, 0.002)
Renter age	0.010***
	(0.007, 0.014)
Renter member #years	0.025
	(-0.085, 0.135)
Owner # of positive reviews	-0,002
	(-0.021, 0.016)
Owner # of negative reviews	-0.076
	(-0.185, 0.032)
Owner age	0.021***
	(0.014, 0.028)
Owner member #years	-0.247***
	(-0.367, -0.130)
Variance intercept renter-level	0.012*** (0.003, 0.046)
Variance intercept owner-level	0,504*** (0.406, 0.625)
PPP	0.000
N	7181

* indicates significance at p = .05 (two-tailed tests)

** indicates significance at p = .01(two-tailed tests)

*** indicates significance at p = .001(two-tailed tests)

95% Confidence Interval in parentheses