Bocconi

WORKING PAPER SERIES
ISSN 2785-1079

Number 06
DECEMBER 2019

GENDER STEREOTYPES AND PRICE DYNAMICS IN THE SHARING ECONOMY: EVIDENCE FROM A CAR SHARING PLATFORM

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Gender Stereotypes and Price Dynamics in the Sharing Economy: Evidence from a Car Sharing Platform[1]

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Abstract

Gender stereotypes are increasingly considered to be as important as gender discrimination in market transactions. In this paper, we show that they influence market outcomes also through the client feedback channel of online platforms. Using a novel panel dataset of listings on the largest peer-to-peer car sharing platform in the U.S., we show that, controlling for quality of the listing, female renters leave more positive reviews. While positive reviews generally induce car owners to increase asking prices, the increase is significantly lower in the case the review was written by a female renter. This finding is consistent with platform users (both males and females) affected by gender stereotypes and implies that price dynamics in peer-to-peer market are affected by priors regarding reviewers ability to appreciate qualities of the good.

Keywords: Gender stereotypes, peer-to-peer markets, sharing economy, car rental.

JEL Classification Codes: D47, L11, L81, L86.

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1 Introduction

How do prices react to feedbacks provided by consumers? Do gender stereotypes influence price dynamics? Answering such fundamental questions implies opening the black box of market mechanisms and ultimately to understand the beliefs and even the psychology of producers and consumers.

The advent of the sharing economy based on digital platforms has brought both the illusion of more efficient markets with more equal access to services for all categories and the possibility to study the microstructure of markets. In this paper, we study the reaction of prices to reviews provided by clients and show that in the car rental market the price demanded by the supplier of the service reacts differently depending on the gender of the client. In particular, by using detailed data from a peer-to-peer car rental platform, we show that the price reacts more to positive feedbacks provided by males, whereas smaller reaction is found in the case of female clients. This result, that is robust across a number of specifications and valid also for only female renters, is consistent with the existence of gender stereotypes which may shape significantly the functioning of (online) markets. It should be noted that the focus on the car rental market is appealing as it allows us to test the eventual consequences of gender stereotypes in a domain where women are often believed to have less competences.

In fact, stereotypes regarding the driving ability of women are spread across cultures and tend to form in the early childhood of individuals (Granié and Papafava, 2011). Women are often associated to inability to take rapid and efficient decisions under stressful conditions (Glendon et al., 1996) or to the lack of caution potentially causing accidents (Lawrence and Richardson, 2005). These stereotypes emerge even if gender differences in reality are clear:

men commit more traffic violations (Aberg and Rimmo, 1998; Blockey and Hartley, 1995; Lonczack et al., 2007; Reason et al., 1990), at a young age, male drivers tend to adopt riskier driving styles (Bina et al., 2006; Harré et al., 1996; Harré et al., 2000), men have also higher mortality risk in the event of an accident (Hanna et al., 2006; Nell, 2002; Ozkan and Lajunen, 2005).

Results of our research are consistent with the presence of stereotypes even in online car rental markets, not necessarily related (only) to the stereotyped driving ability of women, but also to their capacity to appreciate the fundamental quality of a vehicle.

Our research is related to two strands of literature: a) the rising body of evidence on the existence and consequences of gender stereotypes; b) the growing literature on the functioning and on discrimination in markets based on digital platforms.

Recent literature on gender stereotypes has focused on risk preferences (Pondorfer et al., 2017), access to management positions (Johnson and Powell, 1994), performance evaluation (Eckel and Grossman, 2002; Heilman, 2001), behavior in the board room (Adams and Funk, 2012). This wealth of evidence almost unanimously points at an important role played by stereotypes in influencing the decision making process of individuals and consequently leading to sub-optimal outcomes. More recently, Bordalo et al. (2016; 2019) have proposed a social cognition theory for the formation of stereotypes according to which an agent assesses a group of overweighting the representative agent. This implies that when making his/her strategic decision, he/she will over-react to specific signals.

The aforementioned literature is of paramount importance for casting our research in the current debate for two reasons. First, there is no evidence that prices react to stereotypes on clients providing feedbacks. Second, our evidence on the intensity of prices to women's reviews is consistent with the "social cognition theory" in presence of gender stereotypes. In other words, if the renter believes that women are in general less able to assess the quality of a car, than he/she will overweight such belief and he/she will under-react to the review signal or, as an extreme consequence, he/she will not change the requested price, even to positive reviews.

Another strand of literature to which our research is related is the analysis of sharing economy markets.

Einav et al. (2016) provide an introduction to sharing economy business models, their economic implications and open questions on the topic. A number of papers provide empirical evidence about consumer behavior on peer-to-peer sharing platforms. Fraiberger and Sundararajan (2017) use company data from the hourly peer-to-peer car sharing platform *getaround* to examine the impact of a car sharing platform on car purchase decisions. Benjafaar et al. (2018) provide a theoretical framework for the effects of peer-to-peer sharing of durable goods on ownership, usage and welfare. A key finding is that consumers always benefit from the presence of sharing platforms, but the extent to the welfare gains depends heavily on usage patterns and demographics. Weber (2016) develops a theoretical model that jointly explains purchase decisions and price setting for durable goods in the presence of a peer-to-peer rental market.[2]

[2] A large part of the existing literature on the Sharing Economy analyszes its impact on existing industries. Manco and Percoco (2018) show that Uber is not competing directly with taxi operators and its presence may even generate positive spillover effects. Similarly, Cramer and Krueger (2016) analyze the effect of Uber availability on taxi usage in New York City, Farronato and Fradkin (2017) examine the impact of Airbnb on hotel room occupancy and Seamans and Zhu (2014) quantify the effect of Craigslist on local newspaper ads. Gong et al. (2017) investigate the effect of the presence of Uber on durable good purchase decisions. Horton and Zeckhauser (2016) provide a framework for the joint determination of durable good ownership and rental in the Sharing Economy in general.

Most empirical papers on the "sharing economy" use data from *Airbnb*, the largest apartment sharing website. Edelman and Luca (2014), as well as Laouénan and Rathelot (2017) document that hosts from racial minorities charge less than white hosts for similar apartments. Both papers control for a large number of observables and conclude that minority hosts face discrimination and are forced to lower their prices in order to increase demand. Edelman et al. (2017) examine the demand side of the *Airbnb* marketplace. The authors conduct an experiment, during which they send out booking requests from artificially created accounts of users with different ethnicities. They find that booking requests from black users are 12% less likely to be successful, controlling for observables. Another peer-to-peer platform that attracted the attention of researchers is the long-distance ride sharing platform *Blablacar*. Farajallah et al. (2019) examine the dynamics of price setting behavior of drivers on the platform and, similarly as Lambin and Palikot (2019), find that drivers with Arabic-sounding names face discrimination by potential riders. Empirical papers relating asking prices to owner characteristics on *Airbnb* face the issue that platform users typically have a good idea about the quality of an apartment, since they can see the pictures which typically accompany a listing, while this is not contained in a dataset. By using data from a car sharing platform, we can improve upon the existing literature in this aspect, since cars are almost completely characterized by their model and year in which they were built, both of which are variables we observe perfectly.[3]

[3] Although the Sharing (or Gig) Economy has often been heralded as a great equalizer for earnings of men and women, because of flexible hours and transparent remuneration schemes, there is little research on whether this prediction has actually come true. Cook et al. (2018) document and then unpack the substantial difference in hourly earnings between male and female Uber drivers. They use trip-level data to show that the gap is due to differential behavior across genders and not discrimination. Barzilay and Ben-David (2017) document a gender wage gap on a freelance labor online platform, even when they control for task and service provider observable characteristics.

The focus on the reaction of prices to reviews as reputational signals makes our research linked to the existing empirical evidence on housing markets. Teubner et al. (2017) quantify the price effect of favorable ratings on *Airbnb*, whereas Gutt and Herrmann (2015) provide causal evidence that *Airbnb* hosts increase their prices after their previous ratings become publicly visible.

The reminder of the paper is organised as follows. In section 2 a description of the dataset is presented, along with some descriptive statistics, whereas differences in terms of length and content of reviews is presented in section 3. Baseline results of the difference-in-difference model and robustness checks with propensity score matching are in section 4, while section 5 concludes.

2. The Setting: Car Rental Listings on *Turo*

Turo is the largest daily peer-to-peer car sharing platform in the U.S. On the *Turo* website, private individuals may list their vehicles to be rented by other private individuals for a minimum duration of one day. According to *Turo*, the platform is active in more than 4 500 cities across the U.S., its users offer more than 800 different models and have average earnings of $720 per month. The platform claims that its prices are are on average 35% lower than traditional rental car agency prices.

The dataset used in the empirical part of this paper was obtained by scraping the *Turo* website daily from April 1st to August 31st 2018. On each day, the algorithm crawled through different geographical locations in the U.S. and downloaded information about all listed cars in the area. The observed variables are model and model year of the listed car, daily price, included mileage, number of previous trips, average rating for those previous trips, the location of the car, the name of the owner, the description of the car, whether the ’Instant Booking’ feature is enabled and the names and reviews of previous renters.[4] Renters are not obliged to leave a review, but most do, particularly if the car owner has few previous trips (see Figure 1). Summary Statistics for the unique car listings are in Table 1.

In general, there are fewer women than men active on *Turo*. This is true for the demand and supply side and for all levels of car owner experience, as Figure 2 shows. *Turo* suggests a daily rental price to car owners, which is based on seasonality, geography, car characteristics and local competition, but crucially does not depend on the gender of the owner.[5]

The majority of car owners on *Turo* have limited experience and fewer than 25 previous transactions (or trips), as the histogram in Figure 3 shows. The histogram of prices (Figure 3) shows that the modal price is under $50 per day, although there are also some very expensive cars offered on the platform. On average, male car owners charge $ 8.40 more per day than female car owners, an economically and statistically highly significant difference. An important explanation for the difference in prices is given by the fact that men list cars of higher quality on *Turo* than women (see Table 2). Female owners are underrepresented among the listings of expensive car segments, such as electric vehicles or large sedans, but overrepresented among the cheaper hybrids or small SUVs. This illustrates the importance of controlling for the quality of offerings when analyzing peer-to-peer markets, which is

[4] Car owners who have the “Instant booking” feature activated forfeit the right to screen applicants for their car, but commit to renting their vehicle to the first renter to pay the price.
[5] This was confirmed by a *Turo* representative. See also the description on the company website: https://blog.turo.com/news/using-data-to-drive-your-daily-price (Accessed 01.04.2019)

credibly possible in the case of automobiles, but less so for example with apartments, where fewer characteristics are observed.[6]

We infer gender of the car owners and renters by using their first names which are consequently matched with the list of the most popular male and female names published by the U.S. Social security Administration.[7] Observations for which the gender of the reviewer or of the owner could not be assigned were discarded from the dataset. It should be noted that, given the aim of the research, the eventual measurement error arising from such matching procedure is not relevant or desirable at best. Car owners do not observe directly reviewers, so that the influence on their gender is likely to be driven by the recognition of the name as either a male or a female name. This inference is grounded on common knowledge, of which the list we make use of is a reliable source. In other words, the belief on the gender of the reviewer is even more important, in our framework, than the actual gender.

3 Differences in Reviews Across Genders

In this section we examine how male and female *Turo* differ in their behaviour when leaving each other reviews. For each listing in the dataset, we observe the five most recent reviews left by previous renters. The numerical rating (between 0-5 stars) renters leave car owners is not visible, but only the aggregate, average rating of all previous renters is displayed on an

[6] In principle, controlling for the characteristics of the supplied good is possible even in the housing market. However, the number of observable characteristics is larger in the case of cars offered on the *Turo* platform, especially if compared to the standardization of vehicles, thanks to which, even if not explicitly listed in the website, potential clients can access further information on the offered cars on producers website.

[7] The list of names is accessible at the website: https://www.ssa.gov/oact/babynames/decades/century.html.

owner's listing page. Instead, in this paper we use sentiment analysis to assign a number between -1 and 1 to each review, where higher numbers indicate a more positive review. In particular, we use the compound score computed by the VADER[8] sentiment analysis tool (Hutto and Gilbert, 2014).

Female renters write longer reviews (158 words on average) than male renters (143). A t-test for differences in means results in a t-statistic of 11.8, making this difference highly statistically significant at the 99% confidence level. Table 2 shows that this is true when female renters review male as well as female owners. Comparing only reviews left to male car owners, reviews left by female renters are 14.1 words longer on average than those left by male renters. For female owners, the difference is 15.2 words, or around 10% of the average review lenghts. Both differences are highly statistically significant with t-statistics of 10.4 and 4.5, respectively.

Not only do female and male renters leave reviews of different lengths, the sentiment of their reviews also differs. Interestingly, it may also depend on the gender of the car owner who is being reviewed. To measure sentiment, we use the VADER compound score, which ranges from -1 (for very negative reviews) to 1 (for very good ones). The summary statistics show that generally, reviews on *Turo* are quite positive. On average female reviewers leave more positive reviews (average score: 0.761) than male reviewers (0.748), with the two averages being statistically significantly different from each other at the 99% confidence level (t-statistic: 5.5). As with the review length, this is true for reviews left to owners of either gender. The difference in the average sentiment of reviews received by male owners

[8] A short description of the VADER sentiment analysis tool can be found in the appendix of this paper. For details, please refer to the official documentation at https://www.github.com/cjhutto/vaderSentiment

from female versus male owners is statistically significant at the 99% confidence level (t-statistic: 4.99), while for female owners it is only significantly different at the 5% confidence level (t-statistic: 2.12).

A potential concern with attributing differences in review sentiment to the gender of the renter is that male and female renters may use the platform in different ways. For example, female users could prefer renting cars of a higher quality or to use *Turo* in a different context (e.g. on vacation vs. on a business trip), both of which could lead to a more enjoyable experience and hence a more positive review. To exclude such alternative narratives, we regress the sentiment score of each review on dummies for the gender of renter and owner, and include location and car model-year fixed effects.[9] Regression results are in Table 4; column (2) shows that female reviewers leave significantly better reviews, even when controlling for the type of car that was rented and the location it was rented in. Finally, as column (3) shows, the discrepancy does not depend on whether the review was left to a male or female car owner.

Even when controlling for car and location characteristics, it is still possible that female users choose listings of higher quality, for example in terms of service provided by the car owner. In order to exclude this possibility, we re-run the regressions introducing owner fixed effects. These subsume location and car fixed effects, and additionally control for time-invariant unobserved differences across owners. The association of the gender of the reviewer with the review sentiment is hence identified by within-owner variation across reviews. Therefore, those owners for who only one review is observed, are dropped from the

[9] Including car model-year fixed effects means, for example, that we assign one dummy variable to a Fiat 500 built in 2012 and another one to a Fiat 500 built in 2013

analysis. Regression results including owner fixed effects are in Table 5. While the portion of explained variance increases significantly compared to the regression without owner fixed effects, the results remain the same and highly statistically significant. Female reviewers leave better reviews, even when controlling for all observed and unobserved time-invariant owner-specific characteristics, including information car type and location. As before, this result does not depend on whether the reviews were written for a male or a female car owner.

In a related paper, an analysis of differences in price setting on *Turo* across genders shows that local safety conditions as measured by local crime data are important determinants of platform user behaviour (Schmidt, 2019). To test whether safety concerns play a role in explaining the differential reviewing behaviour across genders, we check whether keywords commonly associated with safety appear in reviews.[10] One or more of these words are 54% more likely to appear in a review written by a female compared to a male renter. At least one keyword appears in 1.7% of reviews written by female and 1.1% of reviews written by male renters. This difference is significant at the 99% confidence level with a t-statistic of 6.4. Similarly as above, it does not matter whether these reviews were left to male or female owners; the safety topic is significantly more salient for female than for male reviewers, irregardless of whether they rented from a female or male owner.

To summarize, in this section we show that male and female car renters on *Turo* differ significantly in their usage of the review function. Female renters leave significantly longer and more positive reviews. The differences in sentiment are not driven by differences in the types of cars rented by male and female platform users, nor by the geographical location they

[10] The keywords are: safety, scared, fear, afraid, security, hazard, risk, threat, vulnerable, safe, exposure, danger, peril and trouble.

are rented in, nor by any time-invariant unobserved owner characteristics. In their reviews, female renters are much more likely to talk about safety related issues, suggesting that this aspect is more important to female platform users than to male users. In none of these three dimensions does it matter whether the reviews are left to male or female car owners. Now that we have established these differences in reviewing behaviour, in the next section we examine whether reviews actually have an effect on car owner outcomes. In particular, we test whether having good (or bad) reviews induces car owners to change their asking prices and thereby their profits.

4. The Effect of Reviews on Prices

The main hypothesis of this paper is that gender stereotypes may influence the functioning of online markets. In particular, we aim to test whether priced demanded by car owners react to reviews and whether there are statistically significant differences between female and male reviewers. The simple structure of this hypothesis also reflects our empirical strategy that consists in two steps of analysis.

In this section we explore the effect of reviews on asking prices, controlling for other listing characteristics. The compound VADER sentiment score serves as a measure of how positive or negative a review is. Interacting the score with gender dummy variables allows the effect to differ across the different gender combinations of reviewers and owners.

As a first step, we regress listing prices on car, location and owner characteristics, as well as review sentiment scores to establish the association between reviews of a certain sentiment and asking prices. The regressions we run are of the following form:

$$\textbf{(1)}\ lg(p_{it}) = \lambda_{my} + \lambda_c + \delta \cdot \text{Sentiment of review}_{it} + \beta \cdot X_{it} + \epsilon_{it}$$

p_{it} denotes the asking price of owner i at time t, λ_{my} are car model-year fixed effects, λ_c denotes location fixed effects and X collects control variables, such as the number of trips, miles, year of production, rating. Regression results are in Table 6.

While the allowed mileage is not significantly associated with the asking price, cheaper listings lead to more demand and hence more trips, explaining the consistently negative and significant association between the number of trips and the asking price. As is to be expected and consistent with the existing empirical literature, a better average rating is associated with a higher asking price in all specifications.

Interestingly, a positive VADER review sentiment score is positively related to the asking price, even when controlling for the rating of the car owner (column 1). This association is significant at the 95% confidence level and does not change upon the introduction of dummies for whether reviewer or owner are female (columns 2 and 3).

In column (4) we include three out of the four possible reviewer-owner gender combinations. Upon exclusion of the baseline sentiment score, column (5) shows that the positive association between asking prices and review scores is entirely driven by the sentiment of reviews left by male reviewers, whereas no effect is found if the positive review is written by a woman. This finding is coherent with the existence of gender stereotypes in the platform market, assigning to women a limited ability to assess vehicle quality. Interestingly, this result shows that also female owners may be subject to the gender stereotype since they do not show a significant reaction to positive reviews left by women. The fact that female reviewers tend to be more generous in their reviews as from the results in table 5 may reinforce our argument since the propensity to offer positive feedbacks may be considered as signals with lower credibility.

In order to improve the identification of our research design, we may exploit a particular panel structure embedded in our dataset. Since we observe unique car owners at several points in time, we can compare asking prices before and after receiving a review with a certain sentiment using a difference-in-difference regression framework.[11] In this case, the treatment variable is assumed to be a binary indicator indicating whether the sentiment of the review received is above a given threshold. In particular, we make use of three different treatment variable: *vd1* to indicate that the VADER sentiment compound variable is negative, *vd2* to indicate that the VADER sentiment compound is larger than its median, *vd3* to indicate that the VADER score belongs to the upper quartile.

By including a full set of owner and number-of-reviews fixed effects, we can interpret the treatment coefficient as a causal effect. With this approach, potentially differential effects of positive and negative reviews on asking prices and their dependence on reviewer-owner gender combinations can be identified. The estimating equation is given by:

(2) $lg(p_{is}) = \lambda_i + \lambda_s + \delta \cdot \text{I(Sentiment of review s in certain range)}_{is} + \beta \cdot X_{is} + \epsilon_{is}$

The notation is similar as above: λ_i denote owner fixed effects, while λ_s are fixed effects for having a number of reviews s. Given the full set of owner and number-of-reviews fixed effects, Equation 2 measures the causal effect of receiving a review of a certain sentiment on

[11] This implies that we make use only listings of cars that we observe before and after a review.

the asking price. Finally, it should be noted that the panel structure imposed to the dataset when estimating equation (2) is slightly different with respect to equation (1) since the “temporal” variation is given by changes in prices over the number of reviews. Results of estimation of (2) are in Table 7.

Given the large number of fixed effects included in the regression, neither the lack of statistical significance of the control variables, nor the high fraction of explained variance are surprising. The review sentiment however is a significant determinant of the asking price. Column (1) shows that receiving a negative review (where the VADER compound score is negative) results in a significantly lower asking price. On the other hand, receiving a very positive review with a sentiment score higher than the 75th percentile results in a significant increase in the asking price. Reviews that are only better than most (column (2)) however have no significant impact.

In order to examine potentially differential effects of reviews on prices across genders, we introduce dummy variables for the possible reviewer-owner gender combinations and interact them with the indicator variables described above. Results of these regressions are in Table 8. Column (1) shows that there is not enough variation in the data to attribute the negative effect on prices of reviews with negative sentiment to any of the reviewer-owner combinations. Column (3) however presents an interesting result in line with our previous findings. While the baseline effect of receiving a review with sentiment above the 75th percentile is positive and highly significant, the coefficients on the interactions variables indicating that the review was written by a female renter are large and negative. Therefore, while a positive review generally leads to an increase in the asking price, this is not the case if the review was written by a female renter.

Interestingly, female owners react to reviews left from women more than male owners as the corresponding coefficients are -0.019 and -0.009 respectively. In the framework of our argument, this result indicates that women are subject to gender stereotypes as much or more than men.

In order to test the robustness of the estimated effect of review sentiment on asking prices on *Turo*, we use Propensity Score Matching (PSM). First, we split the sample by review sentiment and compare the effect of receiving a good (or bad) review on the asking price of two observably similar owners, depending on whether the review was written by a male or female renter. Second, we split the sample by reviewer gender and use the review sentiment as the treatment variable. To find observably similar car owners, we match on the following variables: VADER compound score, allowed car segment, car age, owner gender, rating, number of trips and allowed mileage. The matching procedure adopted in the analysis is the nearest neighbour. Estimation results in terms of average treatment effects are in Tables 9 and 10.

The results in Panel A in Table 9 show that after receiving a review from a female renter, car owners charge lower prices than when the review was written by a male renter. The magnitude of the effect of stereotypes is large, ranging from -9.7% for negative reviews to -15.8% for very positive reviews. In Panel B we consider only female owners and find similar results, although with a slightly different path. Reviews written by women induce a smaller change in prices of an order of magnitude equal to -10.5% to -8.9%, depending on the VADER sentiment.[12]

[12] The effect of negative reviews could not be estimated for the scarse variation in the data.

In Table 10 we consider the reverse specification and compare the effect of receiving a review of a certain sentiment in the subsamples split according to the gender of the review writer. The estimation results confirm previous findings; negative reviews lead to lower prices, whether they were written by male or female renters. Positive reviews induce car owners to increase their prices, but more so, when the review was written by a male renter.

5. Conclusion

Stereotypes often influence preferences and the behavior of humans which, in their turn, influence the mechanisms regulating the functioning of institutions, even markets. In this paper, we have studied price dynamics in an online car rental market and found that variation in prices induced by online reviews is coherent with the existence of gender stereotypes.

Using a new panel dataset of listings on a peer-to-peer car sharing platform, we have examined empirically how male and female users differ in their usage of the rating and review system. The data have allowed us to exclude many potential confounders and shows robustly that female users leave reviews with a more positive sentiment than male users, controlling for vehicle quality and geographic location. This result even holds when we control for all other car owner specific observed and unobserved variables.

Furthermore, we have found that review sentiment is positively associated with asking prices both in cross-sectional regressions and in a difference-in-difference framework, with positive reviews by male renters shown to induce substantially larger changes in price than female renters. Interestingly, our results indicate that stereotypes affect also female owners.

The findings of the research presented in this paper suggest that stereotypes influence market outcomes not necessarily through differences in the access to services or in terms of unequal prices paid or working conditions. Rather, we have found that gender stereotypes influence prices through the reviewing system and not through client discrimination. This suggests that the supposed benefits generated by the online feedback mechanism may prove to be less so as differences in the reactions of prices depending on the gender of the reviewer.

Further research may address other markets and other forms of stereotypes to confirm more broadly our results. Furthermore, and perhaps more importantly, an experimental analysis on the formation of stereotypes may shed light on the instruments, other than simple anonymity, to reduce their effect on platform markets.

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Appendix

Throughout the paper we make use of the VADER Sentiment Analysis tool. This is a lexicon and rule-based sentiment analysis tool, which assigns sentiment scores to texts. Intuitively, each word in the lexicon is associated with a valence score, which ranges from -4 (very negative) to 4 (very positive) and was assigned by human raters. For example, the word 'horrible' has a valence score of -2.5, 'okay' a score of 0.9 and 'great' has a score of 3.1.

The VADER compound score for a text, which we use to analyze reviews in this paper, is calculated by summing the valence scores of the words in the text and then normalizing, so that they are between -1 and 1. This is the most straightforward unidimensional sentiment metric for a given review and constitutes a 'normalized, weighted composite score'. For more details, we refer the reader to the official documentation of VADER (https://www.github.com/cjhutto/vaderSentiment).

Figure 1 Percentage of renters leaving a review for owners with different numbers of previous trips.

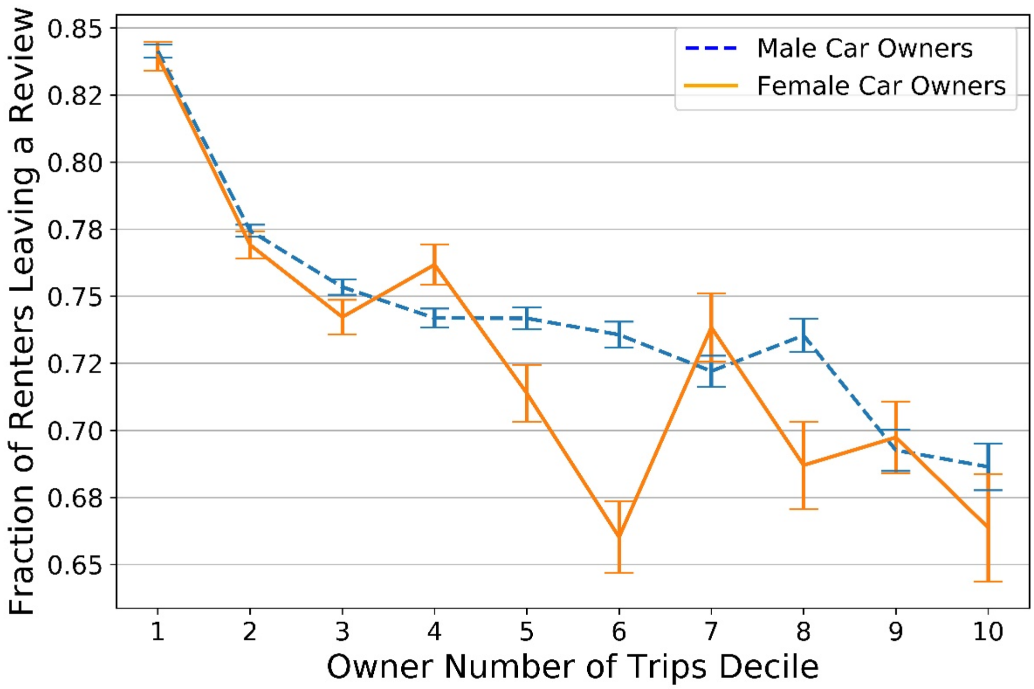

Figure 2 Fraction of female car renters and owners for different levels of owner experience, as measured by the number of previously completed transactions (trips) on the platform.

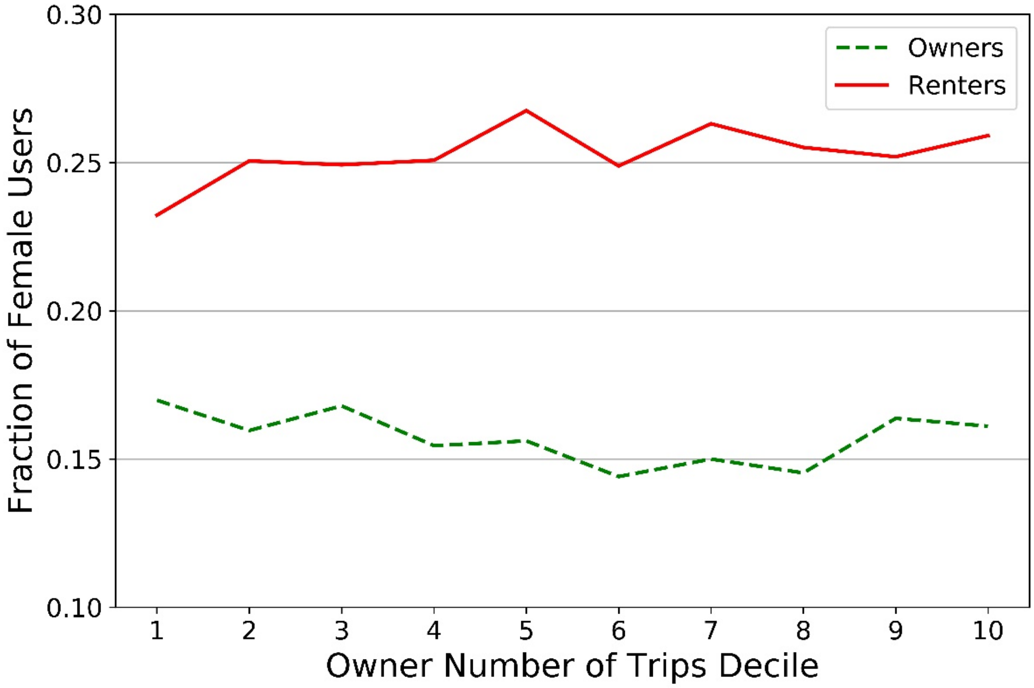

Figure 3 Frequency of the number of previous trips.

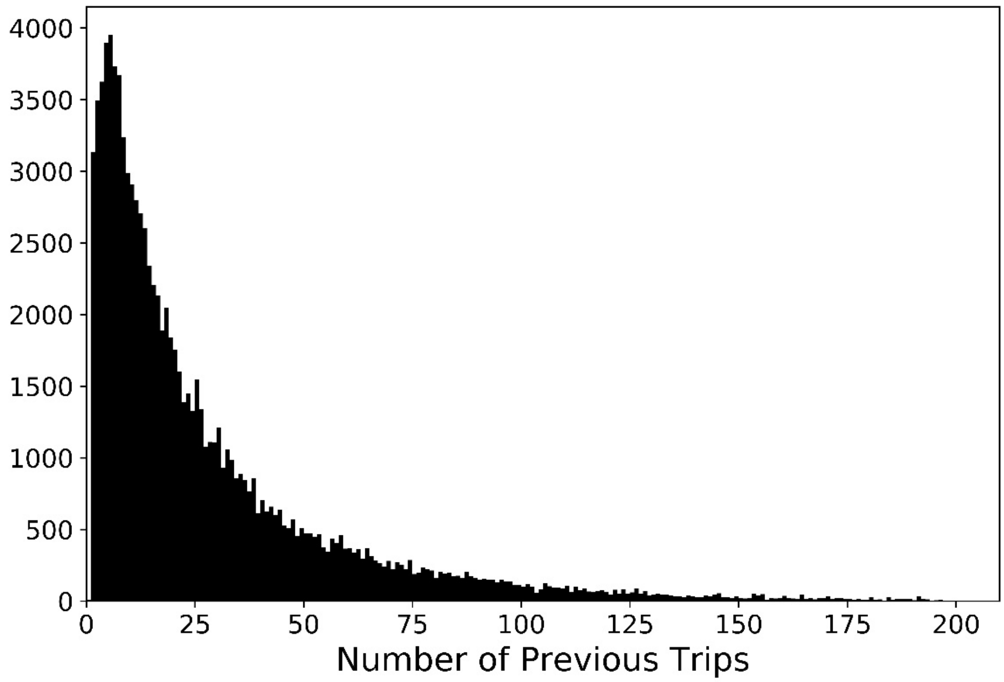

Figure 4   Frequency of asking prices.

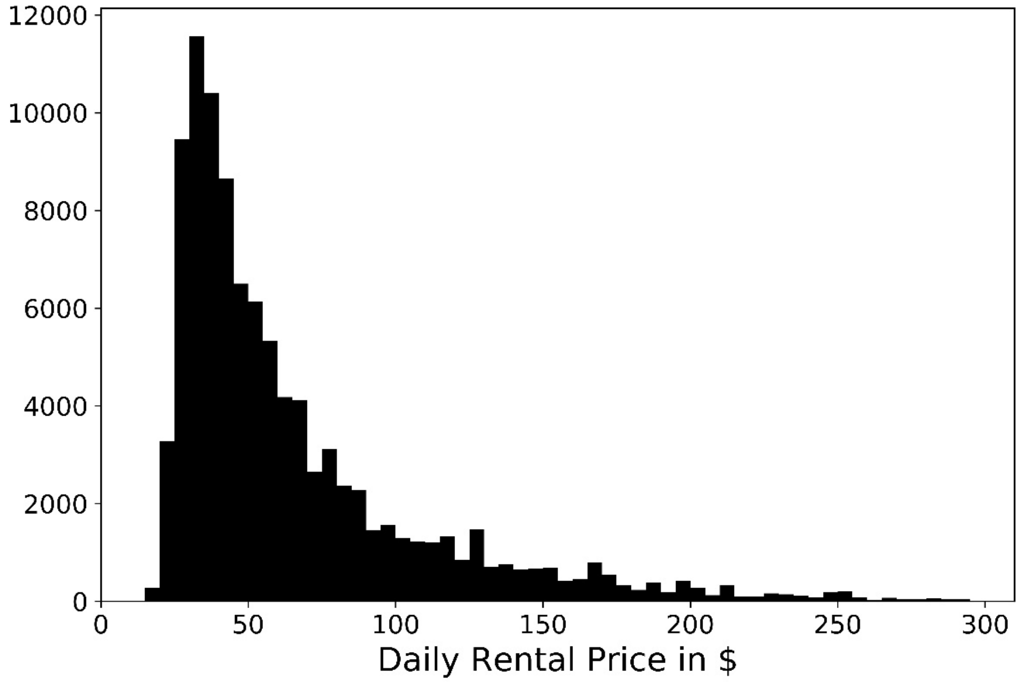

Table 1 Unique listing summary statistics

	Male		Female		
	(N = 17574)		(N = 3676)		
Variable	Mean	Median	Mean	Median	Δ Mean
	(SD)		(SD)		(t-stat)
Price	72.0	52	63.6	49	8.4***
	(60.5)		(48.2)		(7.86)
Trips	18.3	8	17.6	8	0.7
	(25.7)		(25.6)		(1.49)
Miles	890.8	1000	886.0	1000	4.8
	(276.9)		(237.5)		(0.96)
Year	2013.3	2014	2013.4	2014	-0.1*
	(3.9)		(3.8)		(-1.66)
Rating	4.8	5	4.8	5	0.0
	(0.4)		(0.4)		(1.58)

Notes: Price refers to the daily rental price in $.Trips is the number of times the car was previously rented on Turo. Miles refers to the distance renters may drive. Year is the model year of the vehicle. Rating is the average rating of the owner out of five stars.

Table 2 Car segments on *Turo*

Segment	Share in Sample	Female Owners in Segment	Female Renters in Segment	Median Rental Price
Electric	0.056	0.112	0.167	132
Large Sedan	0.045	0.128	0.194	91
Other	0.081	0.107	0.136	85
Medium SUV	0.105	0.172	0.205	75
Pickup Truck	0.032	0.097	0.190	53
All	1.000	0.168	0.249	50
Minivan	0.053	0.194	0.262	50
Small SUV	0.108	0.238	0.282	50
Medium Sedan	0.185	0.186	0.246	45
Hybrid	0.100	0.187	0.301	37
Small Sedan	0.235	0.157	0.307	33

Notes: The table shows the shares of car segments in the overall sample, shares of female owners and renters within the different segments and the median price of all listed vehicles in each segment.

Table 3 Review Summary Statistics

	Panel A: Number of Reviews	
Left to:	Males	Females
Left by:		
Males	49811 (84.4%)	9236 (15.6%)
Females	20450 (82.3%)	4387 (17.7%)
	Panel B: Length of Reviews	
Males	142.9	146.2
Females	157.0	161.4
	Panel C: Review Sentiment	
Males	0.74754	0.75092
Females	0.76	0.76303

Notes: Not all reviewers can be assigned to a gender. The length of the reviews refers to the number of letters. The sentiment was computed using the VADER sentiment analysis tool and ranges from -1 to 1.

Table 4 Gender differences in the review sentiment (Dependent variable: VADER Compound score)

	(1)	(2)	(3)
Female Owner	0.004	0.003	
	(0.005)	(0.005)	
Female reviewer		0.031***	
		(0.002)	
Female reviewer and female owner			0.025***
			(0.006)
Female reviewer and male owner			0.033***
			(0.003)
Male reviewer and male owner			0.001
			(0.003)
Model-Year FE	Yes	Yes	Yes
Zip Code FE	Yes	Yes	Yes
Observations	100,082	100,082	100,082
R^2	0.111	0.113	0.113

Notes: The outcome variable is the compound sentiment score computed using the VADER sentiment analysis tool and ranges from -1 to 1. Standard errors in parentheses. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 5 Gender differences in the review sentiment (Dependent variable: VADER Compound score)

	(1)	(2)
Female Owner	0.031***	
	(0.003)	
Female reviewer		0.022***
		(0.006)
Female reviewer and female owner		0.034***
		(0.004)
Female reviewer and male owner		0.001
		(0.003)
Owner FE	Yes	Yes
Observations	96,291	96,291
R^2	0.241	0.241

Notes: The outcome variable is the compound sentiment score computed using the VADER sentiment analysis tool and ranges from -1 to 1. Standard errors in parentheses. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 6 Determinants of prices (Dependent variable is log price)

	(1)	(2)	(3)	(4)	(5)
Miles	0.000	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Rating	0.020***	0.020***	0.020***	0.020***	0.020***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Trips	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Vader Compound	0.006**	0.006**	0.006**	0.002	
	(0.002)	(0.003)	(0.003)	(0.003)	
Female reviewer*VADER		-0.000			
		(0.002)			
Female owner*VADER			0.001		
			(0.009)		
Female reviewer and female owner*VADER				0.004	0.005
				(0.005)	(0.005)
Female reviewer and male owner*VADER				0.003	0.004
				(0.003)	(0.003)
Male reviewer and male owner*VADER				0.006	0.007**
				(0.004)	(0.003)
Model-Year FE	Yes	Yes	Yes	Yes	Yes
Zip Code FE	Yes	Yes	Yes	Yes	Yes
Observations	96039	96039	96039	96039	96039
R^2	0.889	0.889	0.889	0.889	0.889

Notes: Standard errors in parentheses. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 7 Difference-in-Difference regression results for the effect of reviews on prices (Dependent variable is log price)

	(1)	(2)	(3)
Miles	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)
Rating	0.004	0.004	0.004
	(0.004)	(0.004)	(0.004)
Female reviewer	-0.001	-0.001	-0.001
	(0.002)	(0.002)	(0.002)
vd1	-0.008**		
	(0.004)		
vd2		-0.002	
		(0.002)	
vd3			0.003*
			(0.002)
Owner FE	Yes	Yes	Yes
Nr of Reviews FE	Yes	Yes	Yes
Observations	28 987	28 987	28 987
R^2	0.981	0.981	0.981

Notes: vd1 is equal to one if the VADER sentiment compound variable is smaller than zero, indicating a negative review. vd2 is equal to one if the VADER sentiment compound variable is larger than its median value (0.8481) and vd3 is equal to one if it is larger than the 75th percentile (0.9222). Standard errors in parentheses. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 8 Difference-in-Difference regression (Dependent variable is log price)

	(1)	(2)	(3)
Miles	-0.000 (0.000)	-0.000 (0.000)	-0.000 (0.000)
Rating	0.004 (0.004)	0.004 (0.004)	0.004 (0.004)
vd1	-0.005 (0.007)		
vd1*revff	0.010 (0.019)		
vd1*revfm	-0.004 (0.010)		
vd1*revmm	-0.006 (0.009)		
vd2		-0.002 (0.003)	
vd2*revff		0.012 (0.008)	
vd2*revfm		-0.004 (0.004)	
vd2*revmm		0.000 (0.004)	
vd3			0.008*** (0.003)
vd3*revff			-0.019*** (0.007)
vd3*revfm			-0.009** (0.004)
vd3*revmm			-0.005 (0.003)
Owner FE	Yes	Yes	Yes
Nr of Reviews FE	Yes	Yes	Yes
Observations	28 987	28 987	28 987
R^2	0.981	0.981	0.981

Notes: *vd1* is equal to one if the VADER sentiment compound variable is smaller than zero, indicating a negative review. *vd2* is equal to one if the VADER sentiment compound variable is larger than its median value (0.8481) and *vd3* is equal to one if it is larger than the 75th percentile (0.9222). *rev mm* indicates the interaction between VADER compound, a dummy variable for male reviewer and male owner (analogous for rev mf and rev fm.Standard errors in parentheses. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 9 Propensity score matching results

	VADER <0	VADER > median	VADER > 75th percentile
		Panel A: Whole Sample	
Female reviewer	-0.097***	-0.160***	-0.158***
	(-3.73)	(-24.56)	(-17.33)
Observations	2,824	48,339	24,850
		Panel B: Only female owner	
Female reviewer		-0.105***	-0.089***
		(-7.44)	(-4.47)
Observations		8,050	4,165

Notes: In the first stage of the propensity score matching procedure a logit has been estimated. Female reviewer dummy variable was regressed on VADER compound level, miles, rating, trips, car year dummies, car segment dummies. The table displays Average Treatment Effects on (log) price. Z-statistics are in parentheses. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 10 Propensity score matching results

	(1)	(2)	(3)	(4)	(5)	(6)
VADER < 0	-0.057**			-0.082***		
	(0.028)			(0.028)		
VADER > p50		0.065***			0.047***	
		(0.005)			(0.007)	
VADER > p75			0.066***			0.055***
			(0.006)			(0.008)
Sample	Male reviewer	Male reviewer	Male reviewer	Female reviewer	Female reviewer	Female reviewer
Observations	56,659	56,659	56,659	23,833	23,833	23,833

Notes: In the first stage of the propensity score matching procedure a logit has been estimated. An indicator for the VADER sentiment negative, larger than the median and larger than the 75th percentile respectively is used as a dependent variable, regressed on VADER compound level, miles, rating, trips, car year dummies, car segment dummies. The table displays Average Treatment Effects on (log) price. Z-statistics are in parentheses. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

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