SHARING MEANS CARING? HOSTS' PRICE REACTIONS TO RATING VISIBILITY

Research in Progress

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Abstract

We empirically investigate how hosts on Airbnb, a popular peer-to-peer website for fee-based sharing of under-utilized space, adjust their prices once their offering gets a visible star rating for the first time. We use data for over 14,000 offerings from Airbnb which we collected for New York City. Our findings indicate that hosts whose offerings achieve star rating visibility significantly increase their prices by an average of 2.69 € more than hosts with comparable offerings who do not experience this rating visibility during the time of observation. Out of all offerings who achieve rating visibility, we identify the upper quartile of hosts to be the main driver of this price increase, whereas the first 75% percent show only a marginal price reaction. These results can serve as a first step towards understanding the motivation of people to provide assets to the sharing economy.

Keywords: Sharing Economy, Online Reviews, Price Reactions, Diff-in-Diff Matching

1 Introduction

"The sharing economy is a real trend. I don't think this is some small blip."

"People really are looking at this for economic, environmental and lifestyle reasons."

–Joe Kraus, general partner at Google Ventures (Geron, 2013)

In recent years, the economic importance of the sharing economy has grown exponentially. Peer-to-peer sharing markets, that is, markets where people rent out their under-utilized inventory through fee-based sharing, are emerging in various forms for a variety of goods and services. Airbnb is one of the best-known examples of this phenomenon. Currently Airbnb, for example, has over 800,000 listings world-wide, having connected over 25,000,000 guests with hosts since its foundation in 2008. In New York City alone, the financial impact of Airbnb hosts and guests is estimated at $623 Million in the year 2013 alone with potential tax revenue of about $21 Million (Airbnbnyc, 2014). Not surprisingly, there is a growing interest in research on sharing markets. However, since the rise of the sharing economy has been proclaimed (Botsman and Rogers, 2010), the existing body of literature on this topic has remained quite limited in extent. Selected topics have been investigated by scholars, such as racial price discrimination of Airbnb hosts (Edelman and Luca, 2014) and the consequences of Airbnb market penetration on the hotel industry (Zervas et al., 2014).

An open question concerns the motivation of participants on the supply side of the sharing economy. Concerning a working definition of the sharing economy, sharing can be described as "the act and process of distributing what is ours to others for their use and/or the act and process of receiving or taking something from others for our use" (Belk 2007, p.126), in contrast to pure market transaction.

Furthermore, sharing is non-reciprocal and pro-social (Benkler, 2004). However, "access can differ from pro-social sharing in that access is not necessarily altruistic or pro-social as sharing is, but can be underlined by economic exchange and reciprocity" (Bardhi and Eckhardt 2012, p. 882). We include the term "access" here, as a definition of the European Commission highlights that the sharing economy is about "companies that deploy accessibility based business models for peer-to-peer markets and its user communities" (European Commission 2013, p. 3). Therefore, we assume two competing explanations of why people supply their under-utilized inventory to sharing markets. On the one hand, idealism and altruism may play an important role for early participants of the sharing economy. In particular, O'Reilly argues that "The idea of renting from another person rather than a faceless company will survive, even if the early idealism of the sharing economy does not" (The Economist, 2013). Consequently, idealism (because you like the ideal of sharing) or altruism (because you enjoy the encounter with foreigners for instance) could play a major part in the decision of whether or not to post an offering on sharing markets. On the other hand, probably more economic factors could also play a dominant role in the decision to take part in the sharing economy. For example, participants on Airbnb may just share their apartments because they cannot afford to pay the rent without sharing or because they want to earn some extra money.

The hosts' reaction to the public revelation of quality information in the form of online reviews on the quality of the offered under-utilized inventory may be one weak indication for either of these motivations. Such online reviews which capture the consumers' experiences and reflect the quality of the good or service are particularly important in sharing markets since rating systems endow hosts with commercial credibility (Geron, 2013). In an economy, where the currency is trust (Botsman, 2012), reputational capital is an important asset. Consequently, some studies suggest that hosts can divert their accumulated reputational capital into the rental price (Ikkala and Lampinen, 2014; 2015). In line with the above arguments, Nate Blecharczyk, a co-founder of Airbnb, recommends hosts who list their space for the first time to price "less aggressively" and after reviews appear, hosts will be able to raise their prices (The Economist, 2013). Thus, one could expect that if economic considerations are the main driver for taking part on the supply side of the sharing economy, the availability of positive consumer reviews should have a significant effect on prices in the sharing economy. In contrast, if only idealism and altruism drive the participation in the sharing economy, the availability of such positive information should not affect prices but rather increase the utility of suppliers in non-monetary ways. Therefore, we investigate the effect of the availability of quality information on prices to do a first exploration into the motives of participants on the supply side of the sharing economy. In particular, we answer the following research question:

How do hosts on Airbnb adjust their prices when their offerings receive a visible star rating for the first time?

To address our research question, we employ a dataset collected in September and October 2014 for New York City for over 14,000 offerings with detailed information including prices, ratings and location. Overall, we analyse the price development of hosts whose offerings get a visible star rating. To get a visible star rating on Airbnb, three reviews are necessary. Our identification method hinges on the fact, that on Airbnb, three reviews are necessary for the star rating to be visible. In other words, we observe a phenomenon comparable to a natural experiment, as star ratings of offerings become visible by reaching the threshold of three reviews. Below the threshold of three reviews the star rating of a particular offering is not visible. We observe that hosts whose offerings achieve rating visibility increase their prices significantly more than other hosts. These findings hold if we compare the prior group to offerings who did not yet achieve rating visibility and also when we compare the prior group to offerings who already achieved rating visibility in the past. The effect is mostly driven by the upper quartile of offerings, whereas the first three quartiles show only very slight differences.

With this research in progress, we make new contributions to research in two ways: (1) We contribute to an enhanced understanding of the motivation of people supplying assets to the sharing economy, by showing that some people are determined to extract more money from the market, if their reputation grows. (2) We provide first empirical evidence for the importance of online reviews in sharing markets, by investigating the causal effect of star rating appearance on prices.

2 Data

We used a web crawler to collect a wide variety of information for 14,871 rooms (further on called "offerings") listed on Airbnb for New York City for two observation times from September 15th 2014 to October 6th 2014 as shown in Table 2 in the appendix. In particular, we collected data for the price of the offering per night (price), for total number of reviews of the offering (num_rev), for the district in which the offering is located (dummy variables dum_adr1- dum_adr167), for star ratings on a scale from 1 to 5 in one overall (overall_stars) and 5 subcategories on communication (commu_stars), cleanliness (clean_stars), location (Loc_stars), check-in (Check_in_stars) and price-performance (Price_perf_stars). Moreover we collected the room type (room_type, either private room, common room or whole apartment), the number of people that can be accommodated in the room (num_peop), the number of bedrooms that are contained in the offer (num_room) and information on whether the host has a verified identification (dummy variable verified_ID). We computed the price difference (diff_price), the difference in the number of reviews (diff_rev) and the difference of star rating in the overall category (diff_overall).

Finally, we computed a dummy variable that indicates whether an offering gets star-rating-visibility treatment (star_ind) if an offering gets a treatment between t_0 and t_1. Here, treatment means that an offering with zero, one or two reviews at point t_0 has 3 or more reviews at t_1. Thereby the host achieves visibility of his or her star rating for the respective offering which is not visible under the threshold of three reviews. It should be noted that, as depicted in the summary statistics in table 2 in the appendix, there is a large share of about 50% of the offerings without visible star ratings. Airbnb (2015) states that a visible star rating, among other factors, plays an important role for the offering being displayed in the search results. Commonalities among offerings with no visible star rating as this search result visibility problem, as well as offerings being niche content, hosts being selective with their guests (hosts can decline booking requests) or subpar quality, might lead to this large share of offerings without star rating.

After manually checking the data, we recognized that some hosts changed their pricing plan from "price per night" to "price per month", leading to an over proportional increase in the price which does not represent the variable price appropriately anymore. To control for these outliers we limited our data to a relative price changes of two times the price in t_0. We also control for changes in room types which could be a reason for a price increase. A minor fraction of negative price differences have been identified in the data set, but we will restrict our investigation to positive price changes in this study.

3 Empirical Strategy

For each offering that gets a treatment, we are looking for an equivalent offering for the control group. The control group serves as a kind of benchmark for the price development of the treatment group. Under ideal conditions, the control group has the same quality and is generally as similar as possible to the treatment group. Therefore, if both groups are as equal as possible but only differ in the fact that one group receives a visible star rating and the control group does not, then any price differences would be attributable to the treatment. In the following we formalize this comparison between the treatment and control group.

In line with Heckman et al. (1997), we are seeking to identify the causal treatment effect of star rating visibility on prices by employing a difference in difference strategy with matching in a setting of two points in time. In order to investigate the difference between the average price difference of the treated and the average price difference of the counterfactual, we match the treatment group on a control group that represents the counterfactual of the outcome of the treatment group.

Let $\overline{Y}_1^T$ denote the average price of the offering in the treatment group after the treatment in t_1 and the $\overline{Y}_1^C$ vice versa for the control group, then the difference in difference effect is:

$$\tau_{DiD} = \left(\overline{Y}_1^T - \overline{Y}_0^T\right) - (\overline{Y}_1^C - \overline{Y}_0^C) \quad (1)$$

Consequently, as offerings can only be in one of the two potential states, which is receiving the treatment or not receiving the treatment, the control group represents the outcome (i.e. the price difference) had the treatment group not received the treatment. Consequently, τ_{DiD} only identifies the causal average treatment effect on the treated (ATT), if both would have experienced the same development over time, had the treated not received the treatment. Let the group of the treated be denoted as $D = 1$ and the non-treated as $D = 0$, then

$$E[Y_1^0|D = 1] - E[Y_0^0|D = 1] = E[Y_1^0|D = 0] - E[Y_0^0|D = 0] \quad (2)$$

has to hold in order to identify the ATT. Since the price development of the offerings in the treatment group, had they not gotten the treatment is not observable, the causal inference relies on the construction of a valid group of counterfactuals, the control group, to face this missing data problem. Combining equation (1) and (2), we can write the ATT as follows:

$$ATT = E[Y_1^1|D = 1] - E[Y_0^0|D = 1] - E[Y_1^0|D = 1] - E[Y_0^0|D = 1] \quad (3)$$

The unobservable part of equation (3) $E[Y_1^0|D = 1] - E[Y_0^0|D = 1]$ is therefore identified by the control group which does not get a treatment and the rest of the right hand side of the equation, which represents the treatment group, is observable.

Let the treatment indicator D in the baseline case be $star\_ind \in [0,1]$, whereas the control group ($star\_ind = 0$) consists of offerings that are as similar as possible to the offerings of the treatment group ($star\_ind = 1$) regarding quality. The identification process of the control group is thus crucial to the causality argumentation and will be explained in the following.

3.1 Identification method

This research in progress adopts the method of propensity score matching according to Rosenbaum and Rubin (1983) to pair offerings of the treatment group with offerings as similar as possible but which did not get a treatment. Then the propensity score indicates the probability of receiving a treatment conditional on a vector X of observables, to reduce the problem of dimensionality. There is a wide variety of observables available to match on.

Vector X contains the room type (which has to be the same in both periods), number of people in $t_{0,}$ verified identification in t_0 and overall star rating and the star ratings of the five subcategories in $t_{1.}$ We explicitly match on star ratings in t_1 and not in t_0 because we would like to match offerings with equal quality. That means if a room from the treatment group has a visible star rating after the treatment and had none prior to the treatment, the corresponding room from the control group has a visible rating as well, which technically means it got the treatment even before t_0. We do that because if we matched on pre-treatment star rating, this meant that the quality of the offering in the control group could be too low. In this way, a room that remains without visible star rating might indicate a subpar quality and should be left out of the control group because it does not represent a credible counterfactual of the offering in the treatment group.

Furthermore, we choose a 1:1 nearest neighbor matching algorithm without replacement and set the caliper to 0.001 to identify the rooms for the control group.[1] In line with Caliendo and Kopeinig (2008), we allow for random ordering of the observations, because the quality of nearest neighbor matches is prone to the order in which observations get matched. In general, the high number of observations relative to the number of rooms in the treatment group favors a high matching quality as there is a wide variety in propensity scores and lesser likelihood that two rooms in the treatment group would get matched to the same room in the control group. Throughout this research in progress we comply with the common support condition and confine our matching to those rooms which lie within the support of the propensity score of the rooms.

There are two assumptions crucial to the identification of the causal average treatment effect on the treated. The first is the stable unit treatment value assumption (SUTVA) and the second is the common trend assumption (CA). The first implying, that pre- and post-treatment outcome (prices) of the treated as well as pre- and post-treatment outcome of the untreated can be observed (Caliendo and Kopeinig, 2008). Furthermore, unrepresented versions of the treatment have to be ruled out as well as inference between treatment units, where the post-treatment price of one room depends on the assignment into the treatment group of another room (Rubin, 1986). Moreover, the common trend assumption implies that both groups had experienced the same time trends, had they not received the treatment. The formal representation of the common trend assumption is represented by equation (2). In this case, there would be no significant difference between the price differences of both groups had there been no treatment (Caliendo and Kopeinig, 2008). According to the underlying data and the booking mechanism, we find no indication for a violation on the SUTVA.

Supporting arguments for the CA to hold optimally are multi-period observations as well as an array of non-treated control group. A longer observation time could be a substantial indication of common time trends of both groups. If the treatment has an effect on the treated, this would only be visible in the treatment period and in no other period. Analogue to that, the effect of the treatment would only be visible in the treatment group and in no other control group of non-treated. Here, we cannot provide a time series beyond our observations to confirm the first argument, but we can well control for a range of control groups.

3.2 Balancing test of the propensity score

The propensity score matching method will provide a reliable method to identify the ATT of the star-rating-visibility, conditional on the propensity score, if the potential outcomes Y^1 and $Y^0$are independent of the incidence of rating visibility. Under the assumption of independence conditional on observables, the observables in vector X on room quality should be balanced between rooms which get a treatment and the rooms which do not get a treatment. Therefore it is necessary to clarify that this balancing condition is satisfied by the data (Dehejia and Wahba, 2002).

Table 3 illustrates the results of the balancing test of the relevant variables on 1:1 nearest neighbor matching for the baseline case. After matching, there is no significant bias between the treatment and control group and a substantial bias reduction is achieved by the matching algorithm. As table 3 depicts, there are at least four biased variables before matching. Hence we discern that our identification strategy yields 1:1 matchings for rooms of the treatment and control group of the same quality conditional on the observables in X.

[1]To check for robustness of our identification, also used kernel matching, different calipers and specifications with replacement. Our results proved robust to these variations.

4 Results

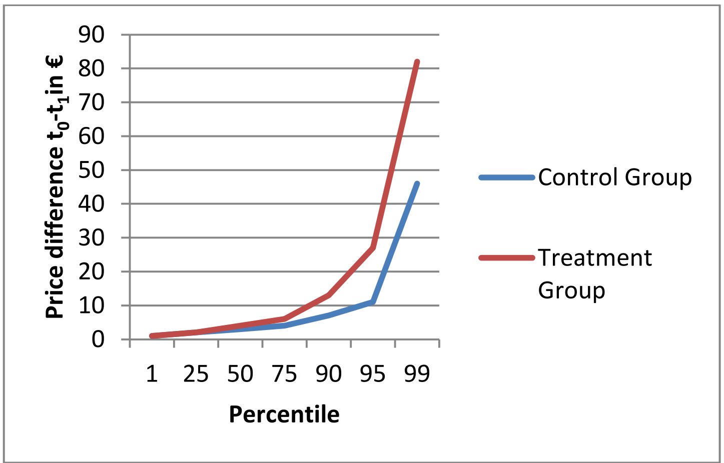
Having established comparability of the treatment and control group conditional on the propensity score estimation, we will discuss the results of the baseline case reported in table 1 which displays the ATT which can be interpreted as the mean differences of prices of the treatment group minus the mean differences of the control group in t_0 and t_1 in Euro currency.

There are a total of 470 rooms that get a treatment between t_0 and t_1. For the 470 locations in the treatment group, we are able to identify 470 matching partners that go into the control group.

Treatment indicator	N	ATT(1)
Star_ind	470	2.69** (0.78)
Note: Standard Errors in Parentheses, * p<0.05, ** p<0.01		

Table 1. Baseline Results

The control group raises the price by 4.57 € on average whereas the treatment group raises the price by an average of 7.26 €. This ATT is statistically highly significant at the 99% level (p=0.006) and with 2.69 € moderate in magnitude. Hence, the owner of an offering that gets a treatment tends to raise the price by 2.69 € more on average compared to owners whose offering does not get a treatment. Similar magnitude in differences are found when taking the median price difference of both groups into consideration, with a median price difference of 4 € for the treatment group and 3 € for the control group. Larger price differences become apparent comparing the upper quartile of both groups, as depicted in figure 1. The price differences for the 75th, 90th, 95th and 99th percentile for the control group are 4, 7, 11 and 46 € compared to respective values for the treatment group of 6, 13, 27 and 82 €.



Note: Standard Deviations: Treatment Group 14.98, Control Group 7.98

Figure 1. Distribution of Price Differences

Our empirical results show, that Airbnb hosts who get the treatment of star-rating-visibility increase their prices significantly more than hosts of similar rooms who do not get the treatment. The average difference is not very large, but taking into consideration the distribution of price differences among both groups shows, that there is a large group of about 75% who do not change their prices after the treatment, but the ATT might be driven by a share of the upper quartile for which the treatment group surpasses the control group substantially.

Further investigation of the composition of the treatment group with respect to the time of when the hosts first signed up on Airbnb reveals that around 42% of the hosts in the treatment are relatively new on Airbnb (they signed up within the timespan between the first and the third quarter of 2014) as opposed to 58% of hosts in the treatment group who signed up during the time from the first quarter of 2009 and the fourth quarter of 2013 (as shown in figure 2). Additionally, among the group of hosts who changed their prices above the average of the treatment group (above 7.26 €), there are more than twice as many hosts who signed up in the third quarter of 2014 than in any other quarter recorded. This might hint to the fact that a share of hosts are pricing in the spirit of a discount to achieve star rating, underlining the economic aspect of motivation to participate in the sharing economy.

5 Robustness checks

In order to test the robustness of our results, we conduct a sensitivity analysis using the Rosenbaum Bounds approach (Rosenbaum, 2002; DiPrete and Gangl, 2004) for potentially unobserved confounding factors. Our test statistic reports values for Γ, which represents the strength of the hidden bias influencing unobserved selection into the treatment. A Γ of 1.2 for example assumes that an unobserved variable causes the odds ratio of treatment assignment to differ between the treatment group and control group by 20%. We report p-values from a Wilcoxon signed rank test, which represent the hypothetical significance level, that is, the bounds on significance that shows which strength of the unobserved confounder is necessary in order to question our conclusion of the treatment effect. We also calculate hidden bias equivalents that illustrate the magnitude an unobserved variable must have in order to make us revise our findings. Here, the hidden bias is expressed at given levels of Γ in terms of the equivalent effect of observables for which we know the impact on assignment to treatment from our propensity score balancing. We use number of rooms and number of people, because the star rating scale is bounded at 5 stars and hence does not serve as a good equivalent, as the equivalent is computed as the product of the covariates empirical mean times $\ln(\Gamma)$ (the log odds coefficient) (DiPrete and Gangl, 2004). Table 4 in the appendix depicts the results of our sensitivity analysis. Our results show robustness up to the strength of an unobserved variable that would cause the odds ratio of treatment assignment to endogenously differ between treatment and control group by 1.5. This critical level of Γ=1.5 would be attained at a difference of 1.2 additional people that could be accommodated on average in an offering from the treatment group as opposed to a control offering or a t a difference of 0.47 more rooms for offerings from the treatment group compared to offerings from the control group.

6 Conclusion

With regard to the growing economic importance the sharing economy and the limited body of literature that exists as of today, we consider this field worthwhile-investigating to understand the forces governing this phenomenon. With this work we contribute towards an understanding of the motivation of the supply side of the sharing economy and on the interplay of online reviews and prices in this environment. To the best of our knowledge, this research in progress is the first to investigate this interplay in a multi-period framework. We find a robust, significantly positive impact of rating visibility on prices, which is in line with the assumptions formulated in previous research (Ikkala and Lampinen, 2014; 2015). Overall, rating visibility causes hosts to increase their prices by an average of 2.69 €. Although it is little surprising to see most offerings' prices to increase during the time period of study, considering steadily increasing rental price indices for US American metropolitan areas (US Bureau of Labor Statistics, 2015), we discern that there is a tendency to convert reputational capital into rental price. We identify the upper quartile of hosts to be key drivers of this effect, whereas a share of the first 75% shows only a slight reaction to rating visibility.

Consequently, we conclude that the revelation of such positive information has an impact on a small share of suppliers in the sharing economy, whereas the other larger part does not show a substantial reaction to this information signal. By disclosing this price reaction to rating visibility, we take a first step into exploring different motivations to supply to sharing markets, which could be idealism and altruism on the one hand and economic considerations on the other hand.

The question of whether people engage in supplying inventory to peer-to-peer sharing markets ultimately refers to their motivation in doing so. Therefore, understanding their motivation will contribute to understanding the further development of these markets. The influx of new participants will finally determine whether the sharing economy is “a real trend” or just “a small blip”. Due to that, this research in progress carries meaningful implications for practitioners and represents a fundament for future research.

Future research could include a longer span of time in order to investigate the importance of price changes attributed to rating visibility within a larger time frame. In doing so, the variability of prices would become a focal point of research. This could be especially interesting when comparing the variability of prices in the sharing economy to prices in the conventional economy, for example during times of high demand. This would have substantial importance for the hotel industry. Another avenue for future research and a promising refinement of our underlying research question would be to investigate how much visible star ratings can de facto reduce consumer uncertainty, taking account of the exclusively high average rating of 4.6 of all offerings (Zervas et al., 2015). Consequently, if star ratings could not discriminate properly between high and low quality hosts anymore, prices could gain more importance as signals for premium quality.

Our results also have considerable implications for sharing platform providers. Platform providers could leverage knowledge of the motivation of suppliers to attract more of them to their platform. If competing motivations exist, providers should take account of this fact. Moreover, if rating visibility has an effect on the prices of offerings which in turn has an influence on the earning of the providers (which is a share of the price of the offering), practitioners could implement more attainable quality signals into their platform design. If quality signals reflect reputation from the demand side, more reputational capital could be diverted into real money.

Appendix

Time	Variable	N	Mean	SD	Min.	Max.
T=0	overall_stars	6307	4.676867	.3572801	2	5
	commu_stars	6307	4.855399	.2775064	2	5
	clean_stars	6307	4.549707	.472888	1	5
	Loc_stars	6307	4.656414	.4161252	2	5
	Check_in_stars	6307	4.813065	.3134584	2	5
	Price_perf_stars	6307	4.589662	.3581868	2	5
	price	12096	154.1461	210.6663	12	5,599
	num_rev	12096	10.05365	18.51057	0	201
	num_peop	12096	3.155506	1.7204	2	16
	num_rooms	12096	1.167824	.7121062	0	10
	verified_ID	12096	.530506	.4990891	0	1
	dum_room2	12096	.6339286	.4817492	0	1
	dum_room3	12096	.0205026	.1417178	0	1
	dum_room4	12096	.3455688	.475573	0	1
T=1	overall_stars	6519	4.669198	.3600303	2.500	5
	commu_stars	6519	4.853198	.2779375	2.500	5
	clean_stars	6519	4.54809	.4704645	1	5
	Loc_stars	6519	4.651097	.4174158	2	5
	Check_in_stars	6519	4.810094	.3150359	2	5
	Price_perf_stars	6519	4.582911	.3592969	2	5
	Price	12096	162.9366	225.3076	16	5,762
	num_rev	12096	10.39418	18.7918	0	205
	num_peop	12096	3.178819	1.742502	2	16
	num_rooms	12096	1.178241	.7172194	0	10
	verified_ID	12096	.6015212	.4896052	0	1
	dum_room2	12096	.6339286	.4817492	0	1
	dum_room3	12096	.0205026	.1417178	0	1
	dum_room4	12096	.3455688	.475573	0	1

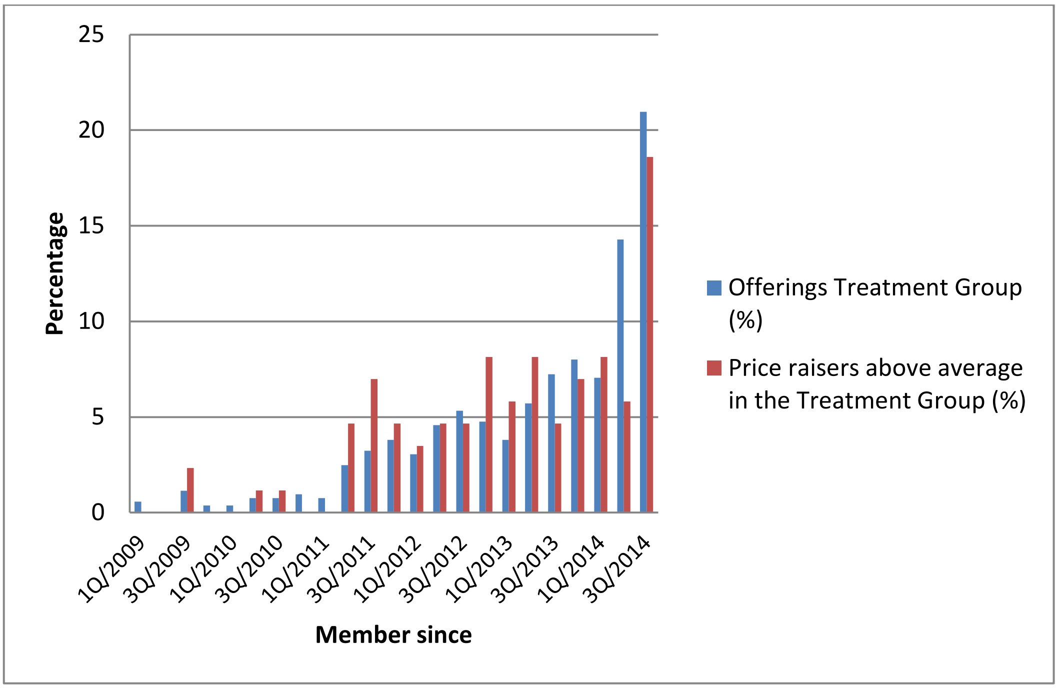
Table 2. Summary statistics

T_0-t_1	Mean (matched)		Before matching	Matched	Matched	
Variable	Treatment	Control	%bias	% bias	t-test	p-value
Overall_stars_t1	4.6074	4.5936	-14.1	3.4	0.49	0.621
Commu_stars_t1	4.8277	4.8138	-7.1	4.6	0.66	0.509
Clean_stars_t1	4.5011	4.4904	-5.7	2.0	0.29	0.774
Loc_stars_t1	4.6064	4.6096	-6.4	-0.7	-0.11	0.915
Check_in_stars_t1	4.766	4.7681	-11.9	-0.6	-0.09	0.932
Price_perf_stars_t1	4.5394	4.547	-9.8	-1.6	-0.22	0.823
Verified_ID_t0	0.63191	0.63617	9.4	-0.9	-0.14	0.892
Num_peop_t0	3.0979	3.0979	-5.9	0.0	0.00	100.0
Num_rooms_t0	1.0745	1.1234	-15.0	-7.9	-1.24	0.217
Room dummies	✓	✓	✓	✓	✓	✓
Address dummies	✓	✓	✓	✓	✓	✓

Table 3: Propensity score balancing in t_0-$t_1$after matching

		Hidden Bias Equivalents	
Γ	p-critical	Num_peop_t0	Num_rooms_t0
1.00	<.0.0001	0	0
1.1	0.00041	0.30075	0.11055
1.2	0.000834	0.57531	0.21149
1.3	0.007848	0.82789	0.30434
1.4	0.040453	1.06174	0.39030
1.5	**0.13062**	**1.27944**	**0.47033**
1.6	0.293612	1.48309	0.54520
1.7	0.500798	1.67440	0.61552
Note: p-critical is $p^+$for the ATT; Hidden Bias Equivalents are computed at the empirical mean of covariates			

Table 4: Rosenbaum Bounds for the treatment effect



Note: Offerings in the Treatment Group N= 470; Price raisers above average in the Treatment Group N= 86; Price raisers above average defined as price increase above 7.26 €.

Figure 2. Time of joining Airbnb

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