Cancellation Policy as a Signal of Trust and Quality in the Sharing Economy: The Case of Airbnb †

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Abstract

We study the effect of cancellation policy settings on listing demand in the context of Airbnb, a popular home-sharing platform. We employ a difference in differences strategy to show that, contrary to previous findings in the traditional accommodation industry, listings with a strict cancellation policy have, on average, four percentage points higher demand than listings with a more lenient policy. We complement these findings with a survey of real Airbnb users aimed at understanding the mechanisms behind our results. We find that Airbnb guests perceive listings with a strict cancellation policy to be of higher quality and their host to be more trustworthy. These results suggest that the cancellation policy of a listing can act as a signal of quality and, in turn, can increase the listing demand. Overall, our findings suggest that sharing economy platforms like Airbnb do not only offer a new business model and value proposition, but they also have the potential to affect consumer behavior and their decision-making process in ways that are different from more traditional settings.

1 Introduction

In the last decade, platforms that allow peer-to-peer based sharing of goods and services, have been gaining tremendous popularity. These platforms, also known as the sharing economy, allow users to share and make use of underutilized assets in a variety of settings. Popular examples include Airbnb, a platform for short-term rental accommodation, and Uber, a rideshare service. These platforms have attracted millions of users, some of them offering and some of them using such assets (Sundararajan 2013, 2016). For example, in 2018, the number of Airbnb guest check-ins across the world has surpassed the 300 million mark.[1]

When users decide to participate in the sharing economy as sellers, they are often required to make strategic business-like decisions to increase business transactions with potential customers. These decisions vary from platform to platform. For example, on Uber, drivers can decide their exact work hours to maximize their profits. On Airbnb, hosts can post high-quality photos to increase the demand for their listing (Zhang et al. 2016), include a detailed description of their properties to reduce potential information asymmetries, or define the general terms and conditions of any future transaction including house rules and the conditions of the deal itself. Among such conditions, hosts are required to set up their cancellation policy.

Airbnb allows hosts to choose among standardized cancellation policies that they enforce to protect both guests and hosts alike. Such policies are divided into three broad categories: flexible, moderate, and strict. Both flexible and moderate cancellation policies are relatively similar and allow the guest to obtain a full refund if the cancellation is effectuated within a certain time from the check-in date (48 hours for the flexible and 5 days for the moderate cancellation policy). Instead, the strict policy guarantees a 50% refund in the best scenario.[2]

Choosing one cancellation policy instead of another can have important effects on the listing demand and, therefore, on the host's revenue. Indeed, past research that looks at

[1]See: `https://press.atairbnb.com/fast-facts/`.

[2]For more information about Airbnb cancellation policies, we refer the reader to `https://www.airbnb.com/home/cancellation_policies#flexible`.

more traditional industries supports an association between lenient policies and increases in demand. For example, in the context of the hotel industry, researchers have found that offering lenient cancellation policies helps stimulate consumers' purchase intentions (Chen et al. 2011). Xie and Gerstner (2007) show that lenient refund policies induce positive attitudes toward the product and signal product quality to consumers that, in turn, can increase profit margins. Instead, no-refund policies have been found to be too restrictive and to negatively affect consumers' patronage (Smith et al. 2015).

Do these findings hold when it comes to sharing economy platforms such as Airbnb? Common sense would suggest that all else being equal, Airbnb listings that offer more lenient cancellation policies should experience higher demand. In principle, there are no reasons to expect that, for example, hotel customers would behave differently than Airbnb users. In both cases, the risk that consumers face is similar, i.e., lose the reservation money in case of an unexpected event. Moreover, we expect consumers to be averse to commitment in similar ways (Cialdini 1987).

However, sharing economy websites such as Airbnb blur the boundaries between social and transactional relationships (Yang et al. 2016). In making a purchase decision, guests on Airbnb take into consideration the identity and the perceived trustworthiness of the host (Ma et al. 2017). Moreover, differently from hotels that can rely on standardized class categories or branding, transaction quality on Airbnb can vary considerably from host to host, and from one occasion to the other. Therefore, consumption decisions on Airbnb must rely on signals or cues of sellers and buyers trustworthiness and quality. Among such signals, user-generated reviews and ratings are an important part of the consumer decision-making process (Fradkin et al. 2017, Proserpio et al. 2018). Moreover, past research identified other cues such as photos or seller status (Zhang et al. 2016, Teubner et al. 2014).

In this paper, we use a monthly panel data of over 230,000 listings and 150,000 hosts covering all the US to study the effect of setting a strict cancellation policy (as opposed to flexible or moderate) on Airbnb listings' demand. To estimate the effect of cancellation policy settings on demand, we employ a difference in differences (DD) strategy that exploits the fact that, in our dataset, about 13,000 listings changed their cancellation policy during our observation period. Our main results show that, contrary to expectations and past research findings, listings with a strict policy exhibit occupancy rates that are, on average, four percentage points higher than listings offering more lenient policies.

To reinforce the causal interpretation of our results, we perform several robustness checks. First, we provide evidence that the DD main identification assumption, i.e, the parallel trend assumption, holds in our settings. Second, we show that our results are robust to the inclusion of a wide set of controls (host and listing characteristics, competition, and zipcode-specific time trends) that are potentially correlated with demand. Third, we show that our results are robust to matching methods such as Coarsened Exact Matching (Iacus et al. 2012). Fourth, we show that our results hold when we control for host behavior and willingness to rent, either directly or indirectly.

Finally, we exploit the richness of our dataset to show that similar results to those obtained with our main DD specification can be obtained using alternative strategies that rely on different identification assumptions. Specifically, we exploit the fact that about 30,000 hosts in our dataset are multilisting-host, i.e, hosts that list more that one property on the Airbnb platform. We focus on this subset of hosts and implement two new identification strategies. The first is an instrumental variable approach that uses the propensity of the host to use a strict policy for all other listings as instrument for whether the focal listing uses a strict policy. The second approach is what we define as a multilisting-host DD. Using this strategy, the effect of changes in cancellation policy is identified by variation in the difference in occupancy rate among listings belonging to the *same* host. In doing so, we are able to effectively control for host unobservable characteristics that can affect listings demand. The results obtained with these two alternative strategies confirm our main results and provide further evidence that the effect we estimate is not driven by spurious correlations.

We next investigate the mechanisms behind our findings. To do so, we use an online survey we conducted on real Airbnb guests. We find that Airbnb guests perceive listings with a strict cancellation policy to be of higher quality, and their host to be more trustworthy and committed to their guests. First, these results provide face validity to our analysis of Airbnb data: listings with a strict cancellation policy experience higher demand because they are perceived to be better listings. Second, the survey results suggest that the cancellation policy of a listing can act as a signal of quality and, in turn, can increase the listing demand. As discussed above, quality uncertainty in sharing economy platforms is much higher than in traditional settings, and consumers try to identify cues (besides reviews and ratings) that can help them make better decisions. The listings cancellation policy seems to be one of these cues.

Overall, our findings suggest that sharing economy platforms like Airbnb do not only offer a new business model and value proposition but also have the potential to affect consumer behavior and their decision-making process in ways that are different from more traditional settings.

2 Related literature

Our study links to multiple literature streams. One stream is the growing body of research on the sharing economy, especially those studying factors that impact sellers' success. Another is the literature on signaling of quality and trustworthiness in online platforms. Finally, our work relates to the literature on cancellation policy strategies in the context of the tourism and accommodation industry.

This work relates to the stream of research studying the success of sellers in the sharing economy. Most of the research in this area focuses on the impact of reputation (ratings and reviews) on prices and demand. Gutt and Herrmann (2015) analyze the price differences before and after a host's average rating is publicly displayed for the first time and show that, on average, hosts increase their prices by 2.69 Euros. Proserpio et al. (2018) exploit the same exogenous change in ratings visibility to confirm these findings. Similarly, Ikkala and Lampinen (2014), after interviewing Airbnb hosts, find that hosts actively exploit their reputational capital either by increasing price or by accepting guest requests more selectively. However, Ert et al. (2016) seem to contradict these findings. The authors show that, in experimental settings, ratings do not affect Airbnb listings demand. Moreover, a study by Lee et al. (2015) show that the number of reviews an Airbnb host receives is, in fact, a better predictor of room sales than ratings. This might be due to the fact that ratings on Airbnb are extremely positive, and thus carry little information (Zervas et al. 2015). Finally, Ke (2017) conducts a large-scale analysis of 2.3 million Airbnb listings to understand the drivers of demand. Ke's results suggest that there is more information (besides reviews and ratings) that affect demand. Among such information, he identifies the 'instant booking" option and whether the seller is a superhost. Differently from previous work that focused on ratings and reviews, in this paper we study the effect of a listing cancellation policy on demand. We show that strict-policy listings enjoy an occupancy rate that is four percentage points higher than listings with more lenient policies.

This work is also related to the body of literature studying trust and reputation in online marketplaces. On peer-to-peer platforms such as Airbnb, information asymmetries between buyers and sellers are generally high. For example, on Airbnb, guests need to place their booking before they can personally verify the quality of the listing, or hosts need to trust strangers to behave and act properly when staying in their properties. To mitigate risks and reduce asymmetries, Airbnb incorporates an information-rich design to increase trust between prospective hosts and guests and to allow users to make informed decisions. For example, hosts can signal the quality of their properties through a variety of elements such as price, descriptions, identity verification, reviews and ratings, or guarantees (Basoglu and Hess 2014).

Past research has focused on studying whether these elements are indeed perceived as informative about the host and listing quality. Fradkin et al. (2017) show that ratings and reviews are informative about the hosts' and guests' quality while Teubner et al. (2014) show experimentally that user photos and avatars bear the potential to foster trust. Similarly, Fagerstrøm et al. (2017) find that negative and absent facial expressions of Airbnb host photos decrease guests' chances to rent out their listing. Finally, Ma et al. (2017) analyze hosts' self-description on their listing and profile pages and show that hosts affect their perceived trustworthiness. In this work, we contribute to this stream of literature by focusing on the role of the listing cancellation policy in signaling the listing quality and host trustworthiness. Our results provide evidence suggesting that a stricter cancellation policy increases Airbnb guests' perceived trust of the host and quality of the listing which, in turn, increases the listing demand.

Finally, this work relates to the literature studying the effect of cancellation policies on performance. Cancellation policies relate to a bundle of terms and conditions in which the consumer can forfeit the financial transaction with the seller. This typically includes the period in which such action is possible as well as any incurring fees or penalties (Wood 2001).

Early research mostly focused on physical product returns by consumers. Such research shows that a lenient product return policy might give a competitive advantage for the retailer or manufacturer (Padmanabhan and Png 1997), and it increases customers' likelihood of purchasing a product in the first place (Chu et al. 1998, Bechwati and Siegal 2005). However, a lenient policy can also lead to more product returns (Davis et al. 1998), and in some cases can lead to the "abuse" of the system and, therefore, to costs that outweigh its benefits (Rust et al. 1996).

Cancellation policies in the tourism industry are different from the ones of regular commerce because customers lack experiential-based information regarding the accommodation (Wood 2001). Therefore, to decrease perceived risks and increase consumers' booking intentions, firms often offer lenient cancellation policies (Schwartz 2008). Hotels traditionally combine these policies with a set of increasing penalties if the guests cancel closer to the check-in date, which helps hotels minimize revenue loss. For example, DeKay et al. (2004) show that the percentage of no-shows fell as much as 5% when such penalties are implemented. Research also suggests that offering a lenient cancellation policy helps stimulate consumers' booking intentions (Chen et al. 2011) while stricter policies or no-refund policies have a negative effect on consumer's patronage (Smith et al. 2015).

More directly related to our work, we find limited research on cancellation policies in the context of Airbnb. Recent research suggests that a flexible cancellation policy may be associated with lower prices. Benítez-Aurioles (2018) use data on Airbnb listings in Barcelona to show that listings with a flexible policy are associated with an average price that is 5.21% lower than an equivalent listing with a strict policy. Wang and Nicolau (2017) survey 33 cities worldwide and find that a non-flexible (moderate or strict) cancellation policy is associated with an increase of 4.58% in the price per night. In this work, we contribute to this literature and study the effect of cancellation policy on perceived quality and demand, an area of research that is currently not addressed.

3 Airbnb & Data

3.1 Airbnb

Airbnb, by most considered one of the pioneers of the sharing economy, is a peer-to-peer marketplace for short-term accommodation rentals. Airbnb hosts offer private or shared accommodation for rent to prospective guests. Hosts can decide when to list their property on the website by setting up a calendar provided by the platform. At any given time, a property listed on Airbnb can be available for rent, busy (i.e., booked or rented), or not available for rent (i.e., the calendar dates are blocked by the host and no guest can book the property). Further, hosts can decide whether to accept or reject a guest request, a feature of the platform that was recently the focus of a heated debate.[3]

To deal with cancellations on the demand side (guests), Airbnb provides its hosts with a set of cancellation policies among which they can choose. Such policies can be broadly classified into three categories: flexible, moderate, and strict. Under a strict policy, any guest cancellation incurs penalties.[4] Flexible and moderate policies are similar in nature, and allow the guests to receive a full refund under certain conditions.[5] The cancellation policy is clearly displayed on the listing's page so guests can take this information into account when they choose which listing to reserve.

3.2 Data

To study the effect of listings' cancellation policies on listings' demand, we use data collected from Airbnb. Specifically, we collected information about 238,218 properties listed on Airbnb in the United States covering 50 states and almost 9,000 cities and that were available on the platform during September 2015. For each listing, we observe whether the property is available for rent, busy, or not available for rent at the daily level for a period of 12 months, from September 2014 to August 2015. Given this information, we compute the monthly listing occupancy rate by computing the fraction of days the property was rented over the days that it was available for rent. Along with the demand information, we also obtained consumer-facing information at the monthly level. This information includes listing price and several listing attributes such as the listing type (private room or entire home/apartment), the number of photos associated with the listing, whether the host is a superhost, whether the

[3]See: `https://www.nytimes.com/2016/08/23/opinion/how-airbnb-can-fight-racial-discrimination.html`.

[4]The minimum penalty is 50% of the reservation price.

[5]A flexible policy will grant the guest a full refund up to one day prior to check-in while a moderate option will grant the guest full refund only up to 5 days prior to check-in.

host activated the Instant Book feature, and the cancellation policy of the listing (flexible, moderate, or strict).[6]

As we discussed above, flexible and moderate policies are similar in nature and allow for a refund, while the strict policy does not. Because of this, and to simplify our analysis and results interpretation, we made the decision to identify listings as having either strict policy or a non-strict policy (i.e., listings with a moderate or flexible policy).[7]

We also collected listing reviews and ratings. The purpose of collecting reviews is twofold. First, ratings can be used as a proxy for listing quality, a variable that we want to control for in our analysis. Second, we use reviews to identify hosts who cancel previously accepted guests reservations: If a host decides to cancel a guest reservation that was previously accepted, Airbnb posts an automated review on the host profile (see Figure 1) and blocks the date of the calendar corresponding to the reservation. This means that listing with many cancellations could potentially look booked often even if they are not. However, hosts tend not to cancel accepted reservations too often because cancellations result in penalties such as the loss of eligibility for superhost status or account suspension.[8]

Finally, we obtained host acceptance rate and response rates for 90% of the hosts in our dataset. The host acceptance rate measures the fraction of requests accepted out of the total number of requests received while the host response rate measures the fraction of guest requests that receive a response by the host.[9]

Descriptive statistics We aggregate the above information at the listing-month level to create a panel containing over 1.1M observations. Out of the 234,524 listings, 85,088 are private rooms and 150,436 entire home/apartments. At the beginning of our observation

[6]The superhost badge is assigned to hosts who satisfy certain quality requirements. For more information see: `https://www.airbnb.com/help/article/829/how-do-i-become-a-superhost`

[7]In Section 4.2, we show that our results hold even when we separately consider these three types of cancellation policies.

[8]For more information about Airbnb penalties related to cancellation of already accepted booking, see: `https://www.airbnb.com/help/article/990/i-m-a-host--what-penalties-apply-if-i-need-to-cancel-a-reservation`.

[9]A response is defined as a message written by the host to the guest, and a response does not imply the acceptance or denial of a request.

period, 142,231 (or about 61%) listings have employed a non-strict cancellation policy (88,855 employ a flexible cancellation policy and 53,376 a moderate one), and 92,293 (or about 39%) have employed a strict one. The average star-rating of all the listings in our dataset is 4.75; however, listings with a strict policy have slightly lower ratings than listings with a non-strict policy (4.72 vs 4.78). Finally, the average occupancy rate appears to be higher for listings with a non-strict policy than for listings with a strict policy. Of course, these numbers represent raw cross-sectional averages and are likely to be biased and may not represent the true relationship between a listing cancellation policy and its demand. Indeed, as we demonstrate in Section 4, after controlling for several factors affecting demand, we find the opposite relationship to hold true.

The listings in our dataset that change their policy during the observation period are 15,019; most of the listings (13,996 or about 93% of those listings that change policy) change policy only once. Moreover, among the listings that change policy only once, 90.3% change from a non-strict to a strict policy.

We report descriptive statistics of our dataset in Table 1 and Table 2.

4 Empirical strategy

4.1 Difference in Differences

To estimate the impact of listings cancellation policy on occupancy rate, we exploit the fact that, in our dataset, some hosts changed the cancellation policy of their listing.

We employ a Difference in Differences (DD) design that compares changes in the occupancy rate of listings that switched policy (treated) to changes in occupancy rates of listings that did not change the policy (controls) over the same period of time. In our main analysis, we limit our dataset to listings that did not change policy or changed policy once and that changed from a non-strict to a strict policy.[10] However, as we demonstrate in Appendix A, our results are robust to the inclusion of all listings.

One of the identifying assumptions that allows a causal interpretation of the DD estimates is that non-strict and strict policy listings' occupancy rates would have evolved in parallel in the absence of treatment (i.e., the change of cancellation policy). While this assumption is not fully testable, the panel nature of our data allows us to test for differences in occupancy rates between the treated and non-treated listings prior to treatment. To do so, we follow the approach used in papers such as Autor (2003), Proserpio and Zervas (2017), Gong et al. (2017), and Greenwood and Wattal (2015) and partition the time around the month each listing changed policy in monthly intervals, taking the offset of the month in which the listing changed cancellation policy to be 0. Then, for example, -1 is the month prior to the change in policy, 0 is the month corresponding to the change in policy, and 1 is the month after the month in which the policy was changed. We focus our trend analysis on four months before and four months after the change in policy, and estimate the following specification:

$$\text{Occupancy Rate}_{izt} = \beta \ \text{Interval}_{izt} + \text{X}_{izt}\gamma + \alpha_{iz} + \tau_{zt} + \epsilon_{izt}, \tag{1}$$

where the dependent variable is the occupancy rate of listing i in zipcode z at year-month t. Interval_{izt}, whose coefficient is of interest, is the set of monthly dummies we described above; its coefficient, β, measures the difference in occupancy rate between treated and control units at different time periods, before and after the change in policy. Additionally, we include in our specification listing fixed effects, α_{iz}, to control for time-invariant unobservables listing (and hosts) characteristics, and zipcode-year-month fixed effects, τ_{zt}, to control for unobserved zipcode-specific time-varying factors (e.g., seasonal variation in demand across different zipcodes). X_{izt} is a vector of time-varying controls in which we account for observable listing and host characteristics that can affect listings' demand while being correlated with the listings' cancellation policy. Among many others, we include variables

[10] Doing so, we removed 2,385 listings and 17,755 observations.

such as the listing price, its star-ratings, the number of photos posted, whether the listing is instant bookable, the number of beds, the person capacity (i.e., how many people are allowed to stay at the property), and how many guests are included with the price posted. X_{izt} also includes a control for competition through a measure of Airbnb supply (excluding the focal listing) at the zipcode level.

We estimate the model in Equation 1 using OLS and, to account for serial correlation in our dependent variable, we cluster errors at the listing level (Bertrand et al. 2004, Donald and Lang 2007). We choose to normalize the coefficient for the -1 interval to 0. Thus, the coefficients of the remaining intervals can be interpreted as differences between treated and controls listings' occupancy rate over time with respect to the interval -1 (our baseline). We present a graphical analysis of our estimates in Figure 2. The figure plots the estimated values of the interval coefficients β, together with their 95% confidence intervals. The figure suggests that in the pre-treatment period, treated and non-treated listings occupancy rates are equivalent as their difference in outcome is indistinguishable from zero. Moreover, the figure foreshadows our results as it shows that following the change in cancellation policy, there is a positive and significant difference in occupancy rates between treated and non-treated listings.

Having verified that pre-treatment trends are indeed equivalent, we proceed to implement and estimate our DD specification, which takes the following form:

$$\text{Occupancy Rate}_{izt} = \beta \text{ Is Strict}_{izt} + \mathrm{X}_{izt}\gamma + \alpha_{iz} + \tau_{zt} + \epsilon_{izt}, \tag{2}$$

where the dependent variable is the occupancy rate of listing i in zipcode z at year-month t. Strict_{izt}, whose coefficient is of interest, is an indicator of whether the cancellation policy of listing i in zipcode z at year-month t is set to strict. The rest of the variables are as per Equation 1.

We report the results of this specification in Table 3. In column 1, we present our simplest model, which includes solely the strict policy indicator. The estimate is positive and statistically significant ($p < 0.01$), and it suggests that switching to a strict cancellation policy increases the listings occupancy rate by about seven percentage points. In column 2 we incorporate the wide set of time-varying controls we discussed above. Our estimate remains positive and statistically significant and similar in magnitude to the previous one. Moreover, the controls exhibit coefficients consistent with our expectations and past literature: higher priced listings are booked less often; more photos, as well as higher ratings, are associated with higher demand.

4.2 DD robustness checks

Arguably, the key concern with our DD specification is selection into the treatment. Because the change in policy is a *choice* of the host, it is possible that the change in policy coincides with some unobservable change (to the researchers) about the listing or its host that positively affect the demand for the property. For example, suppose that the host's commitment to accept guests increases as he decides to change the listings cancellation policy (i.e., the host reject fewer requests), then our results would be positively biased.

In this section, we perform several exercises to rule out possible alternative explanations that could drive our results, in this way reinforcing the causal interpretation of our DD estimate.

Coarsened Exact Matching Recall that, roughly speaking, our DD identification compares a set of treated listings (those that change policy) with a set of untreated listings (those that do not change policy) before and after the treatment (the change in policy). A possible concern with this approach is that treated units are *different* from untreated units, and such differences drive our estimates. To reduce this concern, we combine DD with matching to further limit the potential for unobserved confounders biasing our estimates. Matching methods aim to reduce endogeneity concerns by ensuring comparability between treated and untreated units (Heckman and Navarro-Lozano 2004). Among several matching methods, in this paper, we opt for the Coarsened Exact Matching (CEM) procedure (Iacus et al. 2012) because it is intuitive and works well with categorical data (like most Airbnb listing and host characteristics). CEM works in the following way. First, it creates groups of Airbnb listings that are similar based on a set of observed characteristics chosen by the researchers. In our case, we use the room type (private room or entire apartment), the number of bedrooms, the listing's person capacity, the listing's city, whether the host is a superhost, the year in which the listing was created (to compare listings that have hosts with similar experience), the average number of days that the listing is available for rent in a month (to compare hosts that have similar commitment to rent), and whether the host owns more than one listing, a factor that generally distinguishes professional from more casual hosts.[11] Second, it discards groups that contain only treated or only untreated units. Third, observations in each group are weighted such that in each group treated and untreated observations are balanced.

We re-estimate the DD specification (Equation 2) on the subset of listings matched using CEM and applying the appropriate weights.[12] We report these results in Table 4. We find that, despite dropping a significant amount of observations, the coefficient of interest remains positive, statistically significant, and similar in magnitude to that presented in Table 3. This suggests that the effect of changes in cancellation policy on occupancy rate are robust to the use of CEM.

Stale vacancies A stale vacancy is an Airbnb listing that appears to be part of available supply only because the host neglected to update the availability status of that listing. By analyzing proprietary Airbnb data, Fradkin et al. (2017) find that that between 21% and 32% of guest requests are rejected due to this type of listing. Consistent with these findings,

[11]Some of the variables we use for matching are time varying (person capacity, superhost, and days available), so we take their average for every listing. Because treatment can affect the value of these variables, for treated listings we compute the average using the pretreatment period.

[12]CEM leaves us with 4,805 strata and 46,807 listings, out of which 6,669 are treated.

in our dataset, we find that 62,335 listings (28% of the total listings in our dataset) never had a booking during our observation period. If the likelihood of being a stale vacancy property is different between listings with a strict policy and listings with a non-strict cancellation policy, our results could be biased.

To deal with the above concern, we re-estimate our main specification using different subsets of listings that we consider *active* based on different definitions. Specifically, we check whether our results hold when we use subsets of listings: (1) which occupancy rate is greater than zero in at least a month during our observation period (this removes all stale vacancies); (2) which occupancy rate is greater than zero at least 50% of the months in which we observe the listings; (3) which occupancy rate is greater than zero in at least a month during our observation period, and treated units have occupancy rate greater than zero in any of the three months prior to the change in policy (essentially, we want to guarantee that treated units were active before the change in policy and did not decide to accept guests only after such change); (4) which occupancy rate is greater than zero in all the months in which we observe the listing.

We report the estimates using the above subsets of listings in Table 5. The coefficient of interest remains positive and significant across all specifications, suggesting that our results are robust to possible bias introduced by stale vacancies.

Changes in host behavior Another possible concern with our specification is that our results are partially driven by changes in the hosts' decision to rent. For example, suppose that a host decides to list his property on Airbnb, but then he never accepts any guest requests. However, at some point, he changes his mind and starts accepting guest requests; at the same time, he updates his Airbnb policy to be stricter. This type of behavior will introduce a positive bias in our results.

The tests we presented above partially deal with this concern in an indirect way, i.e., by considering only listings that are "active" depending on predefined criteria. In this section, we provide further evidence that changes in host behavior are not driving our results.

We cannot directly observe the host's willingness to accept bookings, but we do observe three quantities that can act as proxies to this behavior: (1) the host's acceptance rate, i.e., how many requests are accepted out of the total number of requests received; (2) the host's response rate, i.e., the fraction of guest requests that receive a response by the host; and (3) the number of days a listing is made available for rent on the platform.[13]

We re-estimate Equation 2 first by including as controls both the host acceptance rate and the host response rate, and second by limiting our sample to listing that were available for rent most of the time (i.e., the number of available days each month is greater than or equal to 28 days during our observation period). Note that by keeping the listing availability (almost) constant, this test eliminates the effect of listing availability on demand, if any.[14]

We report the results of these tests in Table 6. We observe that in both column 1 (where we include the two additional controls discussed above) and 2 (where we limit our dataset to listings with at least 28 days of availability per month), the coefficient of interest remains positive and statistically significant. These results suggest that changes in host behavior are not a factor driving our results.

From flexible to moderate to strict Until now, we have used as our main dependent variable an indicator for whether the cancellation policy adopted by the listing owner is non-flexible (i.e., moderate or strict). In this section, we explore whether the effect of adopting an increasingly stricter cancellation policy has an increasingly positive effect on demand. We

[13]Intuitively, a host that lists its property for more days each month is more likely to be willing to rent such a property.

[14]Note that we cannot simply control for listing availability because our dependent variable is computed using such quantity as a denominator.

do so by estimating the following specification:

$$\text{Occupancy Rate}_{izt} = \beta \text{ Policy}_{izt} + \text{X}_{izt}\gamma + \alpha_i z + \tau_z t + \epsilon_{izt}, \tag{3}$$

where Policy_{izt}, whose coefficient is of interest, is an indicator identifying each one of the three cancellation policies implemented by Airbnb (flexible, moderate, and strict). The rest of the variables are as per Equation 2. We report the results of this specification in Table 7. Using flexible policy as the reference category, we observe that the impact of the Airbnb cancellation policy on listings demand is increasing as the listings adopt stricter policies. That is, the stricter the policy adopted, the higher the demand for a listing. It is worth noting that these results reinforce the validity of our main estimates. If one wanted to argue that the effect we estimate is the result of spurious correlations, one would have to find a confounder correlated with the timing of the change in policy *and*, at the same time, that affects the demand of listings with a strict policy more than that of listings with a moderate policy.

5 Alternative specifications

As we discussed above, our DD specification is vulnerable to bias arising from changes in host behavior that may be correlated with the change in policy and demand. In this section, we present two alternative identification strategies that exploit the fact that about 30,000 (out of about 156,000) hosts in our dataset listed more than one listing on the Airbnb platform.

The first identification strategy relies on an instrumental variable approach. The second one relies on what we define as a multilisting-host DD, a strategy where we compare the occupancy rate of listings that switch policy, before and after the change of policy, with the occupancy rate of listings that did not switch policy and that belong to the *same* host.

5.1 Instrumental variable

For every listing, we assign an instrument that corresponds to the host $h(i)$'s' (the host of listing i) propensity to use a strict policy. For every listing i in zipcode z at time t, the instrument is defined as follows:

$$Z_{h(i)t} = \left(\frac{1}{n_{h(i)t} - 1}\right) \left(\sum_{k \neq i}^{n_{h(i)t}-1} S_{kt}\right), \tag{4}$$

where $n_{h(i)t}$ is the total number of observations for host h at time t. k indexes the host h listings, and S_{kt} is equal 1 if the host h set a strict policy for listing k at time t. Mathematically, the instrument is the equivalent of a "leave-out mean" of the propensity of host h to use a strict cancellation policy at time t. The resulting two-stage least squares estimator is a Jackknife Instrumental Variables Estimator (JIVE) (Angrist et al. 1999).

The identification assumptions fo this strategy are: (1) $Z_{h(i)t}$ affects the likelihood of the host h to use a strict cancellation policy for the focal listing l and (2) the exclusion restriction, i.e., $Z_{h(i)t}$ is uncorrelated with the error term. The first assumption is testable, and it is simply the first stage regression in a 2SLS regression. The second assumption, the exclusion restriction, is generally untestable. However, our instrument for observation izt is created excluding observation izt, which makes it unlikely for the instrument to be correlated with the error term. In other words, it is unlikely that the propensity of settings a strict policy for the host h other listings should affect the demand of the focal listing i.

We estimate Equation 2 using $Z_{h(i)t}$ as instrument for Is Strict$_{izt}$ using a 2SLS regression. We report the results of the first stage regression in Table 8. The results show that the host propensity to use a strict policy is highly predictive of whether host h uses a strict policy for the focal listing i at time t.

We then estimate the impact of setting a strict policy on demand. First, because we are using a subsample of hosts with multiple listings, we first report the OLS estimates in column 1 of Table 9; in line with previous results, we find that listings with a strict policy have a four percentage point higher occupancy rate. In column 2 of Table 9, we report the 2SLS estimates. The coefficient of interest is positive and significant, confirming our previous results.

5.2 Multilisting-host DD

As discussed above, this specification identifies the impact of changes to a strict cancellation policy on demand by comparing the occupancy rate of listings that belong to the same host. In doing so, we are able to effectively control for host unobservable characteristics that can affect listings demand.

To achieve this, first we limit our dataset to hosts with at least two listings that have a lenient cancellation policy (flexible or moderate) and where at least one listing switched policy (treated) and one listing did not (control). This leaves us with 5,617 listings, out of which 2,426 are treated.

We then estimate the following specification:

$$\begin{aligned} \text{Occupancy Rate}_{izht} &= \beta_1 \text{ Treated}_{izh} + \beta_2 \text{ Is Strict}_{izht} \times \text{Treated}_{izh} \\ &+ \text{Type}_{iz} + \text{X}_{izt}\gamma + \alpha_h + \tau_{zt} + \epsilon_{izht}, \end{aligned} \tag{5}$$

where Treated_{izh} is an indicator for whether the listing i of host h in zipcode z has ever changed policy. Is $\text{Strict}_{izht} \times \text{Treated}_{izh}$, whose coefficient is of interest, is the classical DD estimate, and it measures the impact of switching from a non-strict to a strict policy on demand. Further, we include α_h, the host fixed effect, and zipcode-year-month fixed effects, τ_{zt}. By including the host fixed effects, the effect of changes in cancellation policy is identified by variation in the difference in occupancy rate among listings belonging to the same host. Finally, besides including host and listing time-variant characteristics X_{izt}, we include Type_{iz}, an indicator of whether the listing is an entire apartment or a private/shared room.[15]

We report the estimates of this specification in Table 10. In column 1, we present the results without controls and in column 2 with controls including host acceptance and response rate. The coefficient of interest, $\text{Strict}_{izht} \times \text{Treated}_{izh}$, is positive and significant, suggesting that listings that change policy enjoy an increase in demand of about three percentage points.

Overall, the results presented in this section reinforce the causal interpretation of our main results (Table 3) and suggest that host behavior is not likely to be a driver of our results.

6 Field survey among Airbnb guests

In the previous sections, we showed that listings with a strict cancellation policy enjoy higher demand when compared to listings adopting a more lenient cancellation policy. In this section, we use an online survey that we administered to real Airbnb guests with a reservation for a trip not yet completed to shed light upon our findings' underlying mechanisms.

The goal of the online survey is to understand how Airbnb users perceive their choice of listing before actually experiencing the listing. To this end, we survey each user over a variety of aspects of the reservation including the reservation characteristics, customer characteristics, as well as their perception of the accommodation (e.g., clean, well equipped, etc.) and their perception of the host (e.g., trustworthy, responsive, etc.). We provide the full survey in Appendix B.

6.1 Method

Participants One hundred seventy-four participants (52.3% women; average age = 30.3 years, SD = 8.14) completed an online survey in return for $1 USD. We recruited MTurk

[15]In our main DD analysis, this variable is subsumed by the listing fixed effects.

participants that, at the time of the survey, had a reservation on Airbnb but had not completed the travel yet. In doing so, our goal was to have the users report their perceptions and evaluations about the reserved listing based only on the information presented by the Airbnb website, regardless of their actual experience.

Design and procedure We invited potential participants to take the survey only if they had a reservation for a future trip with Airbnb. To make sure that this was the case, in the first set of questions, participants were asked to provide information about their pending reservation. These questions included a request to report the reserved listing link.

Next, to further increase the reliability of participants' reports, we asked them to provide some information about their upcoming trip (dates of the trip, how long in advance they booked this reservation, how many nights they booked, and the trip's main purpose).

Following these questions, participants were asked to share some information about the technical aspects of the listing in their pending reservation. Specifically, we asked about the type of listing (shared room, private room, or entire home/apartment), the number of beds, and number of bathrooms. Next, we asked participants to provide information regarding the number of reviews and the average star-rating of the listing, the cancellation policy of the listing, and the total cost of the reservation. We subsequently collected information regarding participants' perceptions of their host and the listing reserved. Finally, we collected some information regarding participants' traveling habits (travel frequency, Airbnb usage) and a number of background questions including age, gender, and level of education. For the detailed questionnaire, we refer the reader to Appendix B.

Measures In our analysis, we divided the responses to our question into four groups: (A) customer characteristics (e.g., age, gender), (B) reservation characteristics (e.g., the purpose of the trip, number of nights booked), (C) listing characteristics (e.g., number of beds, number of reviews); and (D) customers' pre-experience perceptions and evaluation of the listing and its host. Similar to our empirical analysis, we compare responses for the reservation of a listing with a strict policy to that of a reservation with a non-strict policy (flexible or moderate). To do so, we use a χ^2 test for categorical variables and independent samples t-tests for continuous ones. In what follows, we elaborate on the items collected in each group:

(A) *Customer characteristics* Customer-specific characteristics include the following items: age, gender, frequency of travels, marital status, education as well as the extent to which they have canceled Airbnb past reservations.

(B) *Reservation characteristics* Reservation-specific characteristics include the following items: main purpose of the trip, how far in advance the trip was booked, the number of nights booked, and the total cost of the reservation.

(C) *Listing characteristics* Listing-specific characteristics include the following items: the number of beds, number of baths, whether the host has activated the instant-booking option, the cancellation policy, the number of reviews, and the average star-rating of the listing.

(D) *Listing Evaluation* Participants were asked to evaluate the accommodation reserved for their upcoming trip over five attributes, on a seven-point Likert scale (1 = strongly disagree to 7 = strongly agree). Such dimensions are: clean, well equipped, will look like in the picture, well maintained, and safe (in terms of personal security).

    Host Evaluation Participants were asked to evaluate the host of the listing reserved over four different attributes, on a seven-point Likert scale (1 = strongly disagree to 7 = strongly agree). The attributes are: trustworthy, committed to their guests, taking good care of their property, and responsive.

6.2 Results

Out of the one hundred seventy-four participants who took this survey, 33.3% reported their listing to have a flexible cancellation policy, 37.9% reported their listing to have a moderate cancellation policy, and the rest (28.7%) reported their listing to have a strict cancellation policy.

(A) *Customer characteristics* As expected, we observe that customers who reserved a listing with strict cancellation policy are not different from customers who reserved a listing with a non-strict cancellation policy. See Table 11 for the full comparisons of these variables.

(B) *Reservation characteristics* Reservations for listings with a strict cancellation policy are not different from those for a listing with a non-strict cancellation policy. See Table 12 for the full comparisons.

(C) *Listing characteristics* We find that listings with a strict cancellation policy are not different from listings with a non-strict cancellation policy. The only exception is the "type of listing" attribute. In this case, we find that the majority of listings with a strict cancellation policy are entire homes/apartments. This is not surprising given that in shared residencies the costs associated with cancellations are generally lower. See Table 13 for a full comparisons of these variables.

(D) *Listing perception* We find that, when compared to listings with a non-strict cancellation policy, listings with a strict cancellation policy are perceived as cleaner, better equipped, more likely to look like the website picture, better maintained, and safer. See Table 14 for a full comparisons of these variables.

Host perception We find that, when compared to listings with a non-strict cancellation policy, hosts of listings with a strict cancellation policy are perceived as taking better care of their property, more trustworthy, more responsive, and more committed to their guests. See Table 15 for a full comparisons of these variables.

Overall, the online survey results show that, while customer and reservation characteristics are similar across listings with different cancellation policies, listings with a strict cancellation policy are perceived to be of higher quality and their host to be more trustworthy than listings with a non-strict (flexible or moderate) cancellation policy.

These results help explaining the empirical findings discussed in Section 4: the cancellation policy of a listing can act as a signal of quality and, in turn, can increase the listing demand.

7 Discussion and conclusion

The academic and practitioner discussion on the sharing economy and its effects on consumers, markets, and cities is still in its infancy. Our study aims to improve the understanding of the relationship between sellers and buyers by focusing on the strategic decision of the cancellation policy and its effect on sellers' demand. By doing so, our research contributes to the study of consumption decisions in the sharing economy and the differences between consumer behavior in traditional economies (e.g., the hotel industries) and the sharing economy.

First, our analysis suggests that the cancellation policy of a listing has a measurable impact on the listing demand. However, contrary to expectations and previous findings in traditional industries, our results show that a stricter policy provides more benefits than a more lenient one. Specifically, we find that on Airbnb, choosing a strict cancellation policy results in an increase of about four percent in a listing's occupancy rate. We arrive at these results by using a DD strategy that exploits the fact that, in our dataset, some hosts start with a lenient cancellation policy but then switch to a strict one. Our results are reinforced by several robustness checks and the use of two alternative identification strategies that lead to the same conclusions.

Second, we conduct an online survey of real Airbnb guests to understand the mechanisms behind our findings. We find that the guests' perceptions of Airbnb listings and their hosts are different depending on the type of cancellation policy adopted: guests perceive listings with a stricter cancellation policy to be of higher quality and their host to be more trustworthy and committed to their guests. Because ratings and reviews are overwhelmingly positive on Airbnb (Zervas et al. 2015), guests are looking for other cues of commitment, quality, and trust. The cancellation policy seems to be one of them.

Overall, our results suggest that the cancellation policy of a service in the sharing economy affects the pre-consumption evaluation of the offering that, in turn, affects its demand. This effect carries some interesting implications. From the seller perspective, our research broadens the scope of factors that are believed to affect consumers' evaluations and decision making. The effect we demonstrate here shows that, contrary to one's expectations, not only does a stricter cancellation policy not deter consumers away from the product, but it serves as a signal of quality, thus attracting them.

Of course, this work does not come without limitations. In observational studies such as ours, the self-selection issue (in our case the host deciding to change their policy settings) is hard to resolve. To reduce endogeneity concerns, we implemented several robustness checks including matching and controlling for host behavior (both directly and indirectly). We also demonstrated that our results hold using different empirical strategies that rely on identification assumptions that are different from those of our main DD strategy. Further, we used an online survey of real Airbnb guests to show that a stricter cancellation policy serves as a signal for quality. This result helps explain why in our empirical analysis listings with a strict cancellation policy have a higher occupancy rate.

Despite our effort, there are alternative explanations that are hard to rule out. For example, we cannot guarantee that our results are not driven by the way in which Airbnb displays search results (e.g., Airbnb might prefer to show listings with a stricter policy because they bring in more revenue). However, a change in Airbnb cancellation policies aimed "to encourage more bookings–especially for more flexible listings" that occurred around 2017 suggests that this might not be the case.[16]

[16]See: `https://blog.atairbnb.com/guest-cancellation/`.

Our survey also has some limitations. Due to privacy concerns, we could not verify that all the participants did have a pending reservation. To mitigate this risk, we have designed our survey so that participants would have to provide the link to their reserved listing, including many verifiable details about the accommodation itself, in this way making participation quite costly for potential fake users.

Finally, in this work, we limit our investigation to the effect of cancellation policy on pre-consumption evaluations and decision making made by consumers. In future work, it may be interesting to explore whether cancellation policies have longer effects, for example by affecting consumers' post-consumption evaluations and behaviors (e.g., satisfaction, reviews, and ratings).

The sharing economy is changing the way in which consumers offer and consume products and services in many, often unexpected, ways. Trust and reputation are a fundamental part of these type of platforms. In this work, we provide evidence suggesting that even small settings such as the cancellation policy can affect the consumer perception of quality and, in turn, demand.

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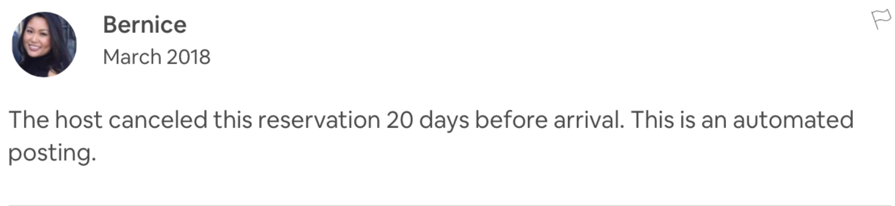

Figure 1: Automated review posted by Airbnb when a reservation is canceled by the host.

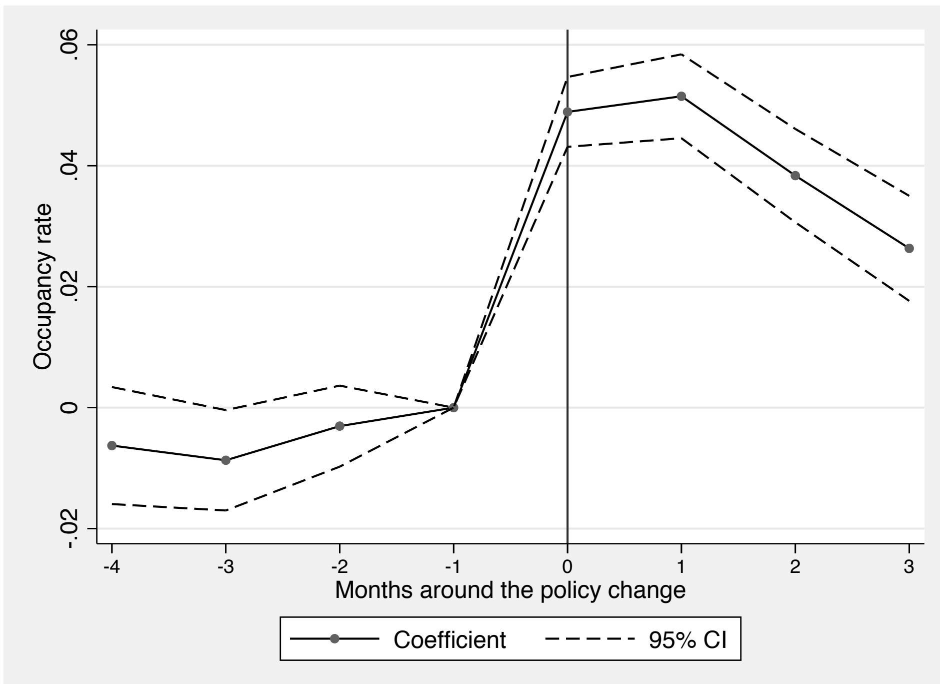

Figure 2: The evolution of treatment effects, i.e., differences in occupancy rate between non-flexible and flexible cancellation policy listings, as a function of a listings decision to change to a non-flexible policy. The solid line plots the β-coefficient estimates from Equation 1, and the dashed lines their respective 95% confidence intervals.

Table 1: Summary statistics

	All listings		Non-strict		Strict	
	Mean	SD	Mean	SD	Mean	SD
Occupancy Rate	0.32	0.36	0.33	0.36	0.31	0.36
Listing Price	205.89	551.24	165.94	572.37	253.34	521.07
Star-rating	4.75	0.33	4.78	0.32	4.72	0.35
Picture Count	16.33	12.06	13.88	10.65	19.25	12.94
Is Instant Bookable	0.11	0.30	0.10	0.29	0.12	0.32
# of Bedrooms	1.67	1.22	1.40	0.96	2.00	1.39
# of Beds	2.36	1.99	1.91	1.59	2.89	2.27
Person Capacity	4.28	2.99	3.48	2.41	5.23	3.31
Guests Included	1.81	1.73	1.56	1.28	2.11	2.10
Superhost	0.14	0.35	0.15	0.36	0.12	0.32
Host Cancellations	0.02	0.17	0.02	0.17	0.02	0.16
Airbnb Zipcode Supply	165.54	288.02	125.03	228.31	213.65	339.56
Host Acceptance Rate	80.84	26.72	81.72	27.51	79.83	25.76
Host Response Rate	92.75	13.13	92.69	13.61	92.83	12.58

Table 2: Number of changes in cancellation policy per listing

# of Changes in Policy	Listings	(Pct.)
1	13,996	(93.18)
2	896	(5.97)
3	113	(0.75)
4	12	(0.08)
5	2	(0.01)

This table reports the number of changes in policy from one policy to another. Out of the 13,996 listings whose policy was changed once, 12,634 (90.3%) were changed from a non-strict to a strict policy.

Table 3: The impact of flexible policy on listings' demand

	(1)	(2)
Is Strict	0.069***	0.043***
	(0.003)	(0.002)
log Listing Price		−0.152***
		(0.003)
log Photos Count		0.077***
		(0.002)
Instant Bookable		0.044***
		(0.002)
# of Beds		0.001
		(0.001)
Person Capacity		0.007***
		(0.001)
Guests Included		0.003***
		(0.001)
Superhost		0.007***
		(0.001)
log Host Cancellations		0.040***
		(0.003)
log Airbnb Zipcode Supply		0.375
		(4.153)
Has Star-rating		−0.060***
		(0.011)
Has Star-rating × Star-rating		0.036***
		(0.002)
N	1118852	1118852
R^2 within	0.0015	0.031

Note: The dependent variable is the occupancy rate of listing i at year-month t. All specifications include listing fixed effects and zipcode-year-month fixed effects. Cluster-robust standard errors (at the individual listing level) are shown in parentheses.

Significance levels: * p<0.1, ** p<0.05, *** p<0.01.

Table 4: DD robustness checks: coarsened exact matching

	(1)	(2)
Is Strict	0.085***	0.054***
	(0.004)	(0.004)
log Listing Price		−0.156***
		(0.007)
log Photos Count		0.096***
		(0.005)
Instant Bookable		0.060***
		(0.005)
# of Beds		−0.001
		(0.005)
Person Capacity		0.004
		(0.003)
Guests Included		0.005*
		(0.003)
Superhost		0.002
		(0.005)
log Host Cancellations		0.059***
		(0.006)
log Airbnb Zipcode Supply		0.261
		(4.669)
Has Star-rating		−0.042
		(0.026)
Has Star-rating × Star-rating		0.036***
		(0.006)
N	230887	230887
R^2 within	0.0052	0.044

Note: The dependent variable is the occupancy rate of listing i at year-month t. All specifications include listing fixed effects and zipcode-year-month fixed effects. Cluster-robust standard errors (at the individual listing level) are shown in parentheses.

Significance levels: * p<0.1, ** p<0.05, *** p<0.01.

Table 5: DD robustness checks: stale vacancies

	(1)	(2)	(3)	(4)
Is Strict	0.042***	0.039***	0.014***	0.019***
	(0.003)	(0.004)	(0.003)	(0.004)
log Listing Price	−0.178***	−0.102***	−0.179***	−0.118***
	(0.004)	(0.004)	(0.004)	(0.006)
log Photos Count	0.084***	0.043***	0.085***	0.079***
	(0.002)	(0.003)	(0.002)	(0.003)
Instant Bookable	0.046***	0.034***	0.046***	0.031***
	(0.002)	(0.003)	(0.002)	(0.003)
# of Beds	0.002	0.001	0.002	0.006*
	(0.001)	(0.002)	(0.001)	(0.003)
Person Capacity	0.007***	0.004***	0.007***	0.003
	(0.001)	(0.001)	(0.001)	(0.002)
Guests Included	0.003***	0.003***	0.003***	−0.000
	(0.001)	(0.001)	(0.001)	(0.002)
Superhost	0.005***	−0.003	0.006***	0.008***
	(0.001)	(0.003)	(0.001)	(0.002)
log Host Cancellations	0.038***	0.114***	0.036***	−0.006
	(0.003)	(0.007)	(0.003)	(0.004)
log Airbnb Zipcode Supply	0.490	0.133	0.491	0.272
	(7.262)	(8.522)	(7.312)	(3.720)
Has Star-rating	−0.072***	−0.096***	−0.071***	−0.023
	(0.011)	(0.025)	(0.011)	(0.016)
Has Star-rating × Star-rating	0.036***	0.033***	0.036***	0.034***
	(0.002)	(0.005)	(0.002)	(0.003)
N	948489	429374	928614	287656
R^2 within	0.031	0.015	0.030	0.047

Note: The dependent variable is the occupancy rate of listing i at year-month t. All specifications include listing fixed effects and zipcode-year-month fixed effects. Cluster-robust standard errors (at the individual listing level) are shown in parentheses.

In column 1, we report the results for a subset of listings whose occupancy rate is greater than zero in at least a month during our observation period; in column 2, we report the results for a subset of listings whose occupancy rate is greater than zero at least 50% of the months in which we observe the listings; in column 3, we report the results for a subset of listings whose occupancy rate is greater than zero in at least a month during our observation period, and treated units have occupancy rate greater than zero in any of the three months prior to the change in policy; in column 4, we report the results for a subset of listings whose occupancy rate is greater than zero in all the months in which we observe the listing.

Significance levels: * p<0.1, ** p<0.05, *** p<0.01.

Table 6: DD robustness checks: host behavior

	(1)	(2)
Is Strict	0.034***	0.038***
	(0.003)	(0.004)
log Listing Price	−0.161***	−0.121***
	(0.003)	(0.004)
log Photos Count	0.068***	0.067***
	(0.002)	(0.003)
Instant Bookable	0.037***	0.037***
	(0.002)	(0.003)
# of Beds	0.002	0.001
	(0.001)	(0.002)
Person Capacity	0.007***	0.007***
	(0.001)	(0.001)
Guests Included	0.002**	0.002
	(0.001)	(0.001)
Superhost	0.005***	0.001
	(0.001)	(0.002)
log Host Cancellations	0.033***	0.014***
	(0.003)	(0.004)
log Airbnb Zipcode Supply	0.216	0.366
	(4.007)	(1.128)
Has Star-rating	−0.060***	−0.055***
	(0.011)	(0.016)
Has Star-rating × Star-rating	0.031***	0.027***
	(0.002)	(0.003)
log Acceptance Rate	0.027***	0.017***
	(0.000)	(0.001)
log Response Rate	0.084***	0.069***
	(0.003)	(0.004)
N	988485	413264
R^2 within	0.033	0.026

Note: The dependent variable is the occupancy rate of listing i at year-month t. All specifications include listing fixed effects and zipcode-year-month fixed effects. Cluster-robust standard errors (at the individual listing level) are shown in parentheses. In column 1, we control for both the host acceptance rate and the host response rate, and in column 2 we limit our sample to listing that were available for rent most of the time, i.e., the number of available days each month is greater than or equal to 28 days during our observation period.

Significance levels: * p<0.1, ** p<0.05, *** p<0.01.

Table 7: DD robustness checks: 3-levels policy indicator

	(1)	(2)
Base level: Flexible		
Moderate	0.072***	0.045***
	(0.003)	(0.002)
Strict	0.106***	0.067***
	(0.003)	(0.003)
log Listing Price		−0.152***
		(0.003)
log Photos Count		0.075***
		(0.002)
Instant Bookable		0.044***
		(0.002)
# of Beds		0.001
		(0.001)
Person Capacity		0.007***
		(0.001)
Guests Included		0.002***
		(0.001)
Superhost		0.007***
		(0.001)
log Host Cancellations		0.039***
		(0.003)
log Airbnb Zipcode Supply		0.374
		(4.163)
Has Star-rating		−0.061***
		(0.011)
Has Star-rating × Star-rating		0.036***
		(0.002)
N	1118852	1118852
R^2 within	0.0032	0.032

Note: The dependent variable is the occupancy rate of listing i at year-month t. All specifications include listing fixed effects and zipcode-year-month fixed effects. Cluster-robust standard errors (at the individual listing level) are shown in parentheses.

Significance levels: * p<0.1, ** p<0.05, *** p<0.01.

Table 8: Alternative identification strategy: IV First stage

	(1)
$Z_{h(i)t}$	0.375***
	(0.008)
log Listing Price	−0.009***
	(0.002)
log Photos Count	0.036***
	(0.003)
Instant Bookable	0.004**
	(0.002)
# of Beds	0.003*
	(0.002)
Person Capacity	0.004***
	(0.001)
Guests Included	0.008***
	(0.001)
Superhost	0.006***
	(0.002)
log Host Cancellations	0.004
	(0.002)
log Airbnb Zipcode Supply	−0.004
	(0.793)
Has Star-rating	0.046***
	(0.011)
Has Star-rating × Star-rating	−0.005**
	(0.002)
N	487631
R^2 within	0.13

Note: The dependent variable is an idicator of whether listing i at year-month t is using a strict cancellation policy. All specifications include listing fixed effects and zipcode-year-month fixed effects. Cluster-robust standard errors (at the individual listing level) are shown in parentheses.

Significance levels: * p<0.1, ** p<0.05, *** p<0.01.

Table 9: Alternative identification strategy: IV

	OLS	2SLS
Is Strict	0.038***	0.050***
	(0.004)	(0.011)
log Listing Price	−0.134***	−0.134***
	(0.004)	(0.004)
log Photos Count	0.066***	0.066***
	(0.003)	(0.003)
Instant Bookable	0.035***	0.035***
	(0.003)	(0.003)
# of Beds	0.002	0.002
	(0.002)	(0.002)
Person Capacity	0.004**	0.003**
	(0.001)	(0.001)
Guests Included	0.004***	0.004***
	(0.001)	(0.001)
Superhost	0.006***	0.006***
	(0.002)	(0.002)
log Host Cancellations	0.038***	0.038***
	(0.004)	(0.004)
log Airbnb Zipcode Supply	−0.231	−0.231
	(1.362)	(1.363)
Has Star-rating	−0.029*	−0.030*
	(0.016)	(0.016)
Has Star-rating × Star-rating	0.026***	0.026***
	(0.003)	(0.003)
N	487631	487631
R^2 within	0.024	0.024

Note: The dependent variable is the occupancy rate of listing i at year-month t. All specifications include listing fixed effects and zipcode-year-month fixed effects. Cluster-robust standard errors (at the individual listing level) are shown in parentheses.

Significance levels: * p<0.1, ** p<0.05, *** p<0.01.

Table 10: Alternative identification strategy: multilisting-host DD

	(1)	(2)
Is Strict × Treated	0.056***	0.028***
	(0.007)	(0.007)
Treated	0.028***	0.031***
	(0.007)	(0.007)
log Listing Price		−0.130***
		(0.010)
log Photos Count		0.035***
		(0.006)
Instant Bookable		0.047***
		(0.011)
# of Beds		0.004
		(0.003)
Person Capacity		0.004
		(0.002)
Guests Included		0.005**
		(0.002)
Superhost		0.011
		(0.015)
log Cancellations		0.074***
		(0.017)
log Airbnb Zipcode Supply		−0.397**
		(0.182)
Has Star-rating		0.123**
		(0.048)
Has Star-rating × Star-rating		0.003
		(0.010)
Private room		−0.100***
		(0.011)
log Acceptance Rate		0.026***
		(0.006)
log Response Rate		0.104***
		(0.026)
N	27437	26866
R^2 within	0.016	0.11

Note: The dependent variable is the occupancy rate of listing i at year-month t. All specifications include host fixed effects and zipcode-year-month fixed effects. Cluster-robust standard errors (at the individual listing level) are shown in parentheses.

Significance levels: * p<0.1, ** p<0.05, *** p<0.01.

Table 11: Customer characteristics: strict vs. non-strict cancellation policy

Variable	Strict		Non-Strict		t-value/
	Mean	SD	Mean	SD	χ^2
Age	31.88	10.03	29.63	7.19	$t(70.16) = -1.44$ ($p = 0.15$)
Gender					$\chi^2(1) = 0.28$ ($p = 0.60$)
Male	0.44		0.48		
Female	0.56		0.52		
Travel frequency					$\chi^2(5) = 2.87$ ($p = 0.72$)
Monthly	0.10		0.17		
Six time/year	0.16		0.19		
Four times/year	0.36		0.26		
Twice a year	0.26		0.25		
Once a year	0.08		0.10		
Less than once year	0.04		0.03		
Airbnb use (# of times)	4.04	2.99	3.87	2.87	$t(172) = -0.35$ ($p = 0.73$)
Marital status					$\chi^2(3) = 0.29$ ($p = 0.96$)
Single	0.50		0.48		
Married	0.42		0.46		
Divorced	0.04		0.03		
Other	0.04		0.03		
Education					$\chi^2(5) = 4.84$ ($p = 0.43$)
Less than 8 years	0.00		0.02		
8-12 years	0.12		0.12		
Bachelors level degree	0.58		0.62		
Masters level degree	0.24		0.18		
Doctorate level degree	0.02		0.05		
Other	0.04		0.01		
Past cancellations	1.42	0.86	1.37	0.69	$t(75.93) = -0.36$ ($p = 0.72$)

Table 12: Reservation characteristics: strict vs. non-strict cancellation policy

Variable	Strict		Non-Strict		t-value/
	Mean	SD	Mean	SD	χ^2
Travel Purpose					
Business	0.16		0.12		$\chi^2(1) = 0.47(p = 0.49)$
Pleasure	0.76		0.83		$\chi^2(1) = 1.16(p = 0.28)$
Family	0.18		0.19		$\chi^2(1) = 0.04(p = 0.84)$
How long in advance have you booked?					$\chi^2(7) = 12.09(p = 0.10)$
Less than a month	0.08		0.16		
Approximately one months	0.18		0.19		
Approximately two months	0.20		0.29		
Approximately three months	0.22		0.13		
Approximately four months	0.18		0.07		
Approximately five months	0.02		0.06		
Approximately six months	0.04		0.07		
More than six months	0.08		0.03		
Number of nights	4.40	3.65	3.89	2.62	$t(70.28) = -0.90(p = 0.37)$
Total trip cost ($)	685.45	1,179.95	646.85	1,387.05	$t(172) = -0.17(p = 0.86)$

Table 13: Listing characteristics: strict vs. non-strict cancellation policy

Variable	Strict		Non-Strict		t-value/
	Mean	SD	Mean	SD	χ^2
Number of Beds	2.12	1.38	2.11	1.36	$t(172) = -0.03(p = 0.97)$
Number of Baths	1.26	0.56	1.31	0.53	$t(172) = 0.51(p = 0.61)$
Instant bookable	0.32		0.47		$\chi^2(1) = 3.18(p = 0.07)$
Number of reviews	81.44	85.32	109.10	459.57	$t(172) = 0.42(p = 0.67)$
Star-rating	4.39	1.37	4.39	1.24	$t(172) = -0.006(p = 0.99)$
Listing type					$\chi^2(2) = 14.31(p = 0.001)$
Shared room	0.00		0.13		
Private room	0.18		0.34		
Entire home/apt	0.82		0.53		

Table 14: Accommodation perception: strict vs. non-strict cancellation policy

Variable	Strict		Non-Strict		t-value
	Mean	SD	Mean	SD	
Clean	6.42	0.70	5.94	1.19	$t(148.18) = -3.27$ ($p = 0.001$)
Well equipped	6.26	0.83	5.78	1.31	$t(140.69) = -2.88$ ($p = 0.005$)
Will look like in the picture	6.22	0.79	5.82	1.37	$t(151.57) = -2.39$ ($p = 0.02$)
Well maintained	6.32	0.74	5.85	1.29	$t(151.93) = -2.98$ ($p = 0.003$)
Safe (in terms of personal security)	6.42	0.70	5.92	1.26	$t(154.79) = -3.33$ ($p = 0.001$)

Table 15: Host perception: strict vs. non-strict cancellation policy

Variable	Strict		Non-Strict		t-value
	Mean	SD	Mean	SD	
Trustworthy	6.10	1.01	5.72	1.29	$t(114.40) = -2.07$ ($p = .041$)
Responsive	6.34	0.85	6.02	1.12	$t(119.04) = -2.02$ ($p = .05$)
Committed to their guests	6.24	0.92	5.76	1.42	$t(172) = -2.22$ ($p = .01$)
Taking good care of their property	6.30	0.79	5.88	1.29	$t(172) = -2.16$ ($p = .01$)

Online appendix

A Main results including all the listings in our dataset

Table 16: The impact of flexible policy on listings' demand

	(1)	(2)
Is Strict	0.052***	0.032***
	(0.002)	(0.002)
log Listing Price		−0.152***
		(0.003)
log Photos Count		0.078***
		(0.002)
Instant Bookable		0.045***
		(0.002)
# of Beds		0.001
		(0.001)
Person Capacity		0.007***
		(0.001)
Guests Included		0.003***
		(0.001)
Superhost		0.007***
		(0.001)
log Host Cancellations		0.039***
		(0.003)
log Airbnb Zipcode Supply		0.373
		(4.166)
Has Star-rating		−0.062***
		(0.011)
Has Star-rating × Star-rating		0.037***
		(0.002)
N	1136560	1136560
R^2 within	0.0011	0.031

Note: The dependent variable is the occupancy rate of listing i at year-month t. All specifications include listing fixed effects and zipcode-year-month fixed effects. Cluster-robust standard errors (at the individual listing level) are shown in parentheses.

Significance levels: * p<0.1, ** p<0.05, *** p<0.01.

B Survey

In what follows we present the questionnaire pages that participants saw during the survey. For clarity of presentation, the text below includes a title for each page. In the experiment participants did not see these titles.

Page 1: filtering questions

Do you have a pending reservation for a future listing on Airbnb? Yes/No

Page 2: Instructions

This is a short survey about Airbnb users' experience and opinions. There are no correct or incorrect answers. We are only interested in your opinion.
Please complete the survey in one go without any breaks in between.
Please answer this survey using a desktop or laptop computers only.
In this survey you will need to provide anonymized information about your Airbnb past and future reservations. Before you start answering the survey, please refer to: https://www.airbnb.com/trips and login to your account.
Note: Low quality survey will not be paid.

Page 3: Upcoming trip information (1/3)

Please refer to: *https://www.airbnb.com/trips* and open the latest listing you booked which is presented under "Upcoming Trips". The following questions refer to this listing:

Please paste bellow the link to the listing on Airbnb:

Please note, we are not interested in your private reservation but only in the general page of the reserved accommodation on Airbnb.

When is your trip planned for:

- April 2018
- May 2018
- June 2018
- July 2018
- Later (please specify the month): __________

How long in advance have you booked:

- Less than a month in advance
- Approximately one month in advance
- Approximately two months in advance
- Approximately three months in advance
- Approximately four months in advance
- Approximately five months in advance
- Approximately six months in advance
- More than 6 months in advance

Page 4: Upcoming trip information (Cont. 2/3)

How many nights have you booked this reservation for?

- 1
- 2
- 3
- 4
- 5
- 6
- 7
- 8
- 9
- 10
- 11
- 12
- 13
- 14
- More than 14 nights

What is the main purpose of this trip? Please choose all the relevant options

- Business
- Pleasure
- Family
- Other: _______________ (please specify)

Please share which city are you travelling to:

____

This listing is –

- A shared room
- An private room
- An entire apartment

How many beds does the listing offer?

- One bed
- Two beds
- Three beds
- Four beds

- Five beds
- Six beds
- More than six beds

How many baths does the listing offer?

- One bath
- Two baths
- More than two baths

Page 5: Upcoming trip information (Cont. 3/3)

How many reviews does the listing currently have? _______

What is the average star rating? _______

What is the cancellation policy of this listing?

- Flexible
- Moderate
- Strict

Please enter the total cost of your reservation (in US$). _______

When you recall the reservation process – which of the following options apply?

- You had to wait for the host's approval
- The listing was instantly booked

Page 6: Host Evaluation

When you think about your future host for this trip, please assess the extent to which she or he is:

	Strongly disagree 1	2	3	4	5	6	Strongly agree 7
Trustworthy (1)	○	○	○	○	○	○	○
Responsive (2)	○	○	○	○	○	○	○
Committed to their guests (3)	○	○	○	○	○	○	○
Taking good care of their property (4)	○	○	○	○	○	○	○

Page 7: Accommodation Evaluation

When you think about your future accommodation, please assess the extent to which it is:

	Strongly disagree 1	2	3	4	5	6	Strongly agree 7
Clean (1)	○	○	○	○	○	○	○
Well equipped (2)	○	○	○	○	○	○	○
Will look like in the picture (3)	○	○	○	○	○	○	○
Well maintained (4)	○	○	○	○	○	○	○
Safe (in terms of personal security) (5)	○	○	○	○	○	○	○

Page 8: Cancelation option

At this point in time - how likely are you to cancel this reservation?

Extremely unlikely 1	2	3	4	5	6	Extremely likely 7
○	○	○	○	○	○	○

Page 9: Traveling preferences (1/2)

The following questions refer to you and your travelling preferences:

How often do you travel (for work or tourism purposes)?

- Monthly
- 6 times a year
- 4 times a year
- Twice a year
- Once a year
- Less than once a year

How many times did you use Airbnb in the past to book rooms or apartments?

- Once
- Twice
- Three times
- Four times
- Five times
- Six times
- Seven times
- Eight times
- Nine times
- Ten times
- More than ten times

Have you ever cancelled a reservation you made in Airbnb?

- No, never
- Yes, I cancelled once
- Yes, I cancelled twice
- Yes, I cancelled three to four times
- Yes, I cancelled more than four times

Page 10: Demographics:

Participants were asked to enter their age, gender, level of education, marital status, and English proficiency.