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# Racial Discrimination in the Sharing Economy: Evidence from a Field Experiment

Referee Report

Covering the paper of the authors Edelman, Luca, and Svirsky

for

Advanced Econometrics (Applications)

Supervisor: Prof. Tom Zimmermann

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# Contents

# 1 Introduction

In this referee report, I will cover the paper "Racial discrimination in the sharing economy: Evidence from a field experiment" by Edelman, Luca, and Svirsky (2017). I will summarize its findings, place it into related literature and examine the research question. Furthermore I will replicate the main findings and assess the randomization of the randomized controlled experiment. Lastly, I will examine the data set used by the authors and give recommendations on further research.

## 1.1 Summary of paper

The paper "Racial discrimination in the sharing economy: Evidence from a field experiment" deals with racial discrimination against African Americans on the short-term rental platform AirBnb. AirBnb allows hosts to rent accommodations and manages communication and payment over their platform. Because it was created with small landlords and intimacy in mind, it allows hosts to decide whether to accept or reject a guest after seeing their profile and previous reviews. This market design choice is expected that it may further enable discrimination. To examine discrimination against black people in this market, the authors used a randomized experiment in form of a field experiment by requesting bookings using fake profiles with "white-sounding" and "African American-sounding" names. Then they compared the application acceptation rate, where they found a statistically significant gap of 16% between white and African American guests.

The authors collected their data across five cities[1] in July 2015 for all properties available on the weekend of September 25 (around 6,400 listings). Each host was contacted only once, if the host had more than one available listing they applied for a random listing. Furthermore, host characteristics[2] as well as location characteristics[3] were retrieved. Lastly, the listings were checked one day before the applied date for whether the listing was ultimately filled or not.

Constructing the fake profiles, the authors used four groups: African American male, African American female, white male and white female. The identification of whether a person is white or African American was constructed by using "white-sounding" and "African American-sounding" names, reusing a name list by Bertrand and Mullainathan (2004). In their paper addressing racial discrimination in the job market, Bertrand and Mullainathan created a list with distinctively white and African American sounding names by using birth certificates in Massachusetts and validating the list with a survey. Five names were assigned to each group, and one fake profile was created for each name,

[1] Baltimore, Dallas, Los Angeles, St. Louis and Washington D.C.

[2] Apart from transparent traits such as the amount of reviews or whether the host has multiple listings, the hosts race, gender and age was determined by mechanical turk workers. By using face-detection API, past guests of the property were categorized by race, gender and age to see whether there was an African American in the review history.

[3] Such as price of the listing, number of bedrooms and bathrooms, cancellation policy, cleaning fee or listing's past ratings.

totalling 20 fake profiles with 10 white and 10 African American sounding names. For the AirBnb fake profiles, there were no profile pictures used and the application message stayed the same, the accounts were identical in all respects except for the name. No information on the guest's age was shared with the host.

The authors categorized the responses of the hosts using text-scrapers into eleven categories, which can be broken down into "Yes", "Conditional yes", "Conditional no", "No" and "No response", however only "Yes" answers have been used as the variable "Host accepts" in the regression of the authors.[4]

The main result the authors find is a gap in the acceptance rate of inquiries of white and African American profiles while controlling for some host and location characteristics (42% for African Americans and 50% for whites, so a 8 percentage point or 16% difference). The authors control for host/guest gender and race combinations, and the gap is persistent except for when both host and guest are African American females. An extensive analysis by controlling for various more captured host and location characteristics yields similar results, the gap remains remarkably robust. However, it can be observed that for hosts with at least one recent review of an African American, the gap shrinks substantially, which according to the authors further validates the findings.

Regarding the possible threat to validity, the authors address the issue of bare fake profiles (no review history, no profile picture). Citing literature on AirBnb's overall rejection and profile characteristics (Fradkin 2015) and comparing it with their findings, nothing indicates a distortion through used fake profiles, as the majority of profiles on AirBnb are bare.

Using the data collected on whether the listed apartment was ultimately filled or not, the authors calculate a cost of discrimination for the hosts of around 65$ to 100$ for the median host.

Lastly, they give suggestions on how AirBnb could change their platform for reduced discrimination. For one, names could be concealed or pseudonyms could be used. Alternatively the already implemented but not frequently used "Instant-Booking" function could be expanded further, which AirBnb actually further promoted in response to the publication of the paper.

## 1.2 Placement in literature

Studies on racial discrimination of African Americans in the USA have been prevalent in economic literature for many years.

Very similar to the paper of the authors, especially regarding the methodology, is the paper "Are Emily and Greg more employable than Lakisha and Jamal? A field experiment on labor market discrimination" of Bertrand and Mullainathan (2004), where

[4] Addressing a possible distortion of the results through this categorization, the authors examined the gap between white and African American applications through various response categories. They found that the observed gap can largely be attributed to a difference in "Yes" and "No" answers.

a randomized experiment was run by sending in fake CV's to job advertisements and comparing the callback rates between races. Both papers even use the same name list for creation of fake profiles and CV's. The authors found that on average, African American people were called back significantly less than their white counterparts with the same qualifications. This is robust throughout various industries and controlling for various CV characteristics. Furthermore, they find that the callback rate gap actually widens with increasing resume quality, defying the hypothesis that African Americans can tackle discrimination in the labour market by increasing their qualifications/ human capital.

AirBnb is part of the so called "Sharing Economy", which promotes (paid) sharing of completely or partly unused resources, in this case accommodations.[5] With a rise of popularity and economic significance of such platforms, the importance and interest of understanding these new parts of the market obviously increases. Examining frictions in online marketplaces, Fradkin (2015) found that AirBnb has substantial search frictions, tackling those frictions completely would allow for roughly a doubling of matches in the marketplace, he proposes an alternative algorithm which could increase matches by around 10-20%. This suggests that while rapidly growing, "Sharing Economy" platforms are imperfect with many frictions to be examined and to be tackled.

## 1.3 Research question

Racial discrimination in the housing and rental market have been a steady problem over the last decades, which has been sought to tackle by policy makers through regulation such as anti discrimination laws. While discrimination is still prevalent in rental markets, the authors state that conditions have improved for minorities. However, it is expected that the discrimination laws largely targeted at larger companies selling and renting accommodations, do not carry over to smaller landlords who are the primary actors on the platform AirBnb. For validating this expectation and for formulating solutions on how to address discrimination on new online marketplaces, the research question of the authors is of great interest.

For the present research question, creating randomized fake applications is a great way to isolate the effect of discrimination. Collecting the data from real AirBnb applications would bring up the problem of the comparability between different application messages, profile pictures, review histories etc. Furthermore the creation of fake applications on AirBnb is fairly simple: When using names for perceiving whether the guest is black or white and not using a profile picture and leaving the application message the same, the only aspect which has to be randomized in the application itself is the name[6].

Putting an emphasis on collecting as many host characteristics and location charac-

[5] Another example for the "Sharing Economy" would be Uber, which is a cab/rental car platform allowing users to enter the cab market without association with a company.

[6] Host and location characteristics obviously still have to be randomized over, e.g. trying not to send most of the applications with African American sounding names to shared property inquiries and applications with white sounding names to non-shared property inquiries.

teristics as possible and then controlling for them using regressions is a valid approach as well. Each time providing an interaction term with the respective host/location trait further excludes possibly missed relationships wrongly attributed to the estimator of the effect of whether the guest is African American.

# 2 Replication

I decided to recompute the main regression used by the authors, as well as the regressions controlling for host and location characteristics. As I go in further detail on that topic for my own analysis, I also recomputed the table of proportion of positive responses by race and gender.

Table 1: The impact of race on likelihood of acceptance

| | Host accepts | | |
|---|---|---|---|
| Guest is African American | -0.08*** | -0.08*** | -0.09*** |
| | (0.02) | (0.02) | (0.02) |
| Host ist African American | | 0.07*** | 0.09*** |
| | | (0.02) | (0.02) |
| Host is male | | -0.05*** | -0.05*** |
| | | (0.01) | (0.01) |
| Host has multiple listings | | | 0.06*** |
| | | | (0.01) |
| Shared property | | | -0.07*** |
| | | | (0.02) |
| Host has 10+ reviews | | | 0.12*** |
| | | | (0.01) |
| ln(price) | | | -0.06*** |
| | | | (0.01) |
| Intercept | 0.49*** | 0.50*** | 0.76*** |
| | (0.01) | (0.01) | (0.07) |
| N | 6235 | 6235 | 6168 |
| $R_a^2$ | 0.006 | 0.009 | 0.039 |

This table reports coefficients from a regression of a "Yes" response on the guest's race and various host and location characteristics. Standard errors are clustered by (guest name) × (city) and are reported in parentheses. *** denotes significance at the 1% level, ** at the 5% level and * at the 10% level.

Looking at table 1, one can see that the recomputed results mirror the tables of the authors, but for the coefficient for "Host has multiple listings" - There is a 3 percentage point difference to the author's results. Some minor differences are to be expected, as the authors used Stata for their computation and I used Python. This can sometimes lead to differences in results caused by computational differences in the respective packages. While the authors did not use significance stars for their tables, I decided to include them to be able to catch further relationships for my own computation. While the results being largely the same as the results of the authors validate the authors findings that African American guests are being discriminated against, it is interesting to see that all included coefficients are highly statistically significant. This indicates that there are dynamics to be observed in the data set which were not yet covered in depth by the authors.

Regarding the two regressions controlling for host and location characteristics (see tables 2 and 3), my computed results are again very similar to the authors reported

Table 2: Are effects driven by host characteristics?

| | Host accepts | | | | |
|---|---|---|---|---|---|
| Guest is African American | -0.07*** | -0.08*** | -0.09*** | -0.08*** | -0.09*** |
| | (0.02) | (0.02) | (0.02) | (0.02) | (0.02) |
| Shared property | 0.00 | | | | |
| | (0.01) | | | | |
| Shared property × guest is African American | -0.02 | | | | |
| | (0.03) | | | | |
| Host has multiple listings | | 0.10*** | | | |
| | | (0.02) | | | |
| Host has multiple listings × guest is African American | | -0.00 | | | |
| | | (0.03) | | | |
| Host has ten+ reviews | | | 0.14*** | | |
| | | | (0.02) | | |
| Host has ten+ reviews × guest is African American | | | 0.01 | | |
| | | | (0.02) | | |
| Host looks young | | | | -0.03 | |
| | | | | (0.02) | |
| Host looks young × guest is African American | | | | -0.01 | |
| | | | | (0.02) | |
| Host has 1+ reviews from an African American guest | | | | | 0.10*** |
| | | | | | (0.01) |
| Host has 1+ reviews from an African American guest × guest is African American | | | | | 0.06** |
| | | | | | (0.02) |
| Intercept | 0.49*** | 0.46*** | 0.42*** | 0.50*** | 0.46*** |
| | (0.01) | (0.01) | (0.01) | (0.01) | (0.01) |
| N | 6235 | 6235 | 6235 | 6235 | 6235 |
| $R_a^2$ | 0.006 | 0.014 | 0.027 | 0.007 | 0.019 |
| Implied coefficient | -0.09 | -0.08 | -0.08 | -0.09 | -0.04 |

This table reports coefficients from a regression of a "Yes" response on the guest's race, various host characteristics, and the interaction between the two. Standard errors are clustered by (guest name) × (city) and are reported in parentheses. Implied coefficient is the implied coefficient on guest is African American + the respective interaction term with the host trait. *** denotes significance at the 1% level, ** at the 5% level and * at the 10% level.

results. There are some minor differences, but only for a few coefficients with no change in sign or with large magnitude. The differences again can be attributed to computational differences between Python and Stata.

Replicating the table reporting the proportion of positive responses by race and gender (see table 4), there are no differences to the authors' reported results whatsoever. It is noticeable that except for two occasions, for both black and white guests, the proportion of positive responses is lower for males than for females. As the influence of the guest's gender has not been covered in depth by the authors, I will focus on that topic for my own computation.

## 2.1 Assessment of robustness

The creation of fake profiles on AirBnb is not that complex as e.g. the creation of comparable but not identical CV's (as has been done by Bertrand and Mullainathan (2004)). Therefore the main concern is whether it was successfully randomized over the host and location characteristics, especially as only one single inquiry has been sent to each host

Table 3: Are effects driven by location characteristics?

| | Host accepts | | | |
|---|---|---|---|---|
| Guest is African American | -0.08*** | -0.08*** | -0.09*** | -0.12** |
| | (0.02) | (0.02) | (0.02) | (0.06) |
| Price > median | -0.06*** | | | |
| | (0.02) | | | |
| Guest is African American × (price > median) | 0.01 | | | |
| | (0.03) | | | |
| Share of African American population in census tract | | 0.05 | | |
| | | (0.05) | | |
| Guest is African American × (share of African American population in census tract) | | 0.02 | | |
| | | (0.07) | | |
| AirBnb listings per census tract | | | -0.00 | |
| | | | (0.00) | |
| Guest is African American × (AirBnb listings per census tract) | | | 0.00 | |
| | | | (0.00) | |
| Probability listing is filled 8 weeks later | | | | 0.56*** |
| | | | | (0.08) |
| Guest is African American × (probability listing is filled eight weeks later) | | | | 0.09 |
| | | | | (0.12) |
| Intercept | 0.52*** | 0.48*** | 0.49*** | 0.24*** |
| | (0.02) | (0.01) | (0.02) | (0.03) |
| N | 6235 | 6223 | 6235 | 6101 |
| $R_a^2$ | 0.009 | 0.006 | 0.006 | 0.030 |

This table reports coefficients from a regression of a "Yes" response on the guest's race, various location characteristics, and the interaction between the two. Standard errors are clustered by (guest name) × (city) and are reported in parentheses. *** denotes significance at the 1% level, ** at the 5% level and * at the 10% level.

and as the authors state that they had difficulties with AirBnb detecting their mass fake inquiries/profiles. Additionally, the authors did not address significance of their findings directly for example by a Fisher Direct Test or provide a discussion on the randomization of the variables. Therefore, I will focus on assessing the randomization over host and location characteristics and perform a Fisher Exact Test.

Taking a look at the results of table 5, the randomization over host and location characteristics seems to have been successful for all but the variable "Host has 10+ reviews". The positive sign of the coefficient indicates that more applications with a black name have been sent to hosts with more than 10 reviews. This is not optimal and probably should

Table 4: Proportion of positive responses by race and gender

| | Guest race/ gender | | | |
|---|---|---|---|---|
| Host race/ gender | White male | African American male | White female | African American female |
| White male | 0.42 | 0.35 | 0.49 | 0.32 |
| African American male | 0.64 | 0.40 | 0.59 | 0.43 |
| White female | 0.46 | 0.35 | 0.49 | 0.44 |
| African American female | 0.43 | 0.38 | 0.53 | 0.59 |

This table shows the proportion of "Yes" responses by hosts of a certain race/gender to guests of a certain race/gender.

Table 5: Assessment of randomization

| | I | | II | |
|---|---|---|---|---|
| Variable | Coefficient | P-Value | Coefficient | P-Value |
| Host is male | 0.001 | 0.896 | -0.013 | 0.423 |
| Host is African American | -0.000 | 0.972 | -0.001 | 0.968 |
| Host has multiple listings | 0.009 | 0.451 | 0.004 | 0.797 |
| Shared property | 0.001 | 0.929 | -0.015 | 0.495 |
| ln(price) | 0.005 | 0.792 | 0.001 | 0.927 |
| Host is female | -0.009 | 0.439 | -0.017 | 0.277 |
| Host has ten+ reviews | 0.026 | 0.041 | 0.030 | 0.041 |
| Host looks young | 0.003 | 0.799 | 0.006 | 0.661 |
| Price > median | -0.004 | 0.772 | -0.011 | 0.584 |
| Share of African American population in census tract | -0.001 | 0.919 | -0.003 | 0.940 |
| Guest is male | -0.010 | 0.408 | -0.012 | 0.350 |
| AirBnb listings per census tract | 0.045 | 0.848 | 0.000 | 0.656 |
| Probability listing is filled 8 weeks later | -0.000 | 0.899 | -0.097 | 0.247 |
| City: Baltimore | -0.001 | 0.906 | -0.008 | 0.778 |
| City: Dallas | -0.006 | 0.311 | -0.034 | 0.240 |
| City: Los Angeles | 0.004 | 0.743 | -0.012 | 0.493 |
| City: St. Louis | -0.003 | 0.382 | -0.039 | 0.373 |
| City: Washington D.C. | 0.007 | 0.505 | | |

This table shows the results of the assessment of the randomization over host and location variables. Column I displays the coefficients and p-values of the regressions of each control variable on their own onto the treatment variable "Guest is African American". Column II displays the coefficient and p-value of the regression of the treatment variable "Guest is African American" on every control variable (One city had to be omitted for addressing the dummy variable trap). Both regression types include intercepts, which are not reported here as they are not of large importance when addressing the randomization.

have been addressed, however the coefficients are with 0.026 and 0.03 not too large (both variables are binary). Additionally, the variable has been included in two regressions of the authors[7] where it did not seem to distort the results, the size and significance of the coefficient of the treatment variable was in the same ballpark as in the other regressions.

I additionally performed a Fisher Exact Test to examine whether the observed difference of 8 percentage points was large enough to conclude a meaningful systematic discrimination. For the Fisher Exact Test, the original treatment effect is compared with the treatment effect of alternative permutations of the treatment variable. As the total number of alternative permutations for ≈6200 observations is too large, I simulated 100.000 alternative random permutations. Out of those, not a single other permutation had a treatment effect larger than the original one. This further contributes to the findings that African Americans are being discriminated against on AirBnb.

## 2.2 Further findings

In the replication of the main results it stood out to me that table 4 indicates a possible discrimination against males, while the variable of whether the guest is male has not been included in any regression by the authors. To further examine this observation, I replicated the regressions of the authors controlling for host characteristics, but added the variable whether the guest is male or female to the regression formula. Additionally, I

[7]The main regression (table 1) and the regressions controlling for host characteristics (table 2).

Table 6: The impact of gender on likelihood of acceptance I

| | Host accepts | | | | |
|---|---|---|---|---|---|
| Guest is African American | -0.08*** | -0.08*** | -0.08*** | -0.08*** | -0.08*** |
| | (0.02) | (0.02) | (0.02) | (0.02) | (0.02) |
| Guest is male | -0.02 | -0.05*** | -0.04** | -0.03* | -0.04** |
| | (0.02) | (0.02) | (0.02) | (0.02) | (0.02) |
| Shared Property | 0.02 | | | | |
| | (0.02) | | | | |
| Shared Property × guest is male | -0.06** | | | | |
| | (0.02) | | | | |
| Host has multiple listings | | 0.09*** | | | |
| | | (0.02) | | | |
| Host has multiple listings × guest is male | | 0.01 | | | |
| | | (0.03) | | | |
| Host has ten+ reviews | | | 0.14*** | | |
| | | | (0.02) | | |
| Host has ten+ reviews × guest is male | | | -0.00 | | |
| | | | (0.02) | | |
| Host looks young | | | | -0.01 | |
| | | | | (0.01) | |
| Host looks young × guest is male | | | | -0.04* | |
| | | | | (0.02) | |
| Host has 1+ reviews from an African American guest | | | | | 0.13*** |
| | | | | | (0.02) |
| Host has 1+ reviews from an African American guest × guest is male | | | | | -0.02 |
| | | | | | (0.02) |
| Intercept | 0.50*** | 0.48*** | 0.44*** | 0.52*** | 0.47*** |
| | (0.01) | (0.01) | (0.01) | (0.01) | (0.01) |
| N | 6235 | 6235 | 6235 | 6235 | 6235 |
| $R_a^2$ | 0.009 | 0.016 | 0.028 | 0.009 | 0.021 |
| Implied coefficient | -0.08 | -0.04 | -0.04 | -0.07 | -0.06 |

This table reports coefficients from a regression of a "Yes" response on the guest's race, gender, various host characteristics, and the interaction between the the host characteristics and the gender. Standard errors are clustered by (guest name) × (city) and are reported in parentheses. Implied coefficient is the implied coefficient on guest is male + the respective interaction term with the host trait. *** denotes significance at the 1% level, ** at the 5% level and * at the 10% level.

changed out the interaction term to be between the examined control variable and whether the guest is male, instead with whether the guest is black.

Looking at table 6 displaying the results controlling for host characteristics, remarkably the estimator for whether the guest is male looses statistical significance when including the variable whether the property is shared and its respective interaction term with "Guest is male". Here the estimator is only -2 percentage points, the lowest in size of the five columns. Furthermore, the estimator for the interaction term is -6 percentage points, being significant at the 5% level. Regarding the regression controlling for "Host looks young" and the respective interaction term displayed in column 4, the estimator for "Guest is male" decreases in size and statistical significance (now only at the 10% level). Other than that, the estimator for whether the guest is male does not vary much in size or statistical significance in the other columns.

Table 7 displays the results of further examination of the interaction between shared property, the guest's gender and the guest's race. Columns one to three display regressions of "Host accepts" onto "Guest is black" and "Guest is male", with all listings, with shared

Table 7: The impact of gender on likelihood of acceptance II

| | Host accepts | | | | |
|---|---|---|---|---|---|
| | All listings | Shared property | Non-shared property | All listings | |
| Guest is African American | -0.08*** | -0.09*** | -0.07*** | -0.08*** | -0.08*** |
| | (0.02) | (0.02) | (0.02) | (0.02) | (0.03) |
| Guest is male | -0.05*** | -0.08*** | -0.02 | -0.05** | -0.03 |
| | (0.02) | (0.02) | (0.02) | (0.02) | (0.02) |
| Guest is African American | | | | 0.01 | 0.02 |
| × guest is male | | | | (0.03) | (0.04) |
| Shared Property | | | | | 0.03 |
| | | | | | (0.02) |
| Shared Property | | | | | -0.05* |
| × guest is male | | | | | (0.03) |
| Shared Property | | | | | -0.02 |
| × Guest is African American | | | | | (0.03) |
| Shared Property | | | | | -0.02 |
| × Guest is African American | | | | | (0.05) |
| × Guest is male | | | | | |
| Intercept | 0.51*** | 0.53*** | 0.50*** | 0.51*** | 0.50*** |
| | (0.01) | (0.02) | (0.01) | (0.01) | (0.02) |
| N | 6235 | 2974 | 3261 | 6235 | 6235 |
| $R_a^2$ | 0.008 | 0.014 | 0.004 | 0.008 | 0.009 |

The first three columns of this table report coefficients from regressions of a "Yes" response on the guest's race and gender for all listings, "Shared property" listings and "Non-shared property" listings respectively. The last two columns reports coefficients from regressions of the guest's gender, race, whether property is shared and respective interaction terms. Standard errors are clustered by (guest name) × (city) and are reported in parentheses. Implied coefficient is the implied coefficient on guest is male + the respective interaction term with the host trait. *** denotes significance at the 1% level, ** at the 5% level and * at the 10% level.

property listings and with non-shared property listings respectively. The comparison of the regressions further displays the interaction of "Guest is male" and "Shared property" observed in table 6. The estimator for "Guest is male" is statistically significant at the 1% level when including all listings and when including only the shared property listings. Notably the estimator also increases in size to -8 percentage points in the regression only including the shared property listings. In the third column one can see that when including only non-shared property listings, the estimator for "Guest is male" drops to the -2 percentage points and is no longer statistically significant at a reasonable level, which was already observed in the first column of table 6.

Importantly, the findings of discrimination against male guests do not weaken the findings of discrimination against African Americans by the authors. In the fourth column one can see that including an interaction term between the guest's gender and race does not change the size of the individual estimators compared to no included interaction term (column 1), only the significance level of "Guest is male" changes from 1% to 5%. Including "Shared property" and respective interaction terms with guest's gender and race as well as a triple interaction term does not change the estimator for "Guest is African American" in size or significance. As expected from the previous regressions, the estimator for "Guest is male" decreases in size and is no longer statistically significant at a reasonable level and the interaction term "Shared property × Guest is male" is with -5 percentage points in the ballpark of the previous regressions (although here only statistically significant at the 10% level). Remarkably, no interaction term with "Guest is black" is statistically significant nor large in size.

Comparing the results of discrimination against male guests with the results of the authors examining discrimination against African Americans, discrimination against males is not as robust and persistent as against African Americans. Moreover, there seems to be a conditional discrimination - people seem to discriminate male guests when the property is shared. For further analysis it would be interesting to take a look at the relationship of "Guest is male" with location characteristics as well as further analysis on the relationship with the age of the host, as one could already observe some relationship with the host looking young in table 6.

# 3 Recommendation

The discrimination against African Americans found by the authors is remarkably robust. Their controls are very sound, the estimator does not change noteworthy throughout all controls and the randomization was good for all but one used variable, "Host has ten+ reviews"[8]. As the creation of fake applications is not very complex and the acceptation or rejection of the application is the main interaction where discrimination can occur[9] and the results being very robust, one can assume that there is an underlying problem of discrimination against African Americans on the platform AirBnb in the observed cities. Certainly universal deviation of the results to the global AirBnb market would be difficult, therefore for further analysis it would be interesting to take a look at AirBnb listings in different countries and continents, as the platform is popular not only in the United States.

Regarding the present data set, apart from the discrimination against African Americans and males, there are some other relationships which could be observed, but were not covered in depth. For example, all estimators in the third column of table 1 displaying the authors main results[10] were large in size and statistically significant at the 1% level. If one wants to further examine the dynamics of the platform AirBnb or of the "Sharing Economy" in general, the data set most probably still provides insights which have not been uncovered in this referee report or in the paper of the authors.

[8]However, including the variable did not change the results and the relationship to the treatment variable "Guest is male" was not that high.

[9]E.g. taking the case of the labour market in the paper of Bertrand and Mullainathan (2004), discrimination may occur in the application process later or in the job itself, but in the case of renting apartments the main field of interest is whether one is accepted or not.

[10]Host is African American, Host is male, Host has multiple listings, Shared property, Host has 10+ reviews, ln(price).

# References

Bertrand, Marianne and Sendhil Mullainathan (2004). "Are Emily and Greg more employable than Lakisha and Jamal? A field experiment on labor market discrimination". In: *American economic review* 94.4, pp. 991–1013.

Edelman, Benjamin, Michael Luca, and Dan Svirsky (2017). "Racial discrimination in the sharing economy: Evidence from a field experiment". In: *American Economic Journal: Applied Economics* 9.2, pp. 1–22.

Fradkin, Andrey (2015). "Search frictions and the design of online marketplaces". In: *Work. Pap., Mass. Inst. Technol.*